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Accelerating electric vehicle uptake favours greenhouse gas over air pollutant emissions

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ABSTRACT

The rapid uptake of new vehicle technologies will change the environmental impact of road transport. The emissions produced in power plants supplying electric vehicles (EVs) and vehicular non-exhaust $PM_{2.5}$ emissions leaves the benefits of EVs unclear. We develop a fleet turnover model to assess how different vehicle technologies, the rate of technological change, and changing transport demand impact vehicle and power station CO_{2eq} and air pollutant emissions. By 2050, the transition to EVs reduces yearly CO_{2eq} emissions by 98% and cumulative CO_{2eq} emissions by over 50%; accelerating or delaying EV uptake by 5 years changes these results by 1% and 17%, respectively. By 2050, EVs reduce annual NO_x emissions by 97%, but have little impact on $PM_{2.5}$ due to vehicular non-exhaust emissions. Accelerating or delaying EV uptake had little impact on air pollution emissions. Reducing vehicle kilometres has the potential to reduce non-exhaust $PM_{2.5}$ emissions by 20% in the long-term.

1. Introduction

For over a century road transportation has been dominated by the internal combustion engine vehicle (ICEV). This technology has shaped the modern world, but is responsible for many negative externalities on the environment and human health (Smil, 2017; ICCT, 2019; HEI, 2022). Road transport is now moving towards a more sustainable system. Electric Vehicles (EVs), and in particular Battery-EVs (BEVs) powered by low emission electricity, have the potential to drastically reduce emissions of greenhouse gases (GHGs) while improving air quality. This has led to forthcoming bans for new sales of internal combustion engine vehicles (ICEVs) by many governments around the world. Yet, there are still unanswered questions surrounding this anticipated shift towards EVs. This is in part due to the uncertainty in the mix of fuels and technologies used in power stations supplying electricity to the vehicle fleet and the resulting emissions attributable to EV charging (Mehlig et al., 2021a). Additionally, EVs are expected to change the amount and composition of non-exhaust emissions (Timmers and Achten, 2016, 2018; OECD, 2020; Beddows and Harrison, 2021) due to new vehicle components and added vehicle weight, leaving the long-term impact of EVs on $PM_{2.5}$ exposure unclear. This study addresses these issues by creating a fleet turnover model of the UK vehicle fleet, calculating both air pollutant and greenhouse gas emissions from vehicles and power stations and how these change in the future under scenarios of rapid EV uptake.

This study starts by introducing the evidence behind the shift away from ICEVs, the tools used to analyse this shift, and the remaining questions surrounding the shift. Next, the stock-flow methods behind the fleet turnover model are given and are followed by

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scenarios designed to address three key issues surrounding the shift to EVs: i) the choice between vehicle technologies, ii) how quickly these technologies are adopted, and iii) changing transport demand effecting how these vehicles are used. Next model results are given for each scenario, giving projections of CO_2 equivalent emissions (CO_{2eq}), $PM_{2.5}$ and NO_x emissions up to 2050. And finally, these results are then discussed to assess whether current policies meet their intended targets, the balance between greenhouse gas and air pollutant emission reductions for EVs, and the remaining improvements needed for air quality and climate mitigation after transitioning away from ICEVs.

2. Literature review

The recent push towards electrification in transport is based upon evidence that BEVs are lower emission than ICEVs, and that a net zero electricity system can deliver a net zero road transport system through BEVs. This is backed up by multiple recent comparisons between individual ICEVs and BEVs using life cycle analyses (LCA) which have found that passenger car BEVs on the road today emit lower levels of GHGs than ICEVs and will be even lower in the future (Hoekstra, 2019; Knobloch et al., 2020; Bieker, 2021). Following from micro-scale LCA comparisons of individual vehicles comes macro-scale research assessing the impacts of the fleet wide adoption of these new vehicle technologies. Road transport stock-flow models are designed for this purpose. These models assess how the fleet and its externalities may change depending on the uptake rates of different vehicle technologies and other fleet-wide factors, such as behavioural change affecting transport demand and the size of the vehicle parc (Bastani, Heywood and Hope, 2012; Brand, Tran and Anable, 2012; Fridstrøm, Østli and Johansen, 2016; Hill et al., 2019; Spangher et al., 2019; Brand et al., 2020; Craglia and Cullen, 2020b). Three key areas affecting fleet wide transition to EVs are given below, highlighting the gaps in the literature that this study addresses.

