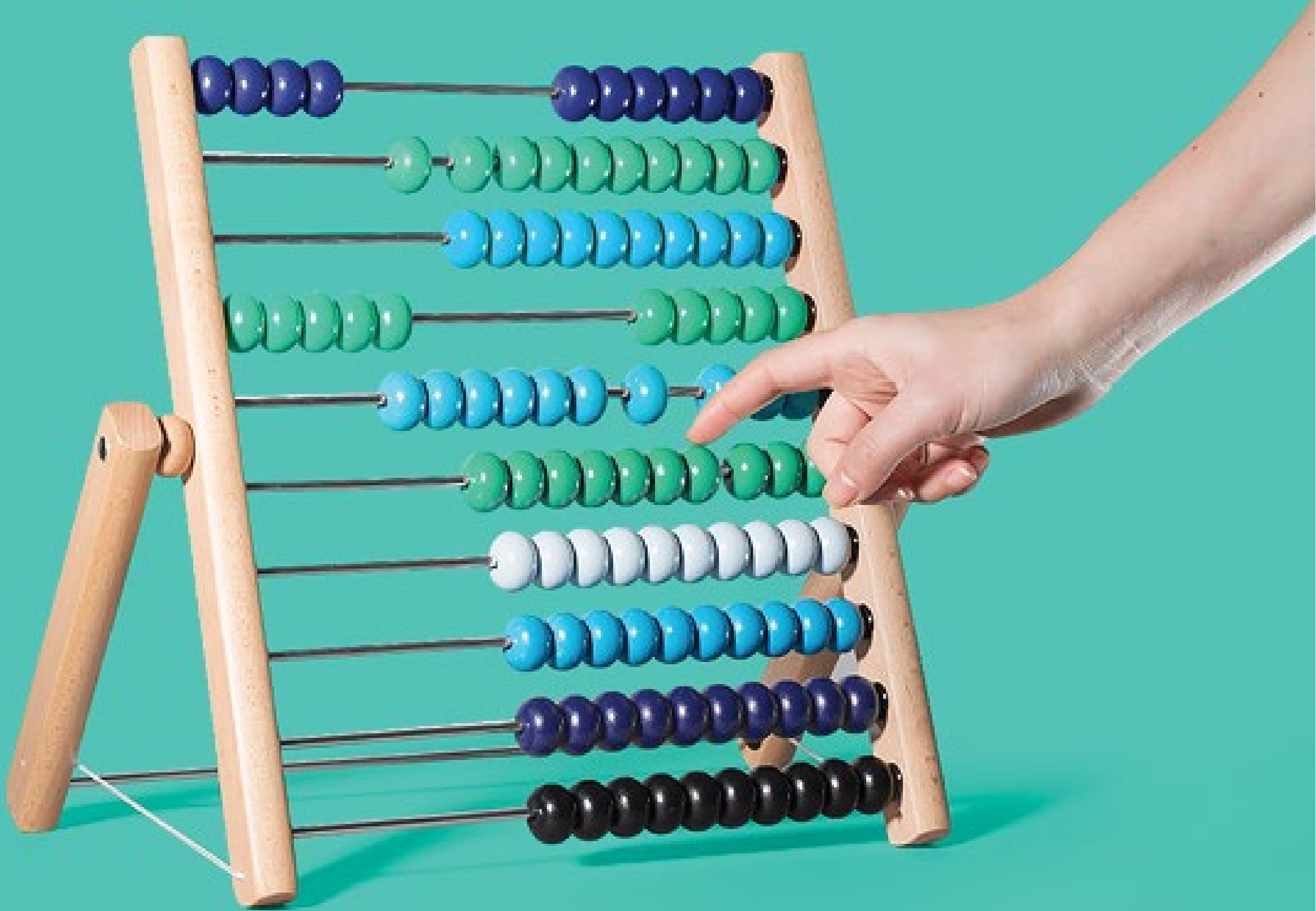
Decarbonisation Strategy

Annex B: Northern Carbon Model (NoCarb) Development Report



TRANSPORT FOR THE NORTH

Document details

Document history

Version	Issue date	Description of changes
1.0	13/04/21	

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1 Glossary

Term	Description
Analytical Framework	Transport for the North’s set of modelling tools
Chainage	Vehicle kilometres travelled
Cohort	Vehicle registration year
CYA	Completed year average (vehicle age in years)
Decarbonisation trajectory	TfN’s emissions trajectory for the North, which represents emissions targets over milestone years.
DfT	Department for Transport
LAD	Local Authority District
MSOA	Middle layer Super Output Area: Macro level ONS zoning system from 2011 census
NAEI	National Atmospheric Emissions Inventory
NELUM	Northern Economy and Land Use model
NoCarb	TfN’s Northern Carbon Modelling Tool
NoHAM	TfN’s Northern Highway Assignment Model
RWC	Real-world correction factors
Scenario years	Milestone years in TfN’s Future Travel Scenario planning (2018, 2020, 2025, 2030, 2035, 2040, 2045 and 2050).
TfN	Transport for the North
Zone	A spatial unit used for aggregating data in a model. NoCarb has zoning that can be flexibly adjusted so long as the zoning system is based on Middle-layer Super Output Areas.

2 Introduction

This report outlines the development methodology for TfN's NoCarb Tool: 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. As part of TfN's Analytical Framework[1], the NoCarb Tool provides essential evidence for TfN's Decarbonisation Pathways, which are intended to show what policies and measures are likely to be required to meet decarbonisation targets (as outlined in TfN's Decarbonisation Strategy). This report also covers technical detail on how NoCarb was applied to inform the Decarbonisation Strategy.

The NoCarb tool takes in four groups of inputs:

- Demand data
- Emissions data
- Vehicle registration data
- Future policy inputs

For cars, vans and HGVs, the model produces emissions estimates disaggregated by year, zone and vehicle attributes. Bus and rail emissions estimates are pan-Northern and only broken down by year. For bus, this aggregate approach is due to a lack of detailed data and modelling tools available at a regional level. For rail, the approach is due to the difficulty attributing vehicle movements and emissions to origin zones.

[1] The Transport for the North (TfN) Analytical Framework is a set of modelling tools, which are used to generate the evidence and insight that underpins TfN's Strategic Transport Plan, Investment Programme and business cases. The job of Analytical Framework is to show how patterns of travel might change in future due to both external factors and the planned improvements that TfN is developing.

3 Background

3.1 TfN’s Analytical Framework

This section outlines some of the key components of TfN’s Analytical Framework modelling suite and provides context about NoCarb as a component within the framework.

The Analytical Framework aims to provide a common approach to data, modelling and appraisal across all regions of the North. It provides the basis to generate evidence to support TfN programme activities.

Consistency across the North requires consistent data, as well as a consistent approach to modelling. The Analytical Framework therefore focuses on maintained datasets that are available for the entire North and, as much as possible, mainland Great Britain.

The first tier of the Analytical Framework modelling system, the Northern Economy and Land Use Model (NELUM),[2] is the key future-year travel scenario exploration tool and is used to generate future travel markets for different land-use scenarios. NELUM is also used as a Land-Use Transport Interaction model, to assess the impact of transport improvements on the location of households and businesses.

The second tier of the Analytical Framework incorporates the Northern Transport Modelling System (NorTMS), which includes the Northern Rail Modelling System (NoRMS) and the Northern Highway Assignment Model (NoHAM). NoRMS focuses on modelling pan-northern rail passenger movements as well as more strategic modelling of longer distance passenger movements. NoHAM is a highway assignment model, covering passenger and freight road vehicles. For freight multi-modal modelling, the Analytical Framework focuses on using the Great Britain Freight Model (GBFM), as updated for the new National Transport Model (NTMv5).

NELUM produces both baseline and future demand estimates that can be fed into NoCarb, with future estimates based on TfN’s four Future Travel Scenarios (see Figure 1). NoHAM also produces baseline demand outputs that can be fed into NoCarb, allowing emissions to be estimated on all roads, or exclusively on the Major or Strategic Road Networks within TfN’s boundary. The functionality to use NoCarb with NoHAM is being finalised and will be applied in business year 2021/22 as part of TfN’s Investment Programme work.

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[2] A detailed overview of how NELUM works can be found here: https://transportforthenorth.com/wp-content/uploads/Future-Travel-Scenarios-Future-Transport-Measures-Solution-Annex.pdf

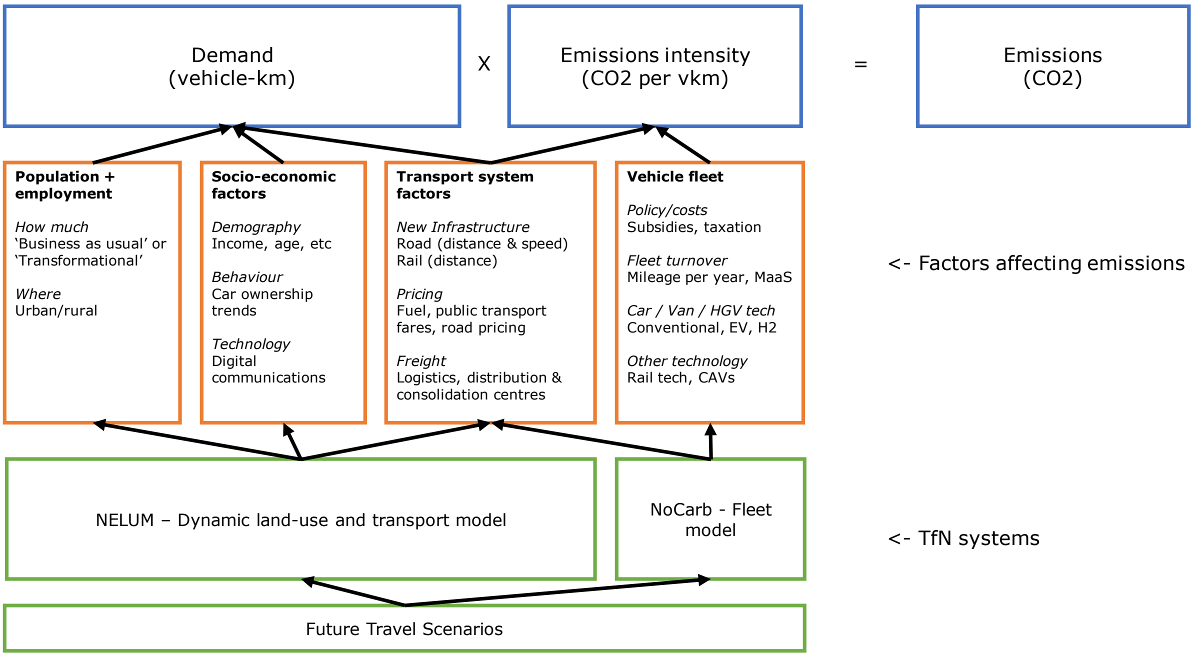


Figure 1: Using the Analytical Framework to model carbon emissions – a visual representation of how the Northern Economy and Land Use Model (NELUM) and Future Travel Scenarios interact with NoCarb to produce emission estimates.

3.2 Future Travel Scenarios

TfN's Future Travel Scenarios[3] explore how trends in society, the economy and national policy could influence the level and distribution of travel demand in the future. By using a series of different Future Travel Scenarios, we aim to future-proof our decision-making as much as possible, making it resilient to wide-ranging and cross-sector uncertainties.

The Future Travel Scenarios represent factors[4] that are external to TfN's direct control, acting as 'reference cases' to test the performance of TfN strategies and policies against objectives. In each scenario, the level of national government ambition and support for decarbonisation in the North is different, as is the level and distribution of travel demand.[5]

As mentioned in the previous section, the factors making up each Future Travel Scenario are fed into NELUM, which in turn estimates demand across future years.

Assessing the decarbonisation 'policy gap' – that is, the gap between each Future Travel Scenario's emissions trajectory and TfN's decarbonisation

[3] TfN's Future Travel Scenarios Report provides a comprehensive overview of the process undertaken to develop the new Future Travel Scenarios. It also delves into the contextual factors underlying each scenario and the expected implications on transport.

[4] A list of travel-related development policies and measures under each Future Travel Scenario can be found in the Future Transport Measures and Solutions Annex.

[5] Key national policy changes up to December 2020 are reflected within the Scenarios.

trajectory - will allow TfN to develop a resilient Decarbonisation Strategy that can adapt to different future circumstances. The policies and measures that are likely to bridge this policy gap are captured in TfN's Decarbonisation Pathways, which address the different levels of additional action required under each of TfN's four Future Travel Scenarios, recognising that the same action applied in different scenarios will result in different levels of efficacy in terms of the emissions reductions required.

The Future Travel Scenarios were developed in collaboration with Local Authority partners, national delivery partners and academic experts and informed by local strategies and priorities. The scenarios represent uncertainty across the following five external factors:

1. Growth in the population and economy;
2. Spatial planning policy and economic distribution;
3. National policy on environment and sustainability;
4. Technological change and advancement; and
5. Social and behavioural change.

The key elements of the scenarios can be summarised using the following set of 'what if' questions:

- **Scenario 1: Just About Managing** - What if society keeps developing broadly following existing trends? What if there is a gradual shift in lifestyles and travel, public and political behaviours do not alter, and we don't give up certain 'luxuries', leaving major developments and change to be shaped by market forces.
- **Scenario 2: Prioritised Places** – What if society becomes focused on quality of life, place-making and community, rather than primarily economic growth? This scenario is led by a change in priorities, with its biggest driver being the push for a fairer redistribution of economic prosperity.
- **Scenario 3: Digitally Distributed** – What if Northern Powerhouse ambitions[6] are realised by using technology solutions to create connections and agglomeration across towns and cities? This scenario is led by technology and some policy influence, as we fully embrace technological change, work remotely, and use an accessible service-based transport system with connected and autonomous shared mobility options.
- **Scenario 4: Urban Zero Carbon** – What if society achieves Northern Powerhouse ambitions by using policy interventions to maximise energy efficient city growth and urban densification? This scenario is led by public and political attitudes to climate action and urban place-making, with the biggest drivers being strong Government policy, resulting in fast action on

[6] As set out in the Northern Powerhouse Independent Economic Review.

zero-emission transport systems and places, with integrated planning across energy, spatial and other sectors.

3.3 Model geography

The NoCarb model produces emissions estimates for travel that takes place within TfN's boundary (the North). This can include trips that began or ended outside of the North, but only relates to the 'Northern' section of that trip.

NoCarb's zoning can be varied depending on the zoning of the input transport demand, although the most granular zoning that can be used is the Office of National Statistics' Middle-layer Super Output Areas (MSOAs), which typically have a population of around 10,000 people. For the Decarbonisation Strategy analysis, transport demand has come from TfN's NELUM model, which has zones that are a one-to-many aggregation of MSOAs. In city centres NELUM zones are MSOA level, but outside of city centres Local Authority Districts are used.

4 Model process flow and inputs

Figure 2 shows a process flow map summarising the functions and flow of data within NoCarb. The main inputs are represented as parallelograms, non-bold squares as pre-processed inputs and bold squares as model functions.