2.1. Vehicle technologies

The literature has extensively covered the choice between vehicle technologies for passenger cars and LGVs in stock-flow models, transitioning from ICEVs to hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs), or BEVs. This literature demonstrates that if the electricity system is sufficiently low-carbon, BEV cars and LGVs are the most effective vehicle technology at reducing GHG emissions (Hill et al., 2019; Brand et al., 2020; Yang et al., 2023). However there are three key aspects surrounding the shift to EVs that have not yet been covered in the literature. Firstly, the fleet wide transition to EVs, including light-duty and heavy-duty vehicles, has not been studied, leaving gap for wholistic analysis of fleet wide electrification. Secondly, air pollution emissions from power stations supplying these vehicles have not been included in previous stock-flow studies due to a lack of emission factor projections. And lastly, recent studies suggests that BEVs will change vehicular non-exhaust $PM_{2.5}$ emissions (Timmers and Achten, 2016, 2018; OECD, 2020; Beddows and Harrison, 2021), leaving the impact of a BEV fleet on $PM_{2.5}$ exposure uncertain (Mehlig et al., 2021a).

2.2. Technology uptake rate

The rate at which new vehicle sales switch to a new vehicle technology, known as the uptake rate, has been demonstrated to be a key variable for long term reductions in GHG emissions (Hill et al., 2019; Brand et al., 2020; Craglia and Cullen, 2020b). Craglia and Cullen (2020b) found that cumulative CO_2 emitted to 2050 was most sensitive to the rate of EV uptake against a broad range of other fleet and vehicle parameters, confirming the focus on this variable by other studies (Hill et al., 2019; Brand et al., 2020). This evidence suggests that a faster EV uptake rate will reduce GHG emissions, yet the same is not clear for air pollutant emissions. This is due to uncertainty on the emissions produced in power plants supplying the EVs (Mehlig et al., 2021a).

2.3. Transport demand

Behavioural change impacting transport demand has been identified as a key variable for road transport GHG emissions (Schwanen, Banister and Anable, 2011). Reductions in transport demand have been found to compliment the transition away from ICEVs, offering additional emission reductions not possible through technological change alone (Anable et al., 2012; Brand et al., 2020). However, with a rapid uptake of BEVs with a similarly rapid decarbonising electricity system, the window where changes in transport demand will impact ICEV emissions and thermal power plants may be shortening.

On the other hand, through BEVs there is a possibility that transport demand may increase through lower running costs. This phenomenon, known as the rebound effect, has been shown to not significantly alter future GHG emissions of a BEV dominated fleet (Craglia and Cullen, 2020b). Yet this increase in demand will have an impact on non-exhaust emissions which has so far not been covered in the literature.

3. Methods and data

A fleet turnover model was created to simulate the road transport fleet of the UK from 2020 to 2050. This section outlines the overall structure of the model, the underlying stock-flow methods, and the input parameters used in the model.

3.1. Model structure

A bottom-up approach using a stock-flow structure was used to model the UK vehicle fleet up to 2050 and is illustrated in the diagram in Fig. 1. The model starts with the 2019 vehicle stock and inputs new vehicles each year based upon an input scenario. Each year vehicles exit the fleet, based upon real world relationships between vehicle age and the proportion of vehicles exiting the fleet. The model includes cars, Light Goods Vehicles (LGVs), rigid and articulated Heavy Goods Vehicles (HGVs), buses, and motorcycles, where within each vehicle type are ICEV, Hybrid EVs (HEVs), Plug-in Hybrid EVs (PHEVs), and Battery EVs (BEVs) vehicle technologies (see Table 1 for the full vehicle type and technology list). The model assigns stochastic parameters that represent the vehicle population, such as the fuel consumption per kilometre or vehicle curb mass, by vehicle type, technology, and registration year. The power stations supplying electricity for road transport are modelled stochastically based upon projections of the UK generation mix, yielding the air pollutant and CO_2 emission intensity of electricity supplying EVs. The relationship between annual mileage and vehicle age are used to determine the proportion of national vehicle kilometres driven (vkm) that is met by each vehicle type, technology, and registration year. National vkm is then input to the model through the scenario which is then used to calculate fleet wide metrics. Well-to-Wheel (WTW) CO_{2eq} emissions were calculated from the sum of CO_2, CH_4, and N_2O using stochastic Global Warming Potential 100 values from the IPCC AR6 report (Forster *et al.*, 2021). For air pollutants only vehicle and power plant sources were included (and so excluding supply chain sources). All data used in the model are publicly available and are referenced in this article.