The grey square on the left encompasses baseline inputs and functions, which prepare the baseline fleet, scrappage curves and speed-emissions curves. The Fleet Projection Tool (blue box) projects the baseline fleet into future years using the scrappage curves and scenario inputs, such as segment and fuel sales and fleet growth. Alongside these scenario inputs sit the demand inputs, which are called in to the model and distributed across the fleet using ANPR data and observed fleet distributions. Once this is complete, the Greenhouse Gas (GHG) Tool takes in the baseline and future fleets, emissions and demand inputs, and scenario-based demand and CO2 reductions to calculate emissions for a given fleet in a given year within each NELUM zone. In addition, the GHG Tool calculates pan-Northern bus and rail emissions by applying scenario-based CO2 reduction factors to baseline inputs.

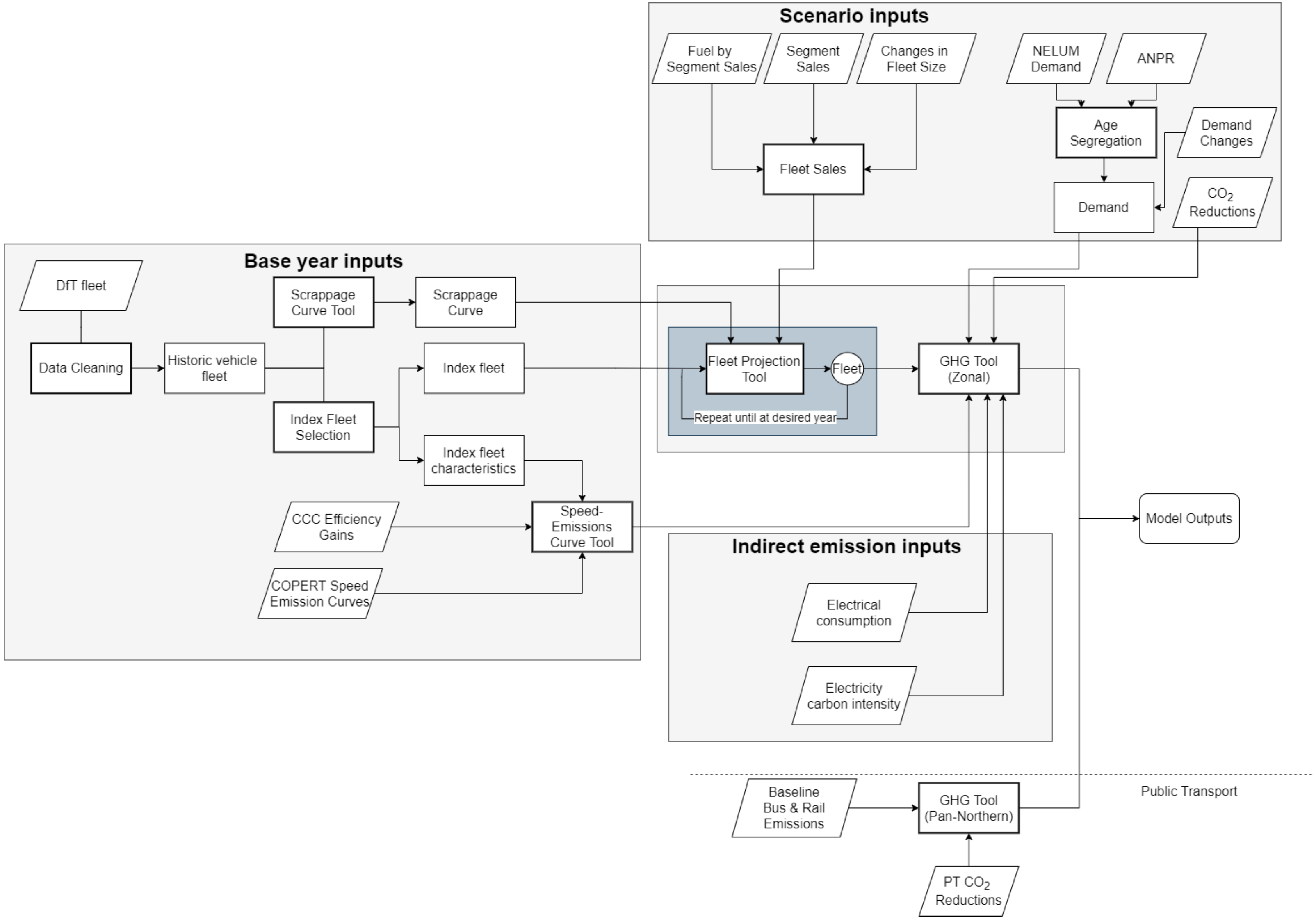


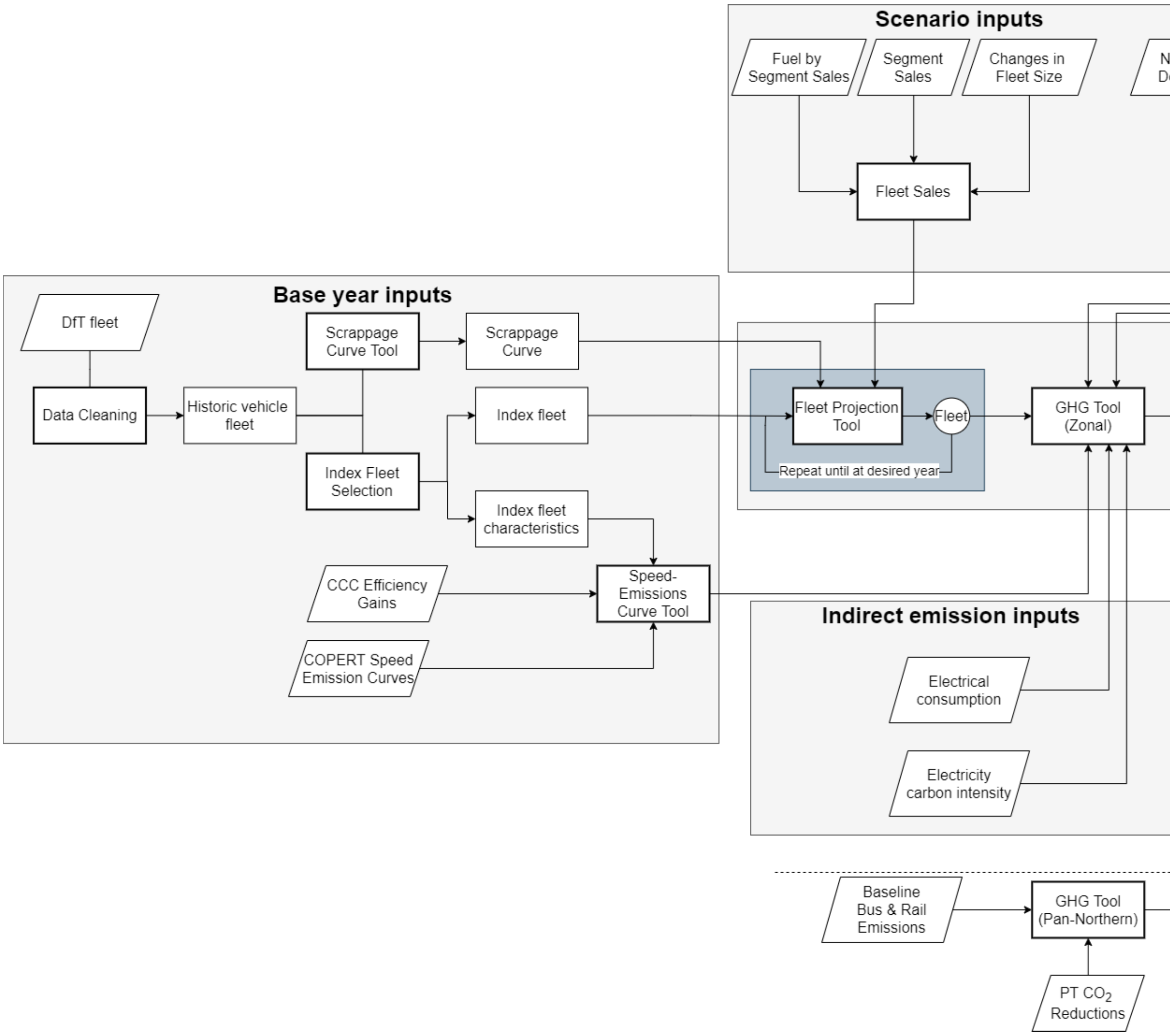
Figure 2: NoCarb model flow. The parallelograms represent the raw inputs that are fed into the model, the bold squares represent a model function and the non-bold squared represent pre-processed or transformed data.

Table 1 summarises all the input data used within the NoCarb model, its sources and methods of processing.

Table 1. Information about NoCarb data inputs.

File Name[7]	Version	Data Source	Data Description	Function	Processing required
DfT Fleet	2003 – 2018	DfT	Includes a record of all vehicle registrations in England, Scotland and Wales by Local Authority District (LAD) from 2003 to 2018. For each year, it outlines the number of vehicles in each segment, fuel and CYA group that exist within in each zone (i.e. 23 3-year-old petrol SUVs existed in zone 4 in 2006). There are three files, one each for cars, vans and HGVs. Alongside each observation, the dataset includes values for average mass, engine size and manufacturers estimate of CO_2 emissions per km.	This input has three functions: 1. Provide the baseline fleet upon which to assign demand and estimate emissions 2. Provide a baseline fleet to project forward into future years using scenario inputs. 3. Derive scrappage curves by vehicle type (cars, vans and HGVs). 4. Provide vehicle characteristics data to derive the real-world correction factors that are applied to NAEI speed emissions curves.	Data cleaning and imputation of the whole DataFrame (**Historic vehicle fleet)**, from which the **Index fleet** is selected. This includes mapping LAD zones to NELUM zones. As LADs are not nested perfectly within NELUM zones, vehicles are proportionately distributed using MSOA tallies and LAD vehicle shares (see Section 5.1.1). Weighted average of vehicle characteristics (**Index fleet characteristics**) for real-world corrections (average CO_2, average mass and average engine size) by tally, grouped by vehicle registration year, vehicle type, segment and fuel (see Section 5.1.1). Calculate the average survival rates by vehicle age and type (i.e. the proportion of cars that survive into their fifth year given they survived into their fourth year) to be used as **Scrappage curves** in the generation of future fleets (see Sections 5.1.2 and 6.2).
MSOA Fleet	2018	DfT	Tallies for cars, vans and HGVs by MSOA in 2018.	This input helps map LAD fleet data (**DfT Fleet**) to NELUM zones (see Section 5.1.1). As MSOAs are nested within NELUM zones, the vehicle type tallies are mapped to relevant NELUM zones (many-to-one), with segment, fuel, cohort and age distributions determined by LAD fleet shares.	None
CCC Efficiency Gains	Extract from the 2019 (RTM	CCC	Relates to CCC estimates of new vehicle emissions (gCO_2/km)	As indicated above, future fleets are projected forward using the	Future emissions intensity figures for each vehicle type were

[7] **The file names correspond to the parallelograms in**



Scenario inputs
Fuel by Segment Sales
Segment Sales
Changes in Fleet Size
Fleet Sales
Base year inputs
DfT fleet
Data Cleaning
Historic vehicle fleet
Scrappage Curve Tool
Scrappage Curve
Index fleet
Index Fleet Selection
Index fleet characteristics
CCC Efficiency Gains
COPERT Speed Emission Curves
Speed-Emissions Curve Tool
Fleet Projection Tool
Fleet
Repeat until at desired year
GHG Tool (Zonal)
Indirect emission inputs
Electrical consumption
Electricity carbon intensity
Baseline Bus & Rail Emissions
GHG Tool (Pan-Northern)
PT CO_2 Reductions

File Name[7]	Version	Data Source	Data Description	Function	Processing required
	Beta.13) of the CCC model (Fifth Carbon Budget)		weighted by vehicle kms according to fuel type. These are broken down by vehicle type and segment (e.g. small cars).	baseline fleet. To reflect future reductions in emissions intensity on-year, CCC estimates of gCO_2/km are applied to new vehicles (2019 and onwards) as reductions on baseline gCO_2/km (calculated using **COPERT Speed Emissions Curves**) for relevant vehicle types, segments and years.	converted into a percentage reduction on the baseline year (see Section 5.1.5).
Real-World Corrections / Fuel characteristics	2016	NAEI	Parameters from the NAEI manual to adjust the speed emission curves based on mass, engine size and manufacturers estimates of CO_2 per km.	This data allows the starting speed-emission curves, which were derived for a series of older vehicles, to be adjusted for newer and future vehicles. The input parameters are combined with data on vehicle characteristics from the DfT fleet file, using the NAEI formulae.	The parameters are applied using a formula (outlined in Section 6.3) to produce real-world correction factors.
COPERT Speed Emissions Curves	2016	NAEI	Speed-related emissions functions (outlined as a set of coefficients) by vehicle type, segment, fuel and vehicle age. A slightly older version (2016 rather than 2017) is used to align with the NAEI current method.	The speed emissions curves are merged into fleet and demand data to calculate gCO_2/km for each vehicle type, segment, fuel, vehicle age (see Section 5.4.1).	A formula (see Section 6.4) is used on the coefficients to fit the speed-emissions curves. This includes applying real-world corrections from **Index fleet characteristics**. The curves are then used to calculate emissions intensity in each speed band (broken down by vehicle type, segment, fuel and vehicle age).
Baseline Bus Emissions	2018	DfT National Road Traffic forecast (Scenario 1)	Pan-northern bus emissions estimate for 2018.	Provides a baseline figure for bus emissions from which future bus emissions are derived (using **Public Transport Reductions**).	PSV emissions figures were summed across Northern regions in 2015 and 2020 and interpolated to 2018. A more sophisticated approach will be explored in future.

Figure 2 and are cross-referenced in purple text throughout the report.

File Name[7]	Version	Data Source	Data Description	Function	Processing required
Baseline Rail Emissions	Internally derived in 2020	TfN/ Network Rail	Pan-northern rail emissions estimate for 2018.	Provides a baseline figure for rail emissions from which future rail emissions are derived (using **Public Transport Reductions**).	Emissions per mile data was sourced from TfN's Rail Operating Expenditure (OPEX) model, which uses factors supplied by Network Rail. These factors cannot be published due to commercial sensitivity. Timetable data (which provides information about distances travelled) was sourced from a 2015 version of TfN's Northern Rail Modelling System, which uses data from MOIRA.
Fuel by Segment Sales; Segment Sales	Scenario inputs developed internally in 2020	TfN	Relates to vehicle sales across scenario years: **1.** Segment share of sales by vehicle type **2.** Fuel share of sales by segment	These sales shares determine the distribution of new vehicles to be injected into future fleets (see Sections 5.2.3 and 6.5.1). The number of vehicles is determined by future **Changes in Fleet Size** and **Scrappage Curves**.	Sales shares are interpolated across intermediary years (i.e. 2021, 2022, 2023 and 2024) so that future fleets can be iteratively built, with old cars removed and new cars injected, on-year.
Changes in Fleet Size	National Car Ownership Model (DfT) run from 2016	TfN	Scaling factors to be applied on-year to determine the size of next year's fleet.	Multiplied against the baseline fleet size (total tally by vehicle type) to determine the number of registered vehicles in each scenario year (see Section 5.2.3). Fleet size in intermediary years is interpolated. A single DfT scenario is used at present. More work is required to directly link car ownership scenarios to car travel demand. TfN is progressing this work in 2021.	The year-on-year factors are converted into proportions of preceding years, upon which a cumulative product is used to give a proportion of the baseline year.
NELUM Demand	2015-calibrated model run in 2020	TfN	Total vehicle kms travelled in each NELUM zone, broken down by vehicle type, road type (motorway, urban or rural) and speed band. Information on how NELUM calculates speeds is provided below. Car demand data is produced for all scenario years but is only available for 2015 for vans and HGVs.	Demand is distributed across the fleet using ANPR data and observed fleet distributions (see Section 5.3). Alongside **COPERT Speed Emissions Curves** and **CCC Efficiency Gains**, demand is then used to calculate gCO_2/km (see Section 5.4.1).	Car demand in 2018 is interpolated from 2015 and 2020 demand under Just About Managing. Van and HGV growth relates to 2015

File Name[7]	Version	Data Source	Data Description	Function	Processing required
Van / HGV growth	Scenario inputs developed internally in 2020	Based on growth ranges from DfT National Road Traffic forecast (2018)	Growth factors to project 2015 van and HGV demand into future years. The growth factors are drawn from the DfT scenario that most closely matches the TfN scenario description. Bespoke, modelled TfN freight scenarios are currently being finalised.	The growth factors are applied to 2015 van and HGV demand (separate files) to produce future demand under each scenario and scenario year.	None.
ANPR	2018	ANPR	Share of demand on a given road type that is undertaken by vehicles of different body types (cars, vans, artic HGVs and rigid HGVs), fuels (petrol and diesel) and CYA.	ANPR data is merged with demand data (on vehicle and road type) and used to disaggregate demand across body types and vehicle ages.	A weighted average across fuels is derived using observed proportions of petrol and diesel vehicles in the baseline fleet (see Section 5.1.5).
PT CO_2 Reductions	Scenario inputs developed internally in 2020	TfN	Emissions reduction factors for bus and rail across scenarios/scenario years.	The reduction factors are applied to baseline bus and rail emissions to derive future emissions (see Section 5.4.2).	None.
Demand Changes	Scenario inputs developed internally in 2020	TfN	Scenario-based scaling factors for demand, broken down by vehicle type, area type and scenario year.	Once demand has been allocated across the fleet, Demand Changes are merged into the DataFrame (on year, vehicle type and road type) and applied (see Section 5.3).	Percentage change converted into a proportion (i.e. -0.1 -> 0.9).
CO_2 Reductions	Scenario inputs developed internally in 2020	TfN	CO_2 reduction factors by vehicle type and segment. This method is only used for further reductions in emissions intensity or mileage that happen on top of the manufacturer's technology-based improvements.	Reduction factors are applied to final gCO_2 estimates (i.e. to reflect fuel efficient driving) by merging into the final DataFrame (see Section 5.4.1). Currently these estimates are applied uniformly across all scenario years from 2025. More detail is provided below.	None.
Electricity Consumption	TAG v1.13.1 (2020) CCC Fifth Carbon Budget (2016)	DfT TAG Data Book (cars and vans) CCC Fifth Carbon Budget model (HGVs)	Electricity consumption per kilometre for battery electric cars, vans and HGVs (kWh per km) by cohort (vehicle registration year).	Electricity consumption is calculated by multiplying demand by electricity consumption per kilometre figures (see Section 5.4.3).	Plug-in hybrid (PHEV) and hydrogen fuels are added by duplicating the DataFrame. A corrective scaling factor of 0.5 is applied to the consumption per kilometre figures for PHEVs on the assumption that PHEVs operate in electric mode 50% of the time, and

File Name[7]	Version	Data Source	Data Description	Function	Processing required
					hydrogen values are kept the same to support a simple illustrative calculation of indirect emissions from alternative fuels (see Section 5.1.5).
Electricity carbon intensity	CCC Sixth Carbon Budget – Balanced Scenario (2020)	CCC Sixth Carbon Budget	Carbon intensity of the electricity grid by year (gCO_2/kWh)	Multiplied against **Electricity Consumption** figures in a given year to derive electricity emissions (see Section 5.4.3).	None
Population	Scenario inputs developed internally in 2020	TfN	Population estimates by NELUM zone, scenario and year, with additional information about NELUM area types.	Used to calculate emissions per head for the output file 'gis_attributes_all'.	None
Look-ups	Internal TfN look-up files	TfN	Zone mapping look-up files for MSOA to LAD and MSOA to NELUM.	Used to map **DfT Fleet** and **MSOA Fleet** data to NELUM zones (see Section 5.1.1).	

5 Process overview

This section goes into further detail about the process (and related functions) taken to project the vehicle fleet into future years and predict emissions in NoCarb. Methodology and formulas underlying the more complex functions are outlined in the following chapter.

5.1 Scenario independent

5.1.1 Data cleaning and pre-processing

NoCarb begins by calling in and cleaning the raw **DfT fleet** data. Pre-processing involves removing entries with negative tallies (number of vehicles), 'other' fuels and unknown zones and imputing fuels and vehicle ages (CYA).[8] This produces a partially pre-processed historic fleet DataFrame, from which the baseline fleet (segmented to only include the baseline year) is derived for advanced cleaning (imputation of segments and emissions characteristics[9]).

Emissions characteristics (average CO_2, mass and engine size) are then split out from the baseline fleet and a weighted mean is derived (using the vehicle tallies) for each cohort (registration year), vehicle type, segment and fuel.

The next step involves mapping the baseline fleet from LAD to NELUM zones. This is done by importing **MSOA fleet** data, which is equivalent to **DfT fleet** data (but only relates to 2018 and only has aggregate vehicle tallies by vehicle type) and nests perfectly within both LAD and NELUM zones. MSOA vehicle tallies are disaggregated by CYA, segment and fuel using the distributions from corresponding LADs. Disaggregated MSOA fleet data is then mapped to relevant NELUM zones using a many-to-one relationship.

5.1.2 Generate scrappage curves

Scrappage curves are derived from historic **DfT fleet** data (which dates back to 2003) for each vehicle type. This involves deriving the average proportion of vehicles that survive in the fleet on-year given they have survived up until that point (e.g. 60% of 5-year-old cars survive into their sixth year). Further information about the methodology for deriving scrappage curves is outlined in Section 6.2.

5.1.3 Convert emissions characteristics into 'real-world corrections'

Emissions characteristics from the baseline **DfT fleet** data (see Section 5.1.1 are merged with fuel consumption parameters (**Fuel characteristics**). A formula (outlined in Section 6.2) is then used to calculate real-world correction factors for each cohort, vehicle type, segment and fuel. These factors are applied to

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[8] See Sections 6.1.1 and 6.1.2 for further information about the methodology used.

[9] See Sections 6.1.3 and 6.1.4 for further information about the methodology used.

COPERT speed-emissions curves to reflect real-world driving conditions (such as driving with air conditioning).

5.1.4 Generate speed-emissions curves

COPERT speed-related emissions functions are merged with real-world corrections. For each segment and fuel, missing parameters are imputed with those of the closest cohort year. Together these coefficients and the real-world correction factors are assembled into a formula (outlined in Section 6.4) that will later be used to calculate speed-emissions curves. For zero-emissions fuels, this formula is replaced with 0 and emissions from the electricity grid are calculated separately (see Section 5.4.3). For hybrids, only 50% of the mileage is assumed to use the Internal Combustion Engine, an assumption that will be refined in the next stage of work (see Section 7 for further information). A further future planned development is for curves that relate speed to electricity and hydrogen consumption to be introduced so that the region-level consumption of alternative fuels can be estimated.

Speeds are introduced into the DataFrame with corresponding values representing the centre of a speed band (e.g. a speed band of "10-30km/h" is given a speed of 20km/h).[10] The formula from the previous step is then applied to the speeds to generate gCO_2 per kilometre for each speed band.

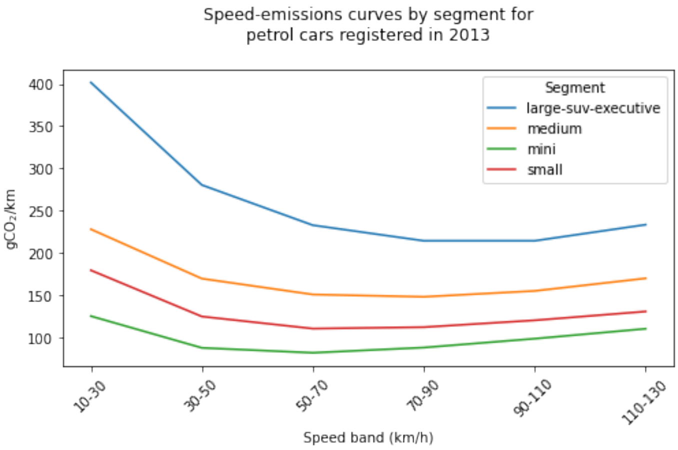

Figure 3: Final speed-emissions curves by segment for petrol cars in 2013 (produced using the steps outlined in Sections 5.1.3 and 5.1.4).

5.1.5 Pre-process general tables

CCC efficiency gains are the percentage improvements in technology-enabled vehicle efficiency estimated due to regulatory and fiscal measures on new vehicle sales. These have been assumed to be scenario independent at this stage, but TfN will explore the impact of variation in these assumptions across scenarios in a later stage of work, for example to represent different fiscal

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[10] The NAEI curves are only fitted for a certain range of speeds. Outside of this range they aren't accurate (e.g. high-speed HGVs). An audit check is built into this function to raise a flag if this occurs.

policies and the phasing out of new engine production by manufacturers.[11] It is important to note that these improvements are applied within a size segment, so changes to the overall fleet efficiency due to changes in the size profile of purchased vehicles is handled separately.

CCC efficiency gains are converted from percentage reductions on the previous year to percentage reductions on the baseline year. This is done by changing the reduction into a proportion of the previous year (-4% to 0.96) and taking the cumulative product.

As **ANPR** data is not perfectly normalised (the proportions do not add to 1), the share of demand by vehicle age is renormalised in the first instance. For cars, a weighted average across fuels is then derived using observed proportions of petrol and diesel vehicles in the baseline **DfT fleet**, after which the shares are normalised again.[12]

As **Electricity Consumption** values exclusively relate to battery-electric vehicles (BEVs), the DataFrame is duplicated twice:

- Once for plug-in hybrid electric vehicles (PHEVs), so that kWh per km values can be multiplied by 0.5 (on the assumption that vehicles operate in electric mode 50% of the time);
- Once for hydrogen vehicles to support a simple, illustrative calculation of indirect emissions from alternative fuels.[13]

The three DataFrames are then combined.

5.1.6 Export pre-processed tables

Several pre-processed tables are saved so they can be imported in future runs. This improves efficiency by allowing NoCarb to skip several pre-processing steps (outlined in Sections 5.1.1 and 5.1.2). The following tables are saved for this purpose:

Table 2: A description of the tables saved following pre-processing, so they can be called in if 'run fresh' is set to False.

Name	Description
characteristics	Pre-processed emissions characteristics (average CO_2, average mass and average engine size) taken from the baseline **DfT fleet** data.
fleet_archive	Partially pre-processed historic **DfT fleet** data.
index_fleet	Fully pre-processed **DfT fleet** data from the baseline year.

[11] Some manufacturers are announcing their last engines being brought into circulation, which suggests that investment in and improvements in engine efficiency are likely to slow to a stop soon. However, the gap could be filled by taxation that pushes people towards lower emitting conventional vehicles.

[12] ANPR data for vans and HGVs exclusively related to diesel, so no weighted average is required.

[13] Data related to hydrogen carbon intensity was not readily available at the time.

scrappage_curve	Survival rates for each vehicle type (i.e. the proportion of a vehicle of age X that will survive in the fleet in each year, given they have already survived). Excludes bus and rail.

5.2 Scenario dependent

All remaining functions are completed separately for each Future Travel Scenario, using bespoke scenario and demand inputs.

5.2.1 Pre-process scenario tables

Scenario inputs undergo basic pre-processing. This includes interpolating values between scenario years[14] and, in the case of **Changes in fleet size**, converting year-on-year percentage changes to a proportion of the index year (as is done for **CCC efficiency gains** in Section 5.1.5).

5.2.2 Prepare NELUM demand data

Unlike car demand data (which is available for each scenario and scenario year), van and HGV data is only available for 2015. Scenario-based growth factors are uniformly applied to this data to derive van and HGV demand in 2018 and future scenario years.

5.2.3 Project fleet

The size of future fleets is determined from the baseline **DfT fleet** using scenario-based scaling factors (**Changes in fleet size**). These factors vary by vehicle type and are multiplied against the respective vehicle-type tallies in the baseline fleet. This returns a DataFrame with total vehicle-type tallies for each scenario and scenario year, which is then interpolated to return fleet-size projections across all years between 2018 and 2050.

A template fleet is created by merging all possible segment-fuel combinations (taken from **Fuel by Segment Sales**) with observed segment purchases in each zone in the baseline year. This preserves regional variation in segment purchasing habits and allows the introduction of new fuels for segments where these have not yet existed in some zones (e.g. hydrogen HGVs).[15]

Future vehicle sales in each zone are determined (see Section 6.5.1 for a formula) by taking the product of baseline segment-zone sales shares (e.g. 2% of all minis were sold to zone 3 in 2018) and scenario-based **Segment Sales** and **Fuel by Segment Sales** in a given year (e.g. 20% of car sales are minis and 25% of mini sales are diesel in 2020).[16] Before performing this operation,

[14] I.e. from 2020 and 2025, linear interpolation is used to derive relevant values for 2021, 2022, 2023 and 2024. The impact of using exponential interpolation will be explored as part of future work.

[15] A potential future area for development through TfN's new Car Ownership Model is to represent how purchasing patterns could vary spatially and over time in response to local and national factors.

[16] Future sales shares under each scenario are based on a review of literature.

the sales shares are merged in with the template fleet. This results in a DataFrame that outlines the segment-fuel-zone proportion of a vehicle type that is sold in each year (e.g. 3% of vans sold in 2025 are n1 class ii, petrol and sold in zone 43). As these vehicles are 'new sales' in a given year, the cohort (vehicle registration year) is set as the relevant sales year.

Future fleets are generated by iterating through each year (starting with the baseline year and finishing in 2050) and using the fleet in that year, scrappage curves and fleet sales to derive the fleet for the following year (see Sections 6.5.2 and 6.5.3 for more information). The new fleet is used to derive the fleet for the year after that, and so on. This approach means it is possible to specify changes in vehicle sales patterns and volumes. Changes in the fleet size and makeup can be represented by varying the rate of sales or the rate of scrappage.