3.2. Monte Carlo methods

The model employs Monte Carlo methods, using stochastic inputs to propagate the uncertainty of parameters to the model results. The uncertainty associated with model results can then be used to interpret the relative strength of the findings for policy decisions (Saltelli et al., 2020). Fleet population data or literature sources were used to define stochastic parameters for the model. The model diagram in Fig. 1 illustrates how each of the stochastic parameters are used within the model. The model was run 1000 times for each scenario to achieve convergence (see Supplementary Material section 6).

3.3. Starting fleet

The data used to populate the starting fleet was taken from the UK Department for Transport's online licensing tables (Department for Transport, 2021d). This data contained the number of vehicles in the fleet at each year from 1994 to 2019, broken down by the year of vehicle registration between 1970 and 2019. This data shows how many vehicles exit the fleet each year for each registration year, enabling the calculation of empirical survival-age relationships.

3.4. Vehicle survival-age relationships

The proportion of vehicles remaining in the fleet year over year as the fleet ages is known as the vehicle survival-age rate. The survival-age rate in the model represents all exit routes of a vehicle from the fleet, such as scrappage and exportation. Survival-age

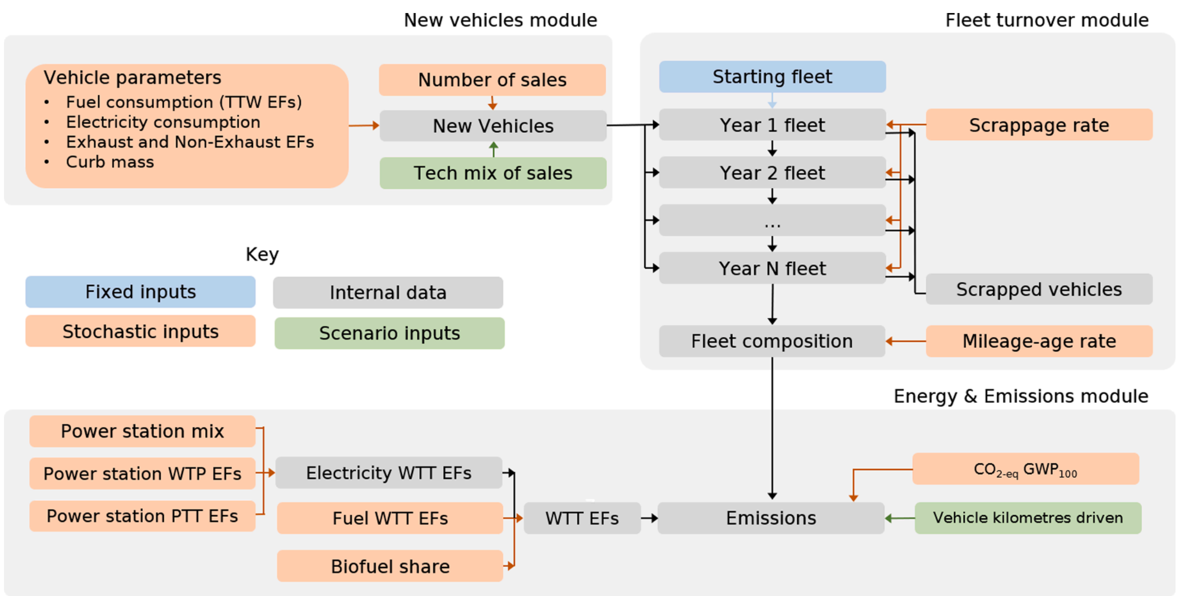

Fig. 1. Structure of the model; WTT = Well-to-Tank, TTW = Tank-to-Wheel, WTP = Well-to-Plant, PTT = Plant-to-Tank. Colours illustrate the different classification of data within the model.

Table 1
Model vehicle types and technologies included, where X shows if the type and technology combination is included. Mild and micro hybrid EVs (mild-HEV, micro-HEVs) were included within each of the ICEV categories as ICEVs could not be separated out from mild-HEV and micro-HEVs for various data inputs. Please refer to Cardoso et al. (2020) for hybrid technology specifications. HEV and ICE sales numbers and vehicle parameters are rarely reported separately for vehicle types other than cars and LGVs, so other vehicle types only have an ICE category with an implicit share of HEV technologies within this technology.

Vehicle Types	Vehicle Technologies						
	Diesel	Diesel HEV	Diesel PHEV	Petrol	Petrol HEV	Petrol PHEV	BEV
Car	X	X	X	X	X	X	X
LGV	X	X	X	X			X
Articulated HGV	X						X
Rigid HGV	X						X
Bus	X						X
Motorcycle				X			X

rates for each vehicle type were derived from table VEH1111 from the UK Department for Transport's online licensing tables (Department for Transport, 2021d) and are given in Fig. 2 for each registration year between 1994 and 2019. The shape this relationship typically follows a Weibull distribution (Zachariadis, Samaras and Zierock, 1995) which has been applied in previous stock-flow models (Zachariadis, Ntziachristos and Samaras, 2001; Brand, Tran and Anable, 2012; Craglia and Cullen, 2019). Empirical survival-age curves were derived from the data in Fig. 2 as the curve shapes of LGVs and motorcycles did not follow Weibull distributions. These empirical curves were produced by taking the most recent survival rate from the available registration years at each vehicle age. This method captures how the survival-age curves of vehicles are changing over time: new cars are lasting longer in the central years of their life, new motorcycles are moving in the opposite direction, and new buses appear to be shifting shape towards that of LGVs while increasing their lifetime.

Uncertainty in these empirical survival-age curves was introduced by using a uniform distribution between an upper and lower survival-age curve. The range between the upper and lower curves were taken from the observed range of survival-age rates across all

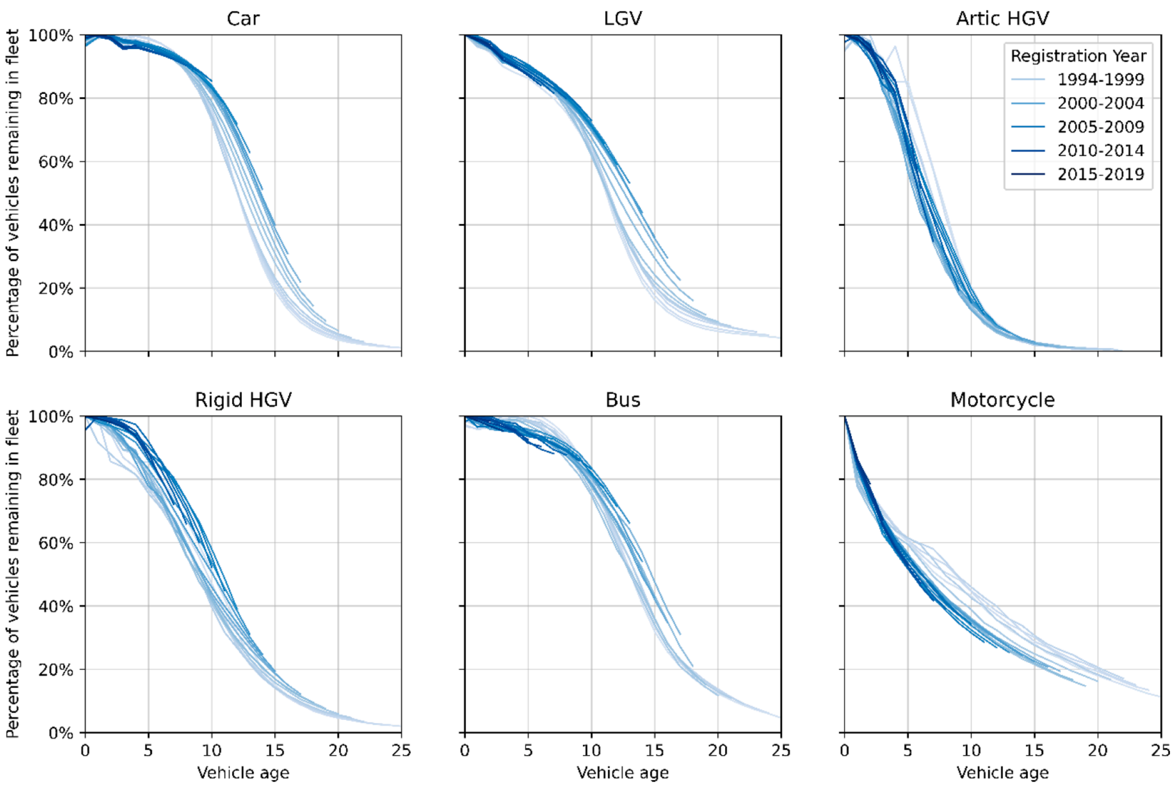

Fig. 2. Net survival-age rates for the given vehicle types for each registration year between 1994 and 2019, where the shade of blue shows the registration year. The net survival-age rate given for cars is the aggregate across both petrol and diesel vehicle types. Data sourced from table VEH1111 from the UK Department for Transport's online licensing tables (Department for Transport, 2021d). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