The output is a large DataFrame outlining vehicle tallies for each year, zone, cohort, vehicle type, segment and fuel. This is then reduced to scenario years for the purpose of emissions calculations.[17]

5.3 Allocate demand

In the first instance, **ANPR** data is merged with and applied to **NELUM demand** data. This provides vehicle-type age distributions of demand on each road type (motorway, urban or rural) in each zone (e.g. two-year-old vans make up 10% of van demand on motorways in zone 43). Demand is then disaggregated by segment and fuel using observed fleet distributions in that year (e.g. petrol minis make up 2% of all two-year-old cars in zone 43 in 2025).

Once the demand is allocated across the fleet, scenario-based scaling factors (**Demand Changes**)[18] are merged in on year, vehicle type and road type (urban, suburban or rural) and applied.

The resulting output is a fleet DataFrame that includes demand for each vehicle and covers all scenario years.

5.4 Predict emissions

5.4.1 Cars, vans and HGVs

Emissions are estimated using the speed-emissions curves, **CCC efficiency gains** and scenario-based **CO_2 reductions**.

[17] TfN's Future Travel Scenarios and Decarbonisation Pathways work focuses on milestone years: 2018, 2020, 2025, 2030, 2035, 2040, 2045 and 2050.

[18] Using NELUM, separate analysis was undertaken to understand how car demand could be reduced in line with scenario-based demand changes (**Demand Changes**). An overview of the process is outlined in Appendix A.

The speed emissions curves are merged into the fleet data on vehicle type, segment, fuel, CYA and speed band (which is brought in with the demand data). As the curves do not relate to future years, vehicles registered after the baseline year are merged with the corresponding curve from the baseline year. The **CCC efficiency gains** seek to correct for this, providing a scaling factor to be applied to baseline emissions intensity to reflect on-year improvements to emissions intensity for each body type (cars, vans, artic HGVs and rigid HGVs).

Emissions are estimated for a given vehicle group in each year by taking the product of:

- gCO_2/km from the speed emissions curves
- CCC efficiency gains
- Demand
- Carbon equivalent emissions factors

Finally, scenario-based **CO_2 reduction** factors are merged in on vehicle type and segment. These represent measures such as improved fuel efficiency (through eco-driver training, drag reduction or reduced speeds) or zero-emissions vehicles driving proportionally more miles (e.g. through a high share of zero-emissions taxis). As a simplifying assumption in the absence of any more detailed data, these factors are uniformly applied to gCO_2 across the whole fleet in all years from 2025.

The output is a scenario-specific DataFrame, which outlines fleet, demand and emissions estimates across scenario years. This is automatically saved as a model output.[19]

5.4.2 Bus and rail

Baseline bus and rail emissions estimates are pan-Northern. Future emissions for these modes are estimated by applying scenario-based reduction factors (**PT CO_2 reductions**) to baseline figures. As noted above, for bus, this aggregate approach is due to a lack of detailed data and modelling tools available at a regional level. For rail, the approach is due to the difficulty attributing vehicle movements and emissions to origin zones. TfN will explore refinements to this approach in a future stage of work.

5.4.3 Indirect emissions

Indirect emissions are estimated by taking the product of **Electricity consumption** values (kWh per km), demand and **Electricity carbon intensity** (gCO_2 per kWh).

This is done by first merging **Electricity consumption** into the fleet data (on cohort, vehicle type and fuel (BEV, PHEV and hydrogen)) and setting kWh per km to 0 for vehicles that are not BEV, PHEV or hydrogen. Electricity consumption

[19] Demand from this output has been compared to the original NELUM demand to check that the transformations and calculations work as expected. This revealed an error, whereby output HGV demand is 6% higher than input HGV demand. This will examined further in future model development.

for each vehicle group is then derived by taking the product of demand and kWh per km.

As a final step, indirect emissions are calculated by merging in **Electricity carbon intensity** (on year) and taking the product of gCO_2 per kWh and electricity carbon intensity.

5.5 Save outputs

Several summary tables and figures are produced by NoCarb.

Table 3: A description of the outputs saved from NoCarb if 'generate outputs' is set to True.

Output type	Name	Description
Table	[scenario]_fleet_emissions	Provides disaggregated figures (by year, zone, cohort, vehicle type, segment and fuel) of gCO_2, vehicle kms and number of vehicles under each scenario. This only relates to cars, vans and HGVs (and does not include bus and rail). There are four tables in total – one for each scenario.
Table	fuel_share	The share of fuels for each vehicle type in 2050, by scenario. This only relates to cars, vans and HGVs (and does not include bus and rail).
Table	gis_attributes_all	A summary output file to support GIS mapping. Includes information for all scenarios, broken down by zone and year. This only relates to cars, vans and HGVs (and does not include bus and rail). The variables include: NELUM area type: Whether a zone is urban, sub-urban or rural North: Whether a zone is internal or external of TfN's northern boundary • Mega-tonnes of CO_2 • CO_2 percentage change compared to the equivalent zone in 2018 • Total CO_2 emissions from cars • Total CO_2 emissions from vans and HGVs • CO_2 per head • Emissions intensity (gCO_2 / vehicle kms) • Total kms travelled • Vehicle km percentage change compared to the equivalent zone in 2018 • Vehicle kms per head • Number of cars
Table	pt_emissions	Emissions estimate (mega-tonnes of CO_2) for bus and rail by year and scenario. Estimates are pan-northern.
Figure	total $MTCO_2$	A summary line plot of emissions from 2018 to 2050, by scenario. This includes emissions from bus and rail, as well as cars, vans and HGVs.
Figure	total $MTCO_2$ + target	Same as above, but with the addition of TfN's decarbonisation trajectory.

Figure	total chainage[20]	A summary line plot of vehicle kms travelled by cars, vans and HGVs from 2018 to 2050.
Figure	cumulative emissions	A summary line plot of cumulative emissions from 2018 to 2050, by scenario. This includes emissions from bus and rail, as well as cars, vans and HGVs.
Scenario-specific figures		
Figure	• HGV fleet for [scenario] • car and LGV fleet for [scenario]	An area plot outlining the fuel share of the fleet from 2018 to 2050 – one plot for HGVs and one plot for cars and vans.
Figure	• HGV sales for [scenario] • car and LGV sales for [scenario]	An area plot outlining the fuel share of sales from 2018 to 2050 – one plot for HGVs and one plot for cars and vans.
Figure	Chainage by: • Area type for [scenario] • Vehicle type for [scenario]	An area plot outlining total vehicle kilometres travelled for a given scenario, broken down by area type and vehicle type (two separate plots).
Figure	$MTCO_2$ by: • Area type for [scenario] • Vehicle type for [scenario]	Same as above but for mega-tonnes of CO_2.

[20] Vehicle kilometres travelled.

6 Methodology for key functions

6.1 Fleet imputation

Table 5 in Section 7 outlines the proportion of missing values in the historic fleet by variable. Only fuel and Completed Year Average (CYA) are imputed in the historic fleet data, while more advanced imputation is undertaken on the baseline fleet. This is because the historic fleet data is only used to derive vehicle-type scrappage curves, meaning that imputation of other columns is not necessary.

6.1.1 CYA

Missing CYA values in the historic **DfT fleet** data are imputed using the distribution of known CYA values for each year, vehicle type and euro standard. This is done by taking the product of the known CYA-tally distribution and unknown CYA tally (both grouped by and merged on year, vehicle type and euro standard) and disaggregating this further by multiplying the grouped imputed tally by the share of unknown CYA observations in relation to remaining columns. The imputed observations are then merged with non-missing observations. An audit check is built into the function to confirm that the tally is unchanged.

This is demonstrated in the following formula:

$$(X) = (Y, V, E)$$

$$P(C_i \neq \emptyset, X) = \frac{T(C_i, X)}{T(C \neq \emptyset, X)}$$

$$\tilde{T}(C_i, X) = T(C_i, X) + P(C_i, X) \cdot T(C = \emptyset, X)$$

Where P, C, Y, V, E[21] are the proportion of vehicles, CYA, cohort year, vehicle type, and euro standard respectively. T is the tally, $\tilde{T}$ is the imputed tally.

6.1.2 Fuel

All observations in the historic **DfT fleet** that had missing fuels were HGVs and all HGVs had missing fuels. As almost all HGVs are run on diesel, these fuels were imputed with diesel.

6.1.3 Segment

Once the baseline DfT fleet has been indexed from the historic fleet, missing segments are imputed. This is first done by comparing a vehicle's average mass to the mass of known segments. For cars, this is done by using the 25th percentiles of each segment's mass as bins (see Figure 4), as this is approximately where the mass distributions of each size category overlap, and determining the segment where a vehicle's mass fits within the relevant bin.

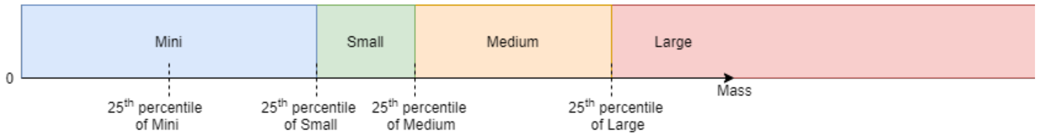

Figure 4: A diagram demonstrating how missing segments are imputed by matching a vehicle's average mass to the 25th percentile of known segments' mass.

For vans, the weight classes for the bins are derived from the EU directives that define them.[22]

Following this step, remaining missing segments are imputed using the distribution of known segments by CYA, fuel and vehicle type. This uses the same methodology as CYA imputation (see Section 6.1.1).

6.1.4 Emissions characteristics

Emissions characteristics (average CO_2, mass and engine size) in the baseline **DfT fleet** are first imputed using a weighted mean (using tally as the weight) for each CYA, fuel and segment group. Battery-electric vehicles that still have missing values after this step are imputed with 0.[23]

Multiple Imputation by Chained Equation (MICE) imputation is then used to impute the remaining missing emissions characteristics. This technique involves running a regression model on the emissions characteristics as well as segment, CYA and fuel columns to iteratively impute each of the emissions characteristics.[24] The process is repeated several times, using the imputed values from the previous round to update the explanatory variables and improve predictions for target variables, until the absolute difference between imputed values becomes very small between rounds.[25]

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[22] As outlined here (Article 5.5): https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52003AG0063&qid=1614613434952&from=EN

[23] As the emissions characteristics are used to calculate real-world corrections to speed-emissions curves – and because battery-electric vehicles do not produce tailpipe emissions – it does not matter if average mass and engine size values are set to 0 for these vehicles.

[24] For example, 'average CO_2' might be set as the target variable and the others used as explanatory variables (with simple imputation methods such as mean imputation used to impute any missing values in the explanatory variables in the first instance). The process is then repeated, this time using 'average mass' as the target variable and the others (including the newly imputed average CO_2) as the explanatory variables.

[25] See here for a more detailed explanation of the MICE algorithm: https://medium.com/@ofirdi/mice-is-nice-but-why-should-you-care-e66698f245a3

6.2 Scrappage curves

In the raw **DfT fleet** data, CYA values are banded into the following age groups: 0, 1, 2, 3, 4, 5, 6-8, 9-11, 12-14 and 15+ (years old). These are separated into single years and the tally is divided by the number of years in each band (e.g. CYA 6-8 has its tally divided by 3). The scrappage rate of a vehicle is given by:

$$s_i = \frac{T_{i+1}}{T_i}$$

where s_i is the proportion of vehicles in year i which are still in use.

We assume that scrappage rates are constant through CYA groups and that the central year in the group has a proportional share of the vehicles (e.g. the middle year in a 3-year CYA group has 1/3 of the group tally). The scrappage rate for a group of n years can then be calculated as:

$$s_{i \to j} = \sqrt[\lceil \frac{n}{2} \rceil]{\left(\frac{T_{i \to j}}{n}\right) \div T_i}, \text{ with } j = i + n - 1$$

Figure 5 below provides a visual depiction:

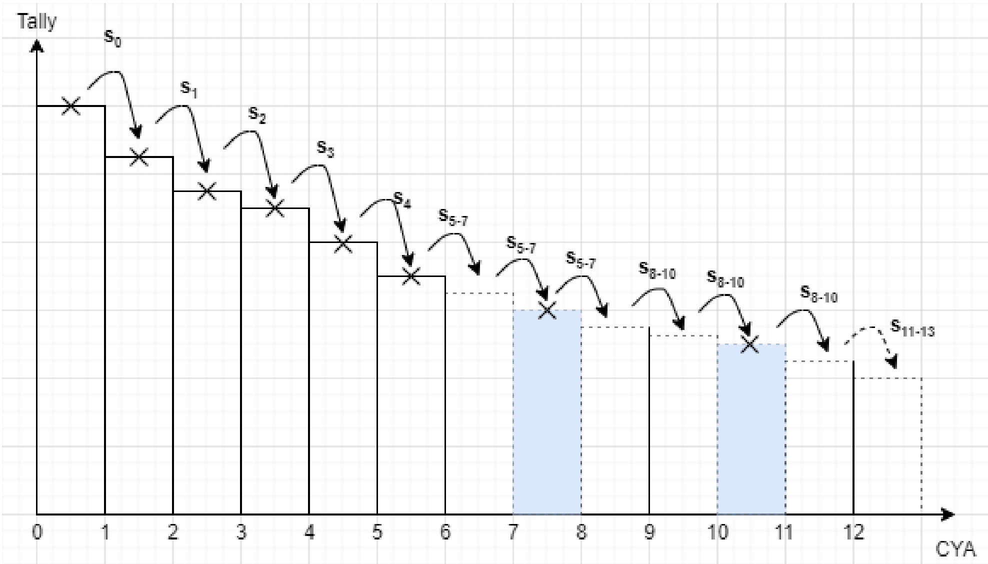

Figure 5: A diagram depicting how a scrappage rate for a group is calculated by assuming the middle year (in blue) hosts an equal proportion of the tally and using that to derive a constant scrappage rate across all years in that band.

6.3 Real-world corrections

To adjust the **COPERT speed-emissions curves** we use a real-world correction multiplier, RWM, given by:

$$FC_{Aprv} = \frac{12}{44} \frac{\langle CO_2 \rangle}{R_{F \to C} \rho_F}$$

$$FC_{In\ Use} = c_1 + c_2 \langle ES \rangle + c_3 \langle M \rangle + c_4 FC_{Aprv}$$

$$RWM = \frac{FC_{In\ Use}}{FC}$$

where FC, ρ_F,$R_{F\rightarrow C}$, are fuel consumption, fuel mass density, and mass ratio of fuel to carbon, and $\langle CO_2 \rangle$, $\langle ES \rangle$, and $\langle M \rangle$ are the vehicle's average CO_2 emissions, engine size, and mass respectively. c_n coefficients are provided by the NAEI.