registration years for each vehicle age. The range found for each age was then centred on the most recent empirical survival-age curve outlined above. The resulting survival-age rates and distributions used in the model are given in Fig. 3. Some survival-age curves do not reach 0% after 25 years. For these vehicle types the survival-age curve is linearly extrapolated to 0% using the survival-age rates from the last 3 years of sample data (23–25 years). The uniform distribution was chosen over other approaches, such as deriving a normal distribution at each vehicle age using the data from each registration year and then shifting the mean to align with the empirical survival-age curve, as it provided the greatest amount of parameter uncertainty.

This method produces an artefact where survival-age rates can increase with vehicle age for the oldest vehicles when there are no further data points for more recent registration years. This occurs for motorcycles that are 20 years and older, as vehicles with earlier registration dates survive for longer than more recently registered vehicles. This can be observed in Fig. 2, where the final data point for each survival-age rate increases for older registration years. This does not affect other vehicle types, as it is only motorcycles which are seeing lower, rather than higher lifetimes in recent years.

The survival-age curve for each vehicle type and model run is produced by taking a uniform sample percentile which defines the relative position of the survival-age curve in the range of the distribution shown in Fig. 3, and so preserves the smooth real-world survival-age curves seen in Fig. 2. The authors are not aware of projections for how vehicle lifetimes are expected to change over time, and so the same survival-age rate distribution was used for all years, where a single curve was used for each vehicle type across all registration years in each run.

To address this limitation, a sensitivity study was conducted to assess the impact of vehicle lifetime continuing to increase in the future. Fig. 2 shows cars LGVs buses and rigids are all lasting longer, where vehicle lifetime has increased from the 2000 registration year onwards. Across these four vehicle types, on average the vehicle age at the 25th, 50th, and 75th percentile of the survival-age curve increased by 3%, 2%, and 1% per year, respectively where registration year data was available (please see Supplementary Material Table S5 for this calculation). To estimate an upper bound for the sensitivity study, the increase in vehicle lifetime of 2% per year for the 50th percentile was used to extend the survival curves up to 2050. As the model samples a single survival-age curve for each run and so cannot apply a year-on-year changing survival-age curve, the extended survival-age curve halfway between 2020 and 2050 was used for all model years. This resulted in the survival-age curves for cars, LGVs, buses, and rigid HGVs extending by 30%. The survival-age rate curves from Fig. 3 were lengthened by resampling the vehicle age, preserving the shape of the curve, to accommodate the extended vehicle lifetime. The results from this sensitivity study are given in section 5.4.4.

ICEV survival-age curves were used for new vehicle technologies (HEVs, PHEVs, and BEVs) as there is currently a lack of published

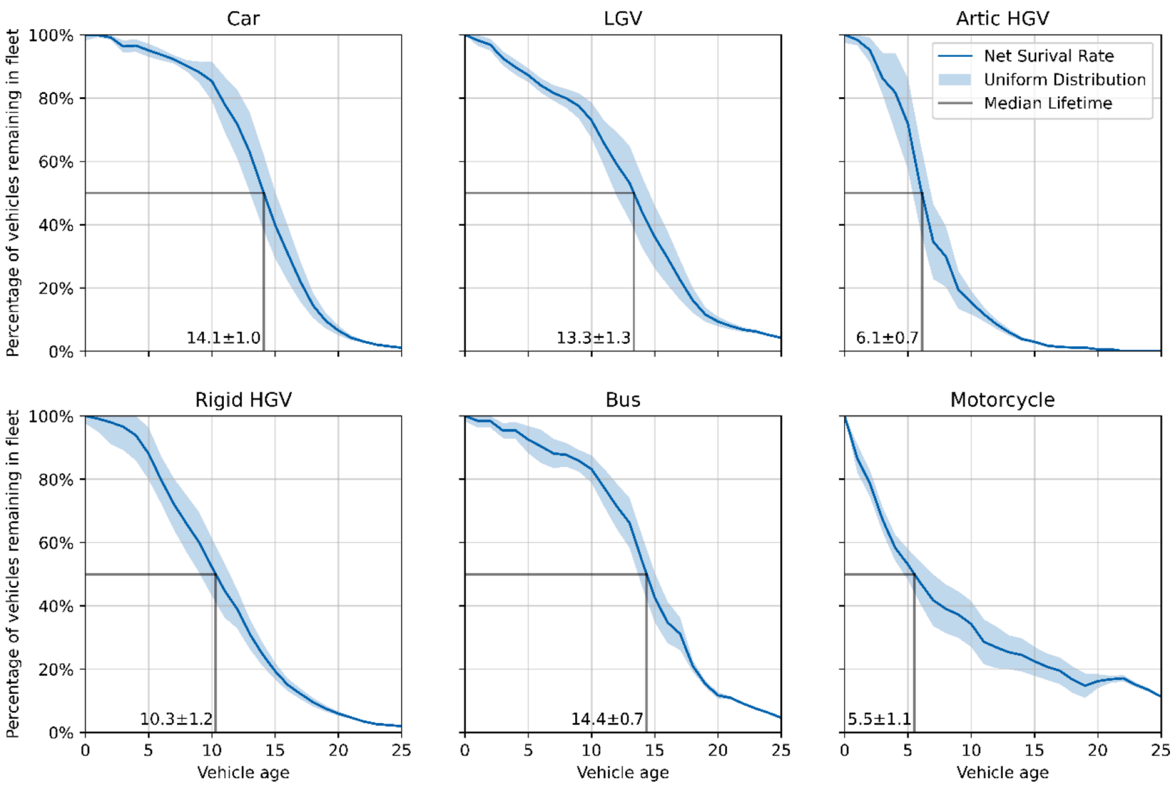

Fig. 3. Net survival-age rates used to model each vehicle type, with the mean given in solid blue, and uniform distribution shown by the shaded area. Grey lines mark the median vehicle lifetime with ± values giving the range from the uniform distribution. The car survival-age rate includes both petrol and diesel cars that individually have median vehicle lifetimes of 14.4 ± 1.0 and 13.6 ± 0.9, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

survival-age curves or the fleet population data to empirically derive these. Some assumptions can be made on the expected lifetime of the components of the vehicle to justify this decision. As HEVs share the majority of their drivetrain with ICE vehicles they can be assumed to have similar survival-age rates. The batteries in modern BEVs have been estimated to last as long as ICEVs when allowing for an 20% decrease in battery capacity, while other BEV components are likely to outlast their ICEV equivalent (excluding consumable parts) (Hoekstra, 2019).

3.5. New vehicle sales

New vehicles are input to the model through the combination of total vehicle sales and the technology mix of new vehicle sales, as illustrated in Fig. 1. The scenario input gave a deterministic percentage mix of vehicle type sales by technology, whereas a stochastic variable was used to represent the total number of sales for each vehicle type. The total number of sales was generated using a random walk with drift for each model run, simulating the ups and downs of the UK's new vehicle market (DfT, 2021d). The random walk was defined using the mean and standard deviation of vehicle sales from the past 20 years and was assigned drift to match the growth of the fleet stock from (DfT, 2021d) (see Supplementary Material Fig. S11 for illustrations of the random walk). New sales have been depressed due to the supply chain issues of 2020, 2021 and 2022, and is accounted for in the model using real world sales figures from these years (Department for Transport, 2021d).

3.6. Vehicle mileage-age relationships

In the UK, vehicles are driven less each year as they age (Dun et al. 2014; Craglia and Cullen, 2020a). The rate that mileage declines with vehicle age is known as the mileage-age rate and depends on vehicle type and technology. Dun et al. (2014) found unique mileage-age rates for diesel cars, petrol cars and LGVs based on UK MOT testing data (annual Ministry of Transport, MOT, road-worthiness test). Here MOT testing data was used to produce mileage-age rates, given in Fig. 4 for cars, LGVs, and motorcycles; the methods used to derive these relationships are given in the Supplementary Material (Department for Transport, 2022a).