Note that the relative atomic mass of Carbon is 12 and the relative atomic mass of Carbon Dioxide is 44. Therefore, $\frac{12}{44}$ represents the proportion of CO_2 that is Carbon.

6.4 Speed-emissions curves

COPERT publishes coefficients for an equation relating speed and emissions as a function of emissions characteristics (engine size, CO_2, mass):

$$I = \frac{\left(\alpha v^2 + \beta v + \gamma + \frac{\delta}{v}\right)}{\varepsilon v^2 + \zeta v + \eta} \cdot RWM \cdot \frac{M_c}{E}$$

where I, v, M_c and E are carbon emission intensity, speed, carbon mass, and energy respectively.

Each fuel-segment combination has a set of the coefficients written as Greek characters.

6.5 Fleet projection

6.5.1 Vehicle sales

Future vehicle sales in each zone are determined by taking the product of baseline segment-zone sales shares from the baseline **DfT fleet** (e.g. 2% of all minis were sold to zone 3 in 2018) and scenario-based **Segment Sales** and **Fuel by Segment Sales** in a given year (e.g. 20% of car sales are minis and 25% of mini sales are diesel in 2020). In parallel TfN is developing a new Car Ownership Model, which will represent patterns of car ownership at a zonal level and may allow a refined approach to modelling these purchasing behaviours over time.

This is demonstrated in the formula below:

$$R(Z_a, S_b, F_c) = R \cdot \tau(Z_a : S_b) \cdot \tau(S_b : \mathbb{U}) \cdot \tau(F_c : S_b)$$

$$R(Z_a, S_b, F_c) = R * \left(\frac{T(S_b, Z_a)}{\sum_j T(S_b, Z_j)}\right) \cdot \left(\frac{T(S_b)}{\sum_j T(S_j)}\right) \cdot \left(\frac{T(S_b, F_c)}{\sum_m T(S_b, F_m)}\right)$$

where Z, S, F, R, T, and $\tau(Z_a : S_b)$ are the zone, segment, fuel type, newly registered vehicles, vehicle tally, and proportion of segment S_b vehicles that are in zone Z_a.$\mathbb{U}$ is the set of all vehicles.

6.5.2 Apply scrappage to withdraw vehicles

As each year is incremented, we first withdraw vehicles from the fleet by taking the vehicle type's associated scrappage curve and multiplying the tally for each vehicle group by the corresponding scrappage value (matched on CYA) to derive the new tally. The CYA value for all vehicles is then incremented by 1 by subtracting the cohort year from the current year.

6.5.3 Use sales to inject new vehicles

After the scrappage has occurred, the required number of new vehicles to be injected into the fleet is calculated from the difference between the existing and projected fleet tally for a given year. This gives the number of required sales:

$$R(V, Y = i) = T_P(V, Y = i) - T_S(V, Y = i)$$

where R, T_P, and T_S are the newly registered vehicles, projected vehicle tally, and after scrappage tally respectively. Once the number of new vehicles to be introduced is known, these are disaggregated by zone, segment and fuel using the sales distribution as calculated in Section 6.5.1.

7 Data assumptions and limitations

The following assumptions were made in developing the model:

- Hybrid-electric vehicles were reclassified as petrol hybrids for cars and as battery-electric for vans and HGVs. For cars, petrol hybrids are by far the most common type. For vans and HGVs, no **COPERT speed-emissions** data was available for hybrid vehicles and extremely low numbers of hybrid vans and HGVs currently exist. There is also a greater focus from manufacturers on zero-emission vans and HGVs rather than hybrids at present.
- The real-world correction and electricity consumption for plug-in hybrid-electric vehicles was set to 0.5[26] on the assumption that they operate in electric mode 50% of the time. It is acknowledged that there is evidence that this assumption is on the high side[27], and that for this to be valid either further policy interventions or technological improvements (e.g. electric range improvements) would be needed. In any case, plug-in hybrids only make up a small fraction of the sales in our ambitious EV uptake pathway, so a deviation from this assumption would have a relatively small effect. Further sensitivity analysis on this point will be undertaken later in 2021.
- The NAEI methodology for LGV and HGV speed-emission curves is different to that of cars and is based on 'Euro standard' vintages (related to air pollution), rather than using the 'real-world' adjustment factor approach used for cars that adjusts for technology improvements and real-world driving styles. However, the speed-emission curve parameters for LGVs and HGVs do account for these factors as they are provided separately for vehicles of different ages and are derived from independent tests that take account of real-world driving conditions. These tests are carried out as part of the development of the EU's COPERT software. The main limitation of this approach is that future-year conventional efficiency improvements for LGVs and HGVs have to be applied at an aggregate level, rather than adjusting the speed emission curves, which is a slightly less accurate method.
- Aggregate scrappage curves were produced for each vehicle type. This assumes that the survival distribution of a vehicle type is unform across

[26] According to the Worldwide Harmonised Light Vehicle Test Procedure, a utility factor of 0.5 implies an electric-run range of 23km. It is expected that utility factors will increase over time as PHEV ranges improve, though,as is discussed, this utility factor is still likely an overestimation.

[27] See https://theicct.org/publications/phev-real-world-usage-sept2020 and https://www.transportenvironment.org/publications/plug-hybrids-europe-heading-new-dieselgate

segments, fuels and registration year. This assumption will be monitored as zero-emission vehicles become more widespread in the fleet.
- Similarly, the distribution of demand by vehicle age (as outlined in **ANPR** data) is only available by vehicle type and relates only to 2018. This assumes the age distribution of demand on a given road type is uniform across segments, fuels and registration year. This data will be refreshed the next time TfN re-bases its transport models, which will likely be in 2022 or 2023.
- Missing fuels in the historic **DfT fleet** data were imputed with 'diesel' on the assumption that the vast majority of HGVs are diesel-run (all observations with missing fuels were HGVs and all HGVs had missing fuels).

There are several limitations to the data:

- NELUM is currently based to 2015. This means that baseline **NELUM demand** estimates (currently 2018) are interpolated between 2015 and 2020 (using a 'Just About Managing' scenario for the latter). Work is underway to re-base NELUM to 2018, at which point the baseline and future demand estimates are likely to be more accurate.
- There is no van and HGV demand in two zones (1 and 41) in the baseline **NELUM demand** data, and rigid HGV demand is completely missing in an additional three zones (and artic HGVs in one additional zone). As this data is scaled using growth factors for future years, this means that these zones have no van and/or HGV demand across all years.
- HGV demand outputted from NoCarb is higher (6% in 2018) than the original input data from NELUM, while LGV demand is slightly lower (-0.33%).[28] This change occurs when the demand data is merged with the fleet data so that it can be disaggregated by observed distributions of body types, segments and fuels for each vehicle type, zone and CYA group.
- The **COPERT speed-emissions curves** are only accurate within certain speeds (see Table 4). As a result, speeds outside of this range are reassigned to the nearest within-range speed band as part of NELUM demand post-processing.

Table 4: Minimum and maximum speeds that can be reliably used to estimate speed-emissions for each vehicle type.

Vehicle type	Min speed (km/h)	Max speed (km/h)
Car	20	130
HGV	12	85
LGV	10	110

[28] Changes to car demand are so minor that they are expected to be due to rounding (<1e5%).

- As outlined in Table 5, the **DfT fleet** data had a relatively high proportion of missing values. With no robust method to impute 'missing tally' data, just over one third of observations had to be removed. Remaining missing values (i.e. segment, fuel, CYA and emissions characteristics) were imputed using several techniques, as discussed in Section 6.1. These points reveal potential flaws in the accuracy of the fleet data, though this was seen as the best approach with the best available data at the time.

Table 5: Percentage of observations in DfT historical fleet data with missing values.

Variable	% of observations with missing data	
	Before removing missing 'tally'	After removing missing 'tally'
Fuel	15%	11%
Segment	21%	20%
Tally	35%	0%
Avg CO_2	59%	51%
Avg Mass	52%	42%
Avg Engine Size	2%	1%

8 Results

8.1 Baseline emissions in the North

Figure 6 provides headline figures related to baseline surface transport emissions in the North. At 26 mega-tonnes of CO_2, surface transport emissions in the North represent nearly one quarter of UK road emissions and 6% of total UK emissions. Over half of those emissions were generated by cars, with HGVs and vans producing 28% and 11% of surface transport emissions respectively. Bus and rail, on the other hand, represent just 5% of emissions.

Table 6: Total mega-tonnes of CO_2 and vehicle kms in 2018 by mode.

Vehicle type	Vehicle kms (billions)	$MTCO_2$
Car	102	13.6
HGV	11	7.1
LGV	13	2.7
Bus	*Not available*	0.6
Rail		0.8

A total of 126 billion kilometres were travelled in the North in 2018, representing 23% of vehicle kilometres travelled in the UK. The majority of the North's travel (56%) was through sub-urban areas, though distance per head was much higher for those in rural areas.

Table 7: Total mega-tonnes of CO_2 and vehicle kms in 2018 by area type.

Area type	$MTCO_2$	Vehicle kms (billions)
Urban	3.1	16.8
Sub-urban	13.7	70.0
Rural	6.6	38.8

The North had 8 million registered cars in 2018. Large and SUV cars, which typically have higher emissions intensity, made up nearly one quarter of those cars and just under one third of new car sales in that year. This reflects a national trend over the last two decades, which has seen a gradual increase in the purchase of larger cars. Only 0.09% of vehicles registered in the North in 2018 were zero-emissions.

Urban areas typically showed lower CO_2 intensity and emissions per head of population than rural areas. However, there was some variation within area types, with coastal areas having slightly more fuel-efficient cars.

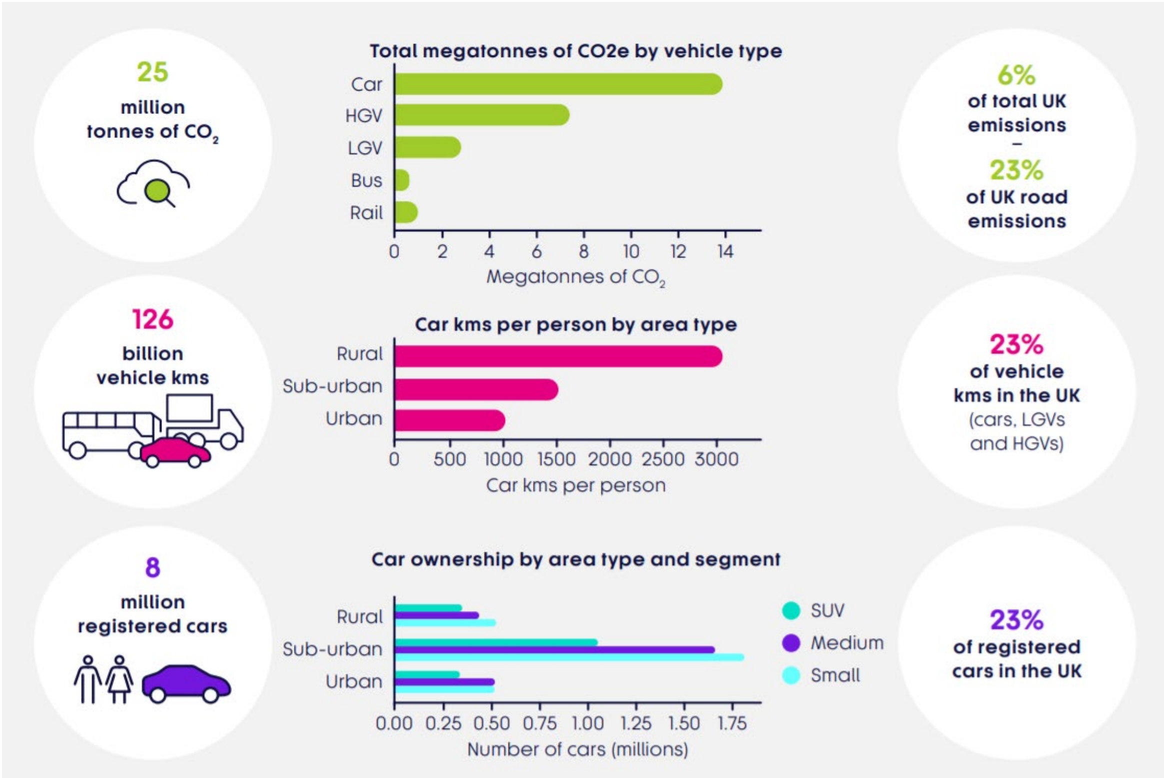

Figure 6: Headline figures related to surface transport emissions in the North in 2018.

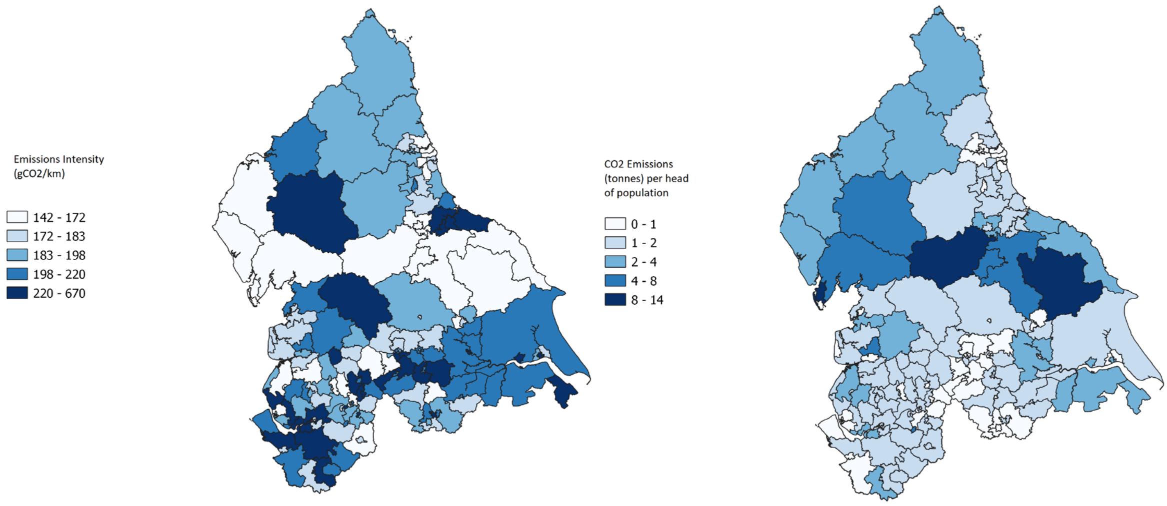

Figure 7: Regional distribution of emissions per capita and emissions intensity in the North in 2018.

8.2 Indirect emissions

Indirect emissions are very low compared to surface transport emissions.

Due to higher carbon intensity associated with electricity and a rapid uptake of zero-emission and plug-in hybrid electric vehicles in the short-term, Urban Zero Carbon and Digitally Distributed show the highest indirect emissions in 2025 and 2030. However, as electricity is increasingly produced by more renewable sources, indirect emissions slowly decrease from 2030 to be close to zero by 2050.