Fig. 4 shows that the first generation of HEVs and BEVs are not being driving with the same usage patterns as typical ICEVs. We have not used these mileage-age curves in this model for HEVs and BEVs since this first generation of EVs are likely not representative of the latest and next generation EVs and EV infrastructure, mirroring the arguments made by Fridstrøm, Østli and Johansen (2016).

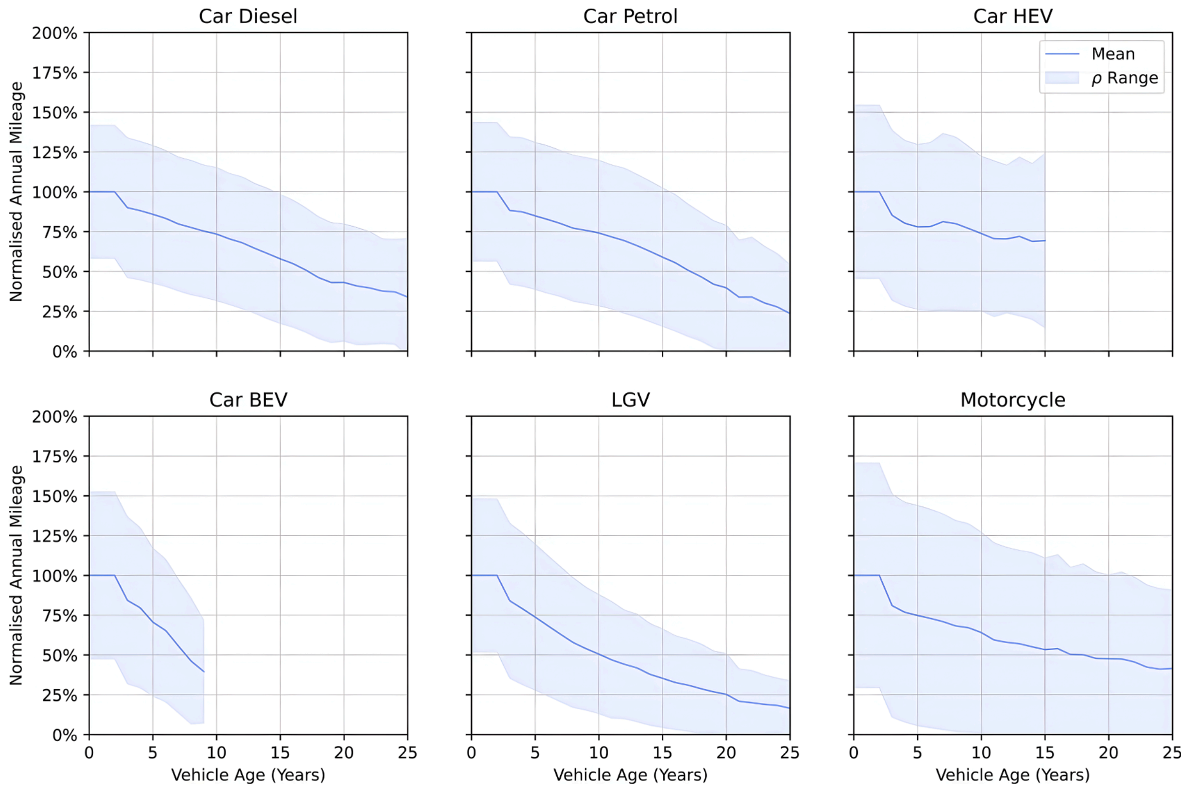

Fig. 4. Mileage-age rate distributions derived from MOT data for the given vehicle type and technology; the shaded area shows the standard deviation range, and the solid line shows the mean mileage-age rate in the distribution. Car HEVs, PHEVs, and BEVs used the combined mean of petrol and diesel mileage-rates given in this figure; the HEV and BEV mileage-age rates shown in this figure are only within the mileage-age rate sensitivity study.

Therefore, the mean mileage-age relationship of petrol and diesel cars was used for HEVs, PHEVs, and BEVs. For all other vehicle types, EVs are assumed to have the same mileage-age relationship as their ICEV equivalent. To evaluate the impact of this assumption, a sensitivity study was conducted where HEVs and BEVs for all vehicle types use their respective mileage-age rates from the MOT data given in Fig. 4 (with PHEVs using the same relationship as HEVs). This represents the worst-case scenario where the mileage of BEVs across all vehicle types falls far quicker than the other technologies in the fleet. The results from this sensitivity study are given in section 5.4.5.