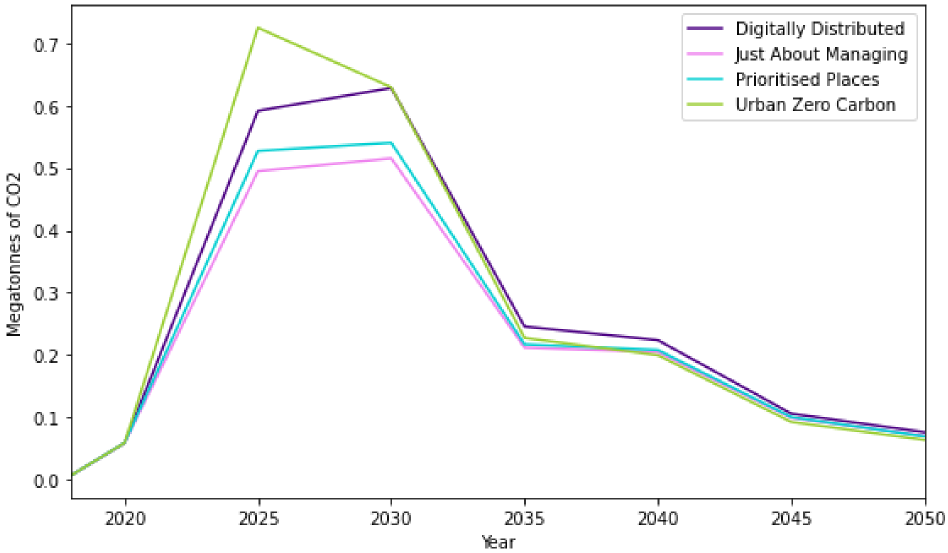

Figure 8: Indirect emissions from electric powered vehicles.

8.3 Scenario results

Aggregate emissions under each scenario appear to align to each scenario's unique context.

Just About Managing, which sees a broad continuation of current trends, shows a slow decrease in emissions, while more ambitious scenarios like Urban Zero Carbon (which sees strong government policy on climate change) show much steeper emissions reductions in the lead up to 2050.

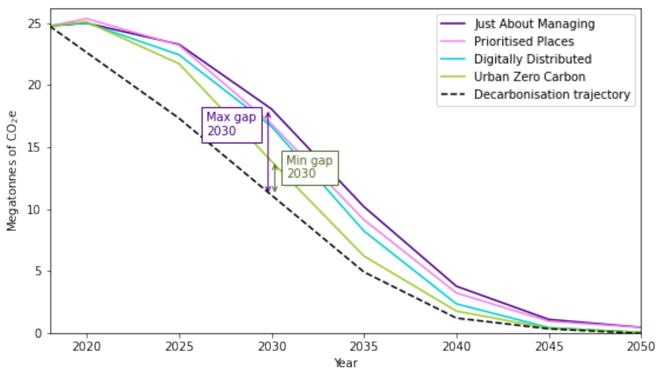

Figure 9: Surface transport emissions in the North under each Future Travel Scenario compared against the decarbonisation trajectory.

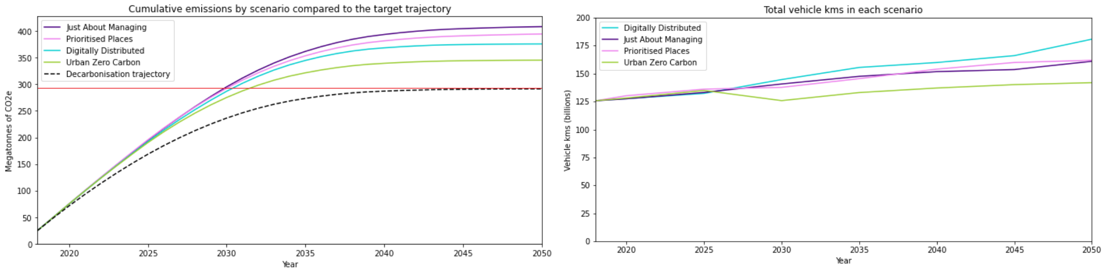

Figure 10: Cumulative emissions[29] (left) and total vehicle kilometres (cars, vans and HGVs) (right) under each Future Travel Scenario.

8.3.1 Just About Managing

Just About Managing sees a 98% reduction in tailpipe emissions from 2018 to 2050. Increases in car and van demand are largely offset by a growing share of zero-emissions vehicles. However, due to a slow uptake of zero-emission HGVs, around 0.5 mega-tonnes of CO_2 remain in 2050.

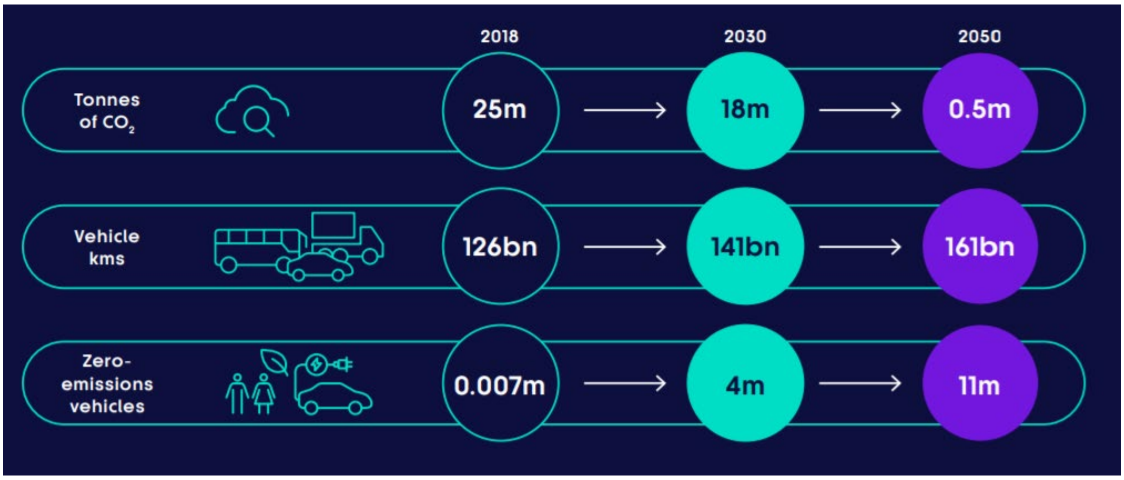

Figure 11: Headline figures related to surface transport emissions, vehicle demand and zero-emissions vehicles in the North under a Just About Managing scenario.

Table 8: Demand growth 2018 to 2050 and CO_2 emissions in 2030 and 2050 by mode under a Just About Managing scenario.

Mode	Demand growth 2018-2050	CO_2 emissions in 2030 (mega-tonnes)	CO_2 emissions in 2050 (mega-tonnes)
Rail	*Not available*	0.6	0.4
Bus		0.3	0.0
Car	28%	10.9	0.0
Van	47%	1.7	0.0
HGV	6%	8.0	0.1

[29] As emission estimates from NoCarb only cover milestone years, emissions in intermediary years were derived through linear interpolation before being cumulatively summed.

Table 9: Total vehicle demand and CO_2 emissions in 2050 by area type under a Just About Managing scenario (excludes bus and rail).

Area type	Vehicle kilometres in 2050 (billions)	CO_2 emissions in 2050 (megatonnes)
Urban	21.9	0
Sub-urban	90.0	0.1
Rural	49.0	0

Table 10: Fuel shares by vehicle type in 2050 under a Just About Managing scenario.

Vehicle type	Fuel type	Share
Car	BEV	99%
Car	PHEV	1%
Van	BEV	98%
Van	PHEV	2%
HGV	BEV	97%
HGV	Diesel	1%
HGV	Hydrogen	2%

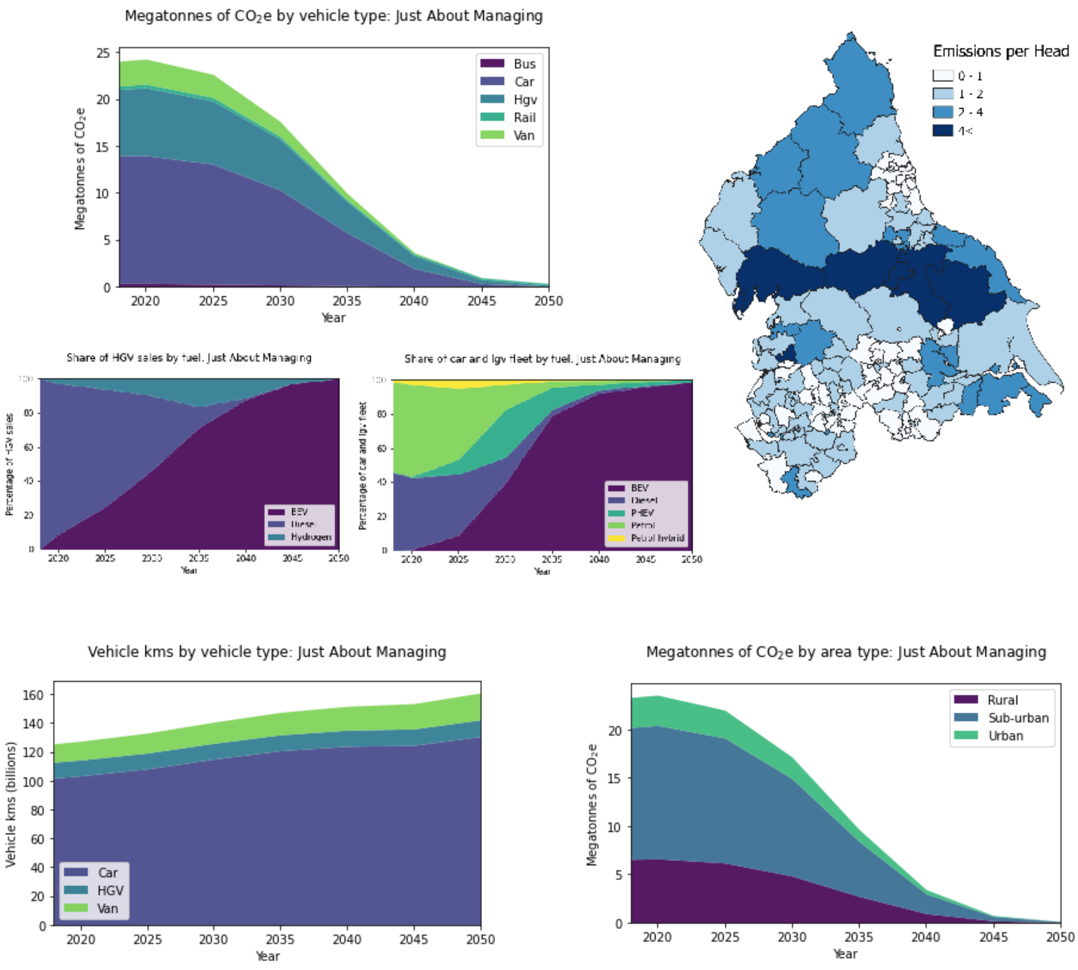

Figure 12: Mode, fuel and area type breakdown of emissions in the North under a Just About Managing scenario.

8.3.2 Prioritised Places

Prioritised Places sees a 98% reduction in tailpipe emissions from 2018 to 2050. Similar to Just About Managing, increases in car and van demand are largely offset by a growing share of zero-emissions vehicles. Near all HGVs transition to zero-emissions technologies, though only a marginal increase in demand means that the emissions are fractionally lower.

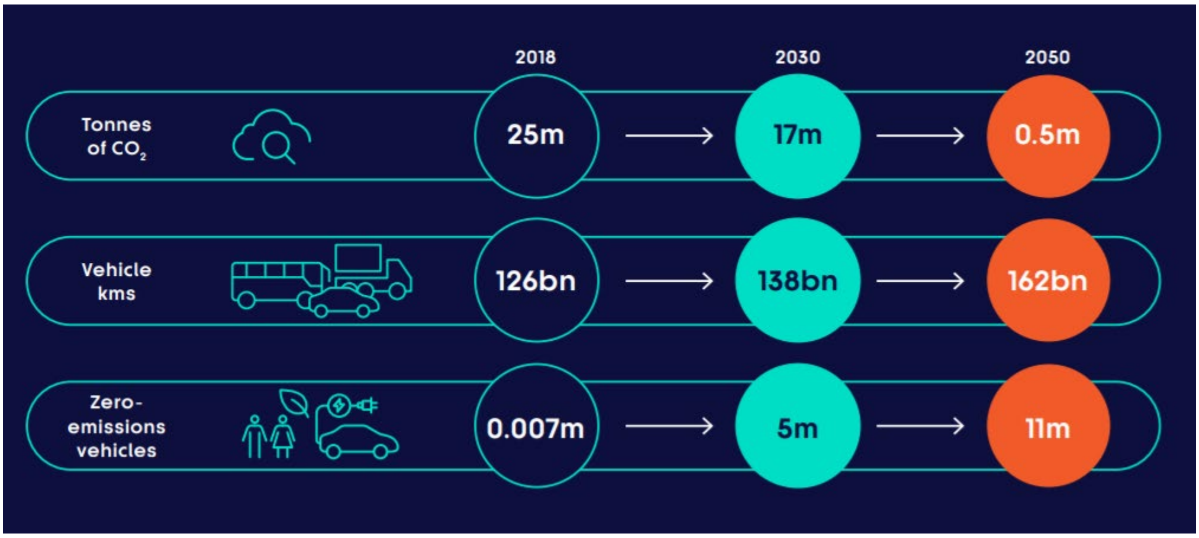

Figure 13: Headline figures related to surface transport emissions, vehicle demand and zero-emissions vehicles in the North under a Prioritised Places scenario.

Table 11: Demand growth 2018 to 2050 and CO_2 emissions in 2030 and 2050 by mode under a Prioritised Places scenario.

Mode	Demand growth 2018-2050	CO_2 emissions in 2030 (megatonnes)	CO_2 emissions in 2050 (megatonnes)
Rail	*Not available*	0.6	0.4
Bus		0.3	0.0
Car	30%	10.0	0.0
Van	47%	1.6	0.0
HGV	1%	7.6	0.1

Table 12: Total vehicle demand and CO_2 emissions in 2050 by area type under a Prioritised Places scenario (excluding bus and rail).

Area type	Vehicle kilometres in 2050 (billions)	CO_2 emissions in 2050 (megatonnes)
Urban	20.7	0
Sub-urban	87.8	0.1
Rural	53.4	0

Table 13: Fuel shares by vehicle type in 2050 under a Prioritised Places scenario.

Vehicle type	Fuel type	Share
Car	BEV	99%
Car	PHEV	1%
Van	BEV	99%
Van	PHEV	1%

HGV	BEV	97%
HGV	Diesel	1%
HGV	Hydrogen	2%

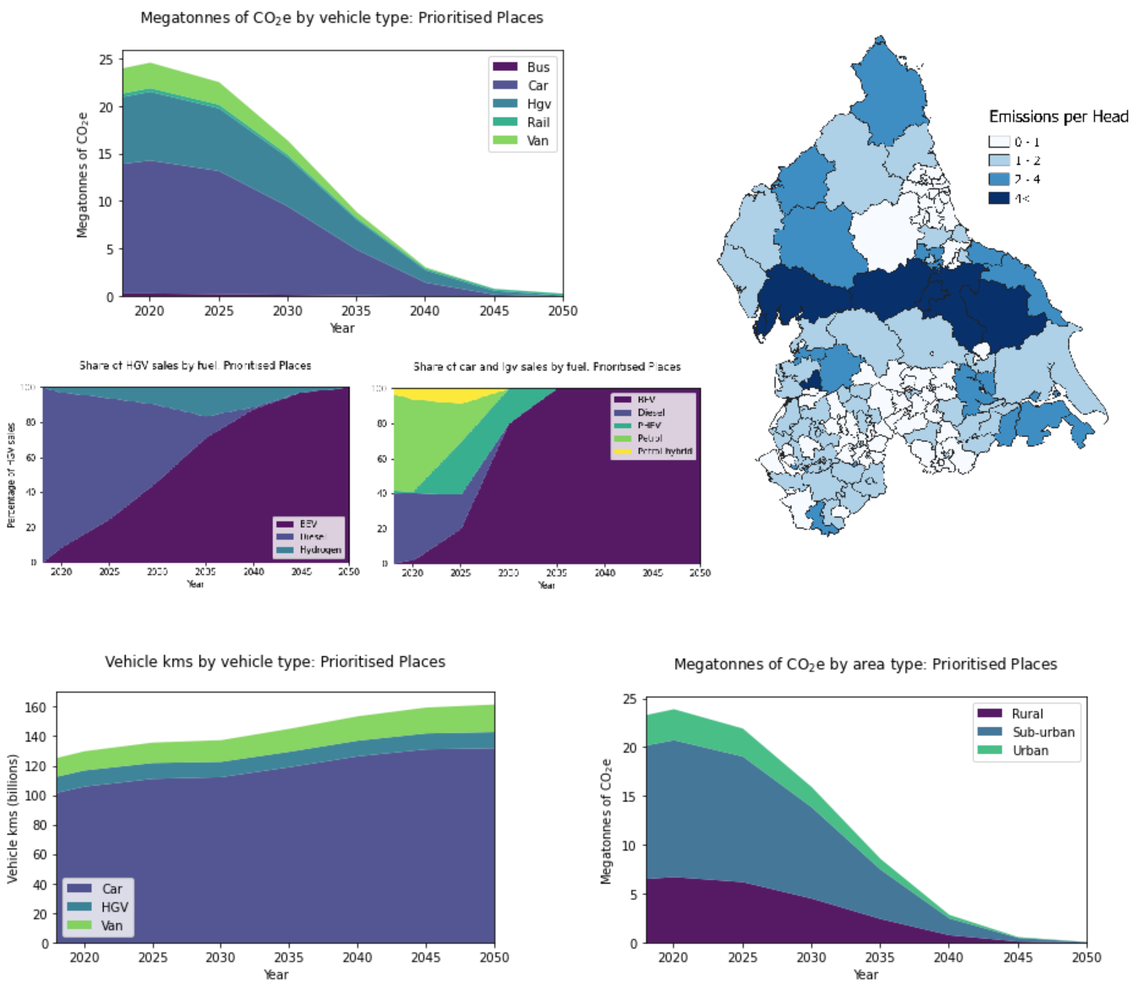

Figure 14: Mode, fuel and area type breakdown of emissions in the North under a Prioritised Places scenario.

8.3.3 Digitally Distributed

Digitally Distributed sees a 99.6% reduction in tailpipe emissions from 2018 to 2050. With just 0.1 $MTCO_2$ of residual emissions in 2050.

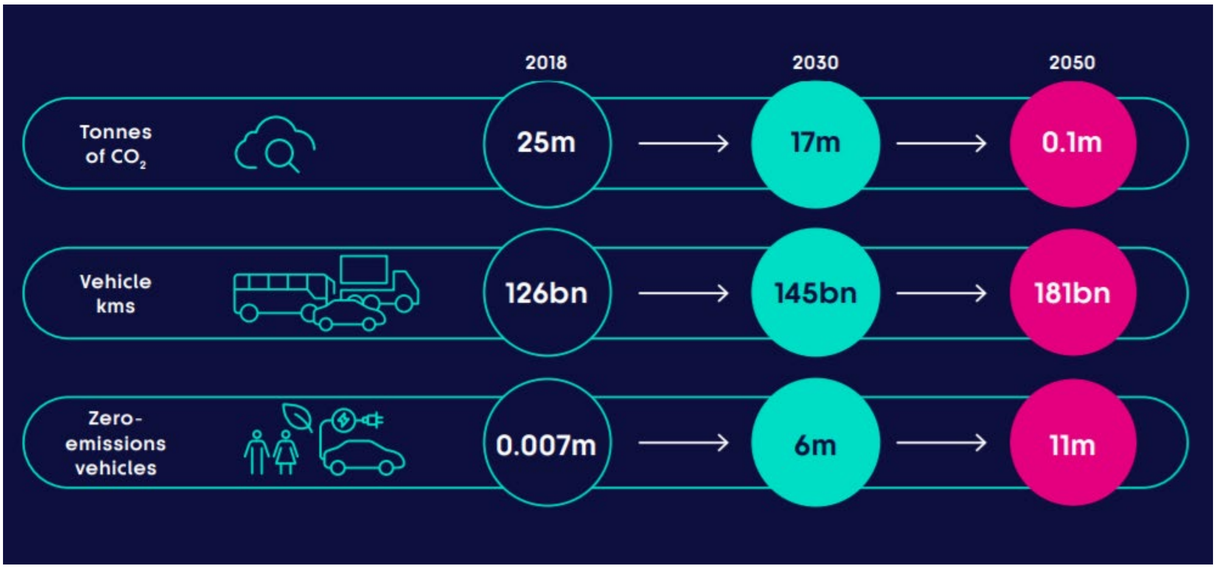

Figure 15: Headline figures related to surface transport emissions, vehicle demand and zero-emissions vehicles in the North under a Digitally Distributed scenario.

Table 14: Demand growth 2018 to 2050 and CO_2 emissions in 2030 and 2050 by mode under a Digitally Distributed scenario.

Mode	Demand growth 2018-2050	CO_2 emissions in 2030 (megatonnes)	CO_2 emissions in 2050 (megatonnes)
Rail	*Not available*	0.6	0.0
Bus		0.3	0.0
Car	44%	9.6	0.0
Van	74%	1.6	0.0
HGV	4%	7.9	0.1

Table 15: Total vehicle demand and CO_2 emissions in 2050 by area type under a Digitally Distributed scenario (excluding bus and rail).

Area type	Vehicle kilometres in 2050 (billions)	CO_2 emissions in 2050 (megatonnes)
Urban	24.4	0
Sub-urban	101.4	0.1
Rural	54.9	0

Table 16: Fuel shares by vehicle type in 2050 under a Digitally Distributed scenario.

Vehicle type	Fuel type	Share
Car	BEV	100%
Van	BEV	100%
HGV	BEV	97%
HGV	Diesel	1%
HGV	Hydrogen	2%

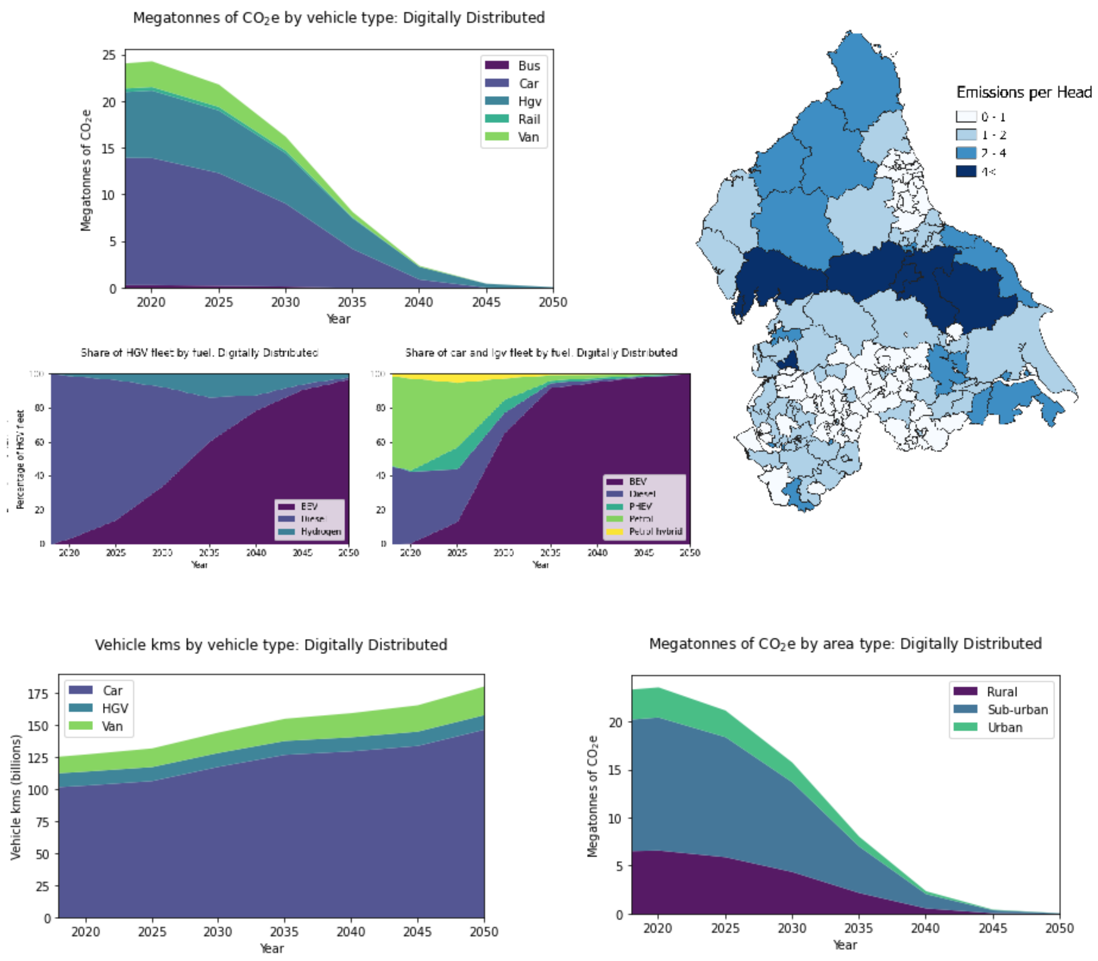

Figure 16: Mode, fuel and area type breakdown of emissions in the North under a Digitally Distributed scenario.

8.3.4 Urban Zero Carbon

Urban Zero Carbon sees a 99.6% reduction in tailpipe emissions from 2018 to 2050. It is the only scenario to see a decrease in HGV demand and is the fastest at shifting to zero-emissions vehicles. Consequently, it sees the lowest residual emissions (attributed to a small number of diesel HGVs) in 2050 at just over 1 $MTCO_2$.

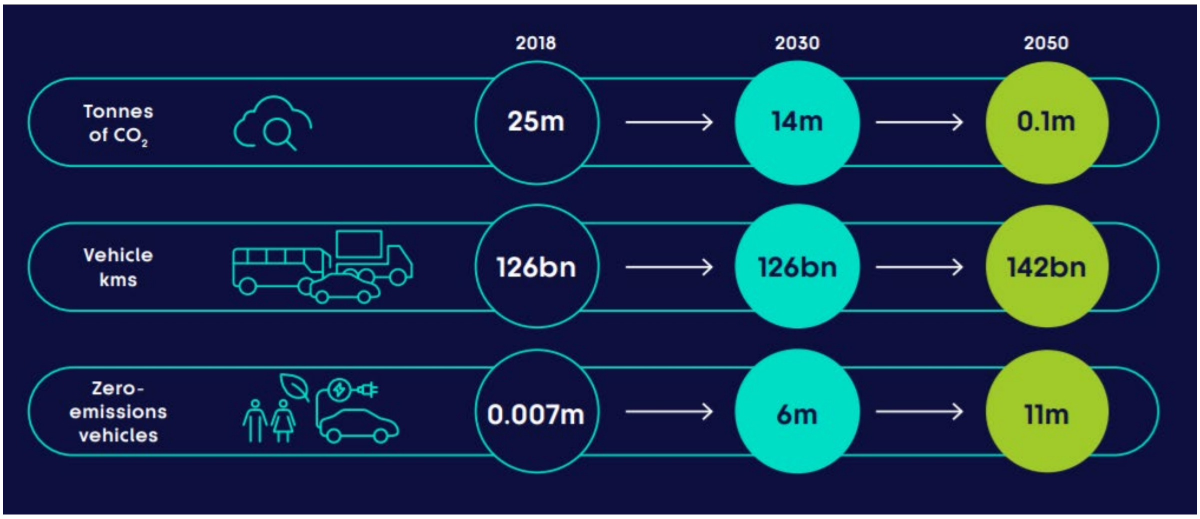

Figure 17: Headline figures related to surface transport emissions, vehicle demand and zero-emissions vehicles in the North under an Urban Zero Carbon scenario.

Table 17: Demand growth 2018 to 2050 and CO_2 emissions in 2030 and 2050 by mode under an Urban Zero Carbon scenario.

Mode	Demand growth 2018-2050	CO_2 emissions in 2030 (megatonnes)	CO_2 emissions in 2050 (megatonnes)
Rail	*Not available*	0.6	0.0
Bus		0.3	0.0
Car	10%	7.1	0.0
Van	50%	1.2	0.0
HGV	-3%	7.6	0.1

Table 18: Total vehicle demand and CO_2 emissions in 2050 by area type under an Urban Zero Carbon scenario (excluding bus and rail).

Area type	Vehicle kilometres in 2050 (billions)	CO_2 emissions in 2050 (megatonnes)
Urban	20.6	0.0
Sub-urban	78.8	0.1
Rural	42.4	0.0

Table 19: Fuel shares by vehicle type in 2050 under an Urban Zero Carbon scenario.