There is no publicly available data on how heavy-duty vehicle mileage declines as the vehicles age. Therefore, we have assumed that heavy duty vehicles follow the mileage-age relationship of LGVs. This assumption of declining mileage over time is backed up by anecdotal evidence from automatic number plate recognition data used in the NAEI which revealed that the age distribution of HGV vehicle kilometres driven was much newer than the age distribution of the vehicle stock (NAEI, 2018).

Mileage-age rates are used in the fleet turnover module to convert the stock of vehicles into a fleet composition giving the percentage contribution of each vehicle type, vehicle technology, and vehicle registration year, to the overall vehicle kilometres driven by the fleet.

3.7. Vehicle kilometres driven

Transport demand is input to the model as a deterministic scenario input, as shown in Fig. 1. This input gives the total vehicle kilometres driven (vkm) for each vehicle type for each year. This input vkm is multiplied with the fleet composition to give the vkm driven in each year broken down by vehicle type, vehicle technology, and registration year.

3.8. Vehicle parameters

For all vehicle types and technologies in the model, parameters are determined by the registration year. These parameters represent vehicles from the given registration year for the given vehicle type and technology. These parameters include the exhaust NO_x emissions, exhaust N_2O emissions, exhaust and non-exhaust $PM_{2.5}$ emissions, fuel or electricity consumption, and curb mass. Each parameter is expressed as a normal distribution with mean and standard deviation, allowing for the uncertainty of the vehicle parameters to be propagated to the model results.

3.8.1. Fuel consumption

Fuel consumption was taken from the EEA CO_2 car and LGV monitoring database, where the population the statistics were used to define normal distributions for fuel consumption by registration year, using sales between 2011 and 2019 for cars and between 2017 and 2019 for LGVs, with fuel consumption for older vehicles taken from UK government statistics (EEA, 2020). These fuel consumption distributions represent the existing car and LGV fleet's segment market share up to 2019, where cars have seen the share of Sports Utility Vehicles (SUVs) rise to one quarter of all new sales (SMMT, 2020). The EEA CO_2 monitoring data reports the type-approval fuel consumption, which is known to significantly underestimate real world consumption. And so, correction factors from Dornoff et al. (2020) were used to adjust the EEA values by fuel type, technology type, and registration year. Population fuel consumption data for HGVs, buses and motorcycles are not publicly available, so HGV and bus fuel consumption was taken from (Element Energy, 2017) and motorcycle fuel consumption was taken from (European Environment Agency, 2019).

Projections for the reduction in fuel consumption due to efficiency improvements were taken from Element Energy (2017) for cars, LGVs, and buses from 2020 to 2035, and extrapolated to 2040. The projections from Element Energy (2017) were chosen as they provide the widest coverage of vehicle technologies found in the vehicle fleet, that are typically not found in the literature such as diesel car HEVs, and diesel car PHEVs. Moreover, the projections apply a consistent methodology across vehicle types and technologies that considers specific automotive trends for the UK fleet (Element Energy, 2017). Motorcycles were assumed to reduce at the same rate as cars. Projections were taken from Sacchi et al. (2021) for HGVs using the mean mass of rigid and articulating HGVs in the UK fleet.

Over the last decade, the share of Sports Utility Vehicles (SUVs) sold in the UK has quadrupled, reaching a quarter of all new car sales in 2019 (SMMT, 2020). This historical increase in vehicle size and the corresponding increase in fuel consumption are captured by the model by using fleet wide fuel consumption statistics from the car EEA CO2 monitoring database up to 2019 (EEA, 2020). Future shifts in car segments are not captured by the model as segment specific projections of fuel consumption, segment market share, and the rate of uptake of HEVs, PHEVs, and BEVs are not avaiable as far as the authors are aware. Therefore, the model assumes that future trends in fuel consumption and the uptake new technologies are consistent across vehicle segments. The authors are not aware of any projections suggesting that relative improvement rates will be different across SUVs and other car types, and note that the share of SUVs in the UK car fleet has plateaued at 27% for the past two years (SMMT, 2022, 2023), suggesting these assumptions are grounded. Additional data giving segment granularity would improve this aspect of the model and is a subject for future work.

Figs. S2-S7 in the Supplementary Material plot the fuel consumption parameters for each vehicle type and technology. Fuel consumption for each vehicle type was projected to decrease up to 2040, for cars the decrease