Vehicle type	Fuel type	Share
Car	BEV	100%
Van	BEV	100%
HGV	BEV	97%
HGV	Diesel	1%
HGV	Hydrogen	2%

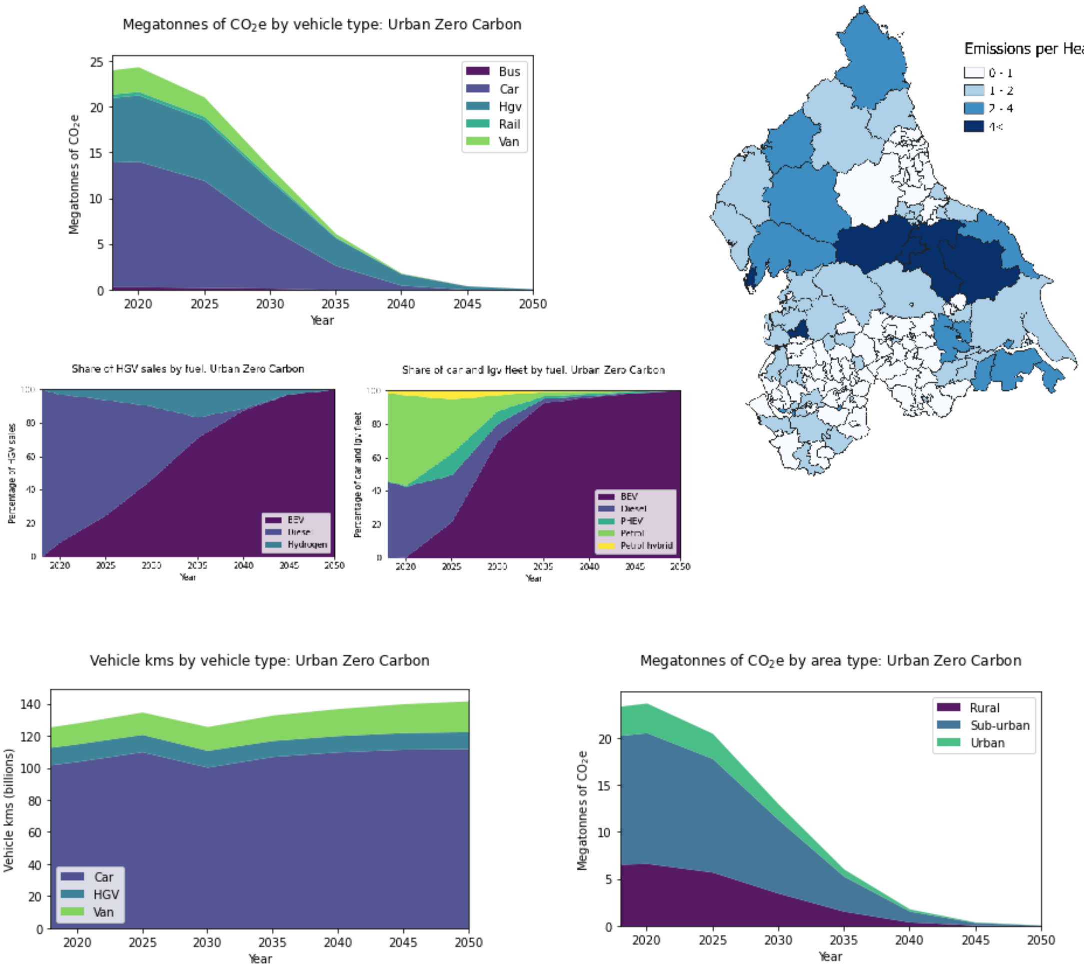

Figure 18: Mode, fuel and area type breakdown of emissions in the North under an Urban Zero Carbon scenario.

9 Quality assurance

9.1 Comparison checks against independent sources

There are limited independent sources available to check estimates of emissions at a sub-national level. The most definitive validation available is the amount of road fuel sold in any given year, but this data is only available at a national level. Total vehicle kilometres travelled are also very difficult to measure independently and is usually estimated using a base year model that takes account of a range of observed data, such as traffic counts and trip rates.

The DfT's National Transport Model has the advantage of being a national model, which can have its base year carbon emissions calibrated to the observed base year road fuel sales. With a well calibrated total, the main uncertainty is around the split between geographic regions and vehicle types. The DfT publishes estimates of vehicle kilometres travelled and emissions by region and vehicle type, which we have used for this comparison check. Table 20 below sets out the comparison for vehicle kilometres travelled.

Table 20: Total vehicle kilometres in the North by vehicle type – a comparison between DfT's 2015 estimate and NoCarb's 2018 estimate.

Billion vehicle-km by vehicle type	NoCarb (2018)	DfT National Transport Model (2015)
Car	102	92
HGV	11	17
LGV	13	7
Total	126	116

While the match is reasonably good, there are two main inconsistencies that need to be addressed:

- The NoCarb figures are generally higher than the National Transport Model figures. The first explanation for this is that the NoCarb figures represent 2018 demand, rather than 2015 demand, and there was some growth in traffic over that period. The second explanation is that the geographical scope of the Northern regions in the two models do not perfectly overlap. The National Transport Model uses the three Northern Government Office Regions, whereas NoCarb uses a version of the TfN administrative boundary, which includes parts of Derbyshire and Nottinghamshire. Furthermore, it is not clear whether National Transport Model figures attribute demand to regions based on origin zone or on where the emissions take place, as in NoCarb. Further discussions with DfT will be arranged by TfN to clarify the source of these differences.
- NoCarb has a higher share of vehicle kilometres attributed to HGVs relative to LGVs than the National Transport Model. Both models take inputs from the Great Britain Freight Model, but they use different versions and may also use different validation datasets. There is a known

issue of classification between large LGVs and small HGVs and we are confident that differences in how this classification is done is the main cause of this difference. During 2021, we will work with DfT to understand these differences and update our own modelling assumptions as required.

In terms of CO_2 emissions, the National Transport Model has a total for the Northern regions of 25Mt, compared to NoCarb's 24Mt, around a 4% difference. The difference in emissions estimates is smaller than the difference in vehicle kilometres, suggesting small differences in the emissions intensity assumptions used within the calculation. Given the National Transport Model's calibration to national fuel sales, this closer match on emissions is perhaps more important than the match on demand. Overall, this close match gives good confidence that the two approaches are broadly aligned and that TfN's work is aligned to the best available alternative sources of data. Going forward, we will also look to undertaken further validation against local tools within the North.

9.2 Error handling

NoCarb is written in PEP-8 compliant Python 3.7 standard as per TfN's Coding Standards document. The code has been designed to ensure the audits are conducted throughout any given run. Using Python ensures that the analysis is repeatable and can be adjusted for future iterations if required.

Care has been taken to check for anomalies throughout with audit messages and outputs to ensure that functions have executed as planned as the results are within expected ranges.

10 Future iterations and improvements

There are several opportunities to improve the model:

- Once NELUM has been re-based to 2018, the results will be updated. It is expected that this will improve the accuracy of both baseline and future car demand estimates.
- Full integration with NoHAM for Future Travel Scenarios, which will also include more detailed modelling of future van and HGV demand.
- At the moment, the model reflects CO_2e tailpipe emissions and high-level electricity emissions. There is an opportunity to update the model to calculate and reflect:
    - Consumption of hydrogen and more detailed estimates of electricity emissions;
    - Well to wheel emissions;
    - Life cycle emissions; and
    - The carbon impact of infrastructure proposals.
- The role of car ownership on car fleet size, car use, average vehicle mileage and fleet turnover, and how purchasing patterns could vary spatially and over time in response to local and national factors. This will be undertaken using the new Car Ownership Model TfN is developing in 2021.
- An additional step could be added into the tool to recommend the zero-emissions sales and demand reductions required to meet the decarbonisation trajectory and/or offset the carbon impact of infrastructure proposals.
- There is an opportunity to consider how demand reductions due to lift-sharing and other policy levers could be modelled in Analytical Framework travel demand tools and then reflected in NoCarb.
- CCC efficiency gains are based on analysis from their Fifth Carbon Budget. A request could be made to the CCC to access to the latest figures, so they can be updated in NoCarb. Parallel to this, there are plans to explore the impact of variation in technology-enabled vehicle efficiency, for example to represent different fiscal policies.
- As discussed in Section 7, sensitivity analysis related to the proportion in which PHEV vehicles operate in electric mode will be undertaken later in 2021.
- As mentioned in Section 5.2.1, explore the impact of using exponential instead of linear interpolation for scenario tables, such as vehicle sales.

11 References

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Appendix A: Quantifying demand change using NELUM

Process overview

A separate piece of analysis was undertaken using NELUM to understand how car demand could be reduced in line with scenario-based demand changes (**Demand Changes**).

Using Just About Managing scenario inputs as a baseline, NELUM was run several times, tweaking one demand-related input at a time to derive an associated car demand reduction. The demand reductions associated with changes in each input (see Results

The demand reductions associated with each input change are outlined in Table 21. The figures have been reviewed by Element Energy and are believed to provide sensible estimates for the impact of different measures in reducing car demand.

Table 21 for the list of inputs) were calculated by:

1. Taking the total car kilometres in 2030, 2040 and 2050 using the full set of Just About Managing scenario inputs.
2. Adjusting one scenario input (in most cases, this involved replacing the relevant values with those used for Urban Zero Carbon).[30]
3. Comparing the resulting demand against baseline demand projections (Step 1) to derive the associated demand reduction in each year.[31]

An extra step was then required to convert the metric for road-user charging (one of the demand-related inputs) from a percentage of generalised journey time (GJT) to an average additional pence per kilometre charge.[32] This was done by:

1. Taking the base GJT matrix and applying scaling factors that correspond to the percentage of GJT increase associated with road-user charging.[33]

[30] The input values were introduced 5 years prior to the demand measurement (2025, 2035, 2045) so that they had time to take effect.

[31] If the input change was the same across more than one year, the demand reduction was taken as the mean across those years.

[32] Road-user charging would typically be introduced as a pence per kilometre charge, making it a more intuitive metric.

[33] For the purposes of this analysis, these scaling factors were uniform across intra and inter-zonal trips (as is the case under Urban Zero Carbon). However, in some scenarios, road-user charging varies depending on

2. Retrieving the absolute difference in GJT between the new GJT matrix and the base GJT matrix.
3. Calculating the pence per kilometre charge using the formula below:

$$VoT = \frac{7}{60}$$

$$P = \frac{\sum_{i=1}^{n}(D_i \cdot VoT \cdot 100)}{n}$$

where VoT is value of time (pounds per hour converted to minutes)[34], P is the average additional pence per kilometre charge, and D is the difference in GJT for zone i. The pounds per kilometre charge is converted to pence by multiplying it by 100.

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whether trips are intra or inter-zonal, meaning that the scaling factors are merged with the base GJT matrix based on flow type.

[34] The value of time of £7 per hour was drawn from the DfT Transport Analysis Guidance (TAG) databook.

Results

The demand reductions associated with each input change are outlined in Table 21. The figures have been reviewed by Element Energy and are believed to provide sensible estimates for the impact of different measures in reducing car demand.

Table 21: Demand-related NELUM scenario inputs and their variable descriptions. The blue text represents the metrics for each input.

Demand-related scenario input	Description	JAM baseline input	New input	Input change	Demand reduction
Shared transport/ usership	Bus travel in modelling used to represent both traditional and new shared transport solutions. Bus connectivity for **X flow types** (none, intra-sector or all flow types).	none	intra	none-intra	-2.6%
		intra	all	intra-all	-1.4%
		none	all	none-all	-4.0%
Micro-mobility	Active travel in modelling used to represent both traditional and new micro-modes. Micro-mobility in walk/cycle travel time with average speed of **XXkph / X% share of active travel.**	0/0	20/10	20/10	-1.1%
		10/10	20/10	10/0	-0.6%
		0/0	20/20	20/20	-1.8%
		10/10	20/20	10/10	-1.5%
PT fare subsidisation	**X% lower fares for intra-sector trips / X% lower fares for other flow types.**	0/0	-20/-10	-20/-10	-0.4%
RUC	**Average additional pence per km charge across all zone pairs.** Corresponds to 10%, 15%, and 20% of increase in car GJT respectively.	0	1.0	1.0	-7.9%
		0	1.5	1.5	-12.4%
		0	2.0	2.0	-17.1%
Sustainable access to rail stations	**X% lower perceived costs for access/egress.**	0	-20	-20	-0.6%
Densification	**City and town densification.**	Most growth in urban and sub-urban areas	Growth mainly weighted towards urban areas with very little growth in rural areas	Less growth in sub-urban and rural	-0.3%

Sustainable transport access GJT	**X% lower bus GJT for intra-sector trips / X% lower GJT for walk and cycle trips.**	0/0	-10/-10	-10/-10	-1.6%
WFH/Business trip adjust	**Days per week WFH in occupations where this is possible / X% business to business trip rate adjustment.**	1/0	2/-10	1/-10	-3.1%

Using these figures, different 'packages' of measures could be employed to achieve a specified demand reduction. Figure 19: Using the demand reductions from Table 21, this outlines three different methods in which car demand can be reduced by 10% under a Just About Managing scenario in 2030. demonstrates this, showing three different methods in which to bridge the 10% car demand reduction required in Just About Managing in 2030.

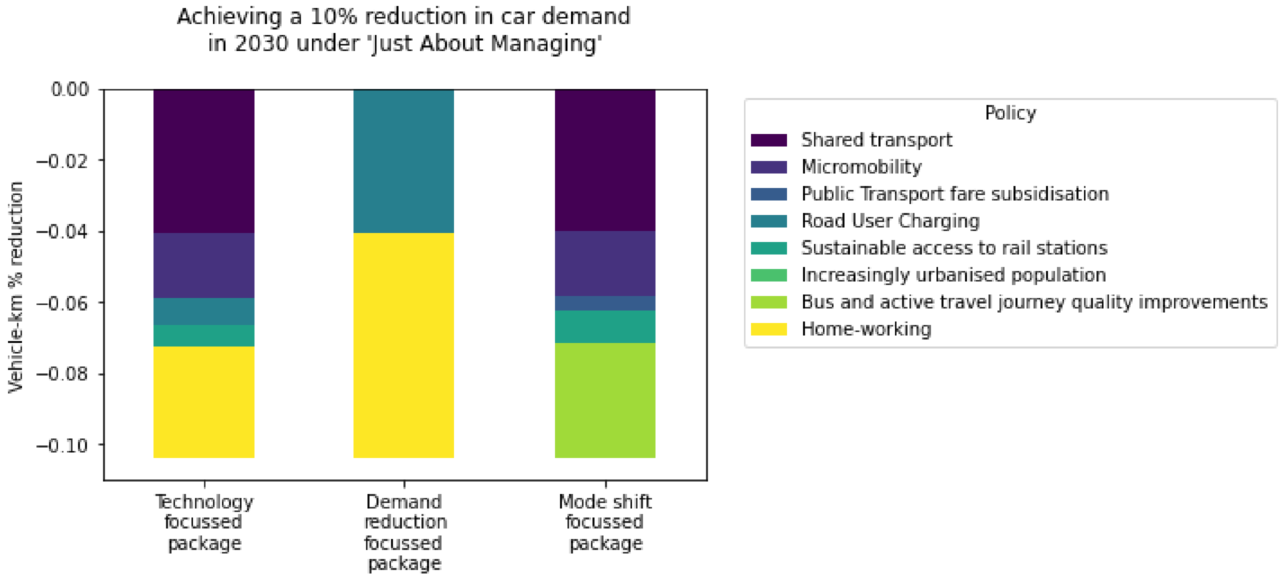

Figure 19: Using the demand reductions from Table 21, this outlines three different methods in which car demand can be reduced by 10% under a Just About Managing scenario in 2030.

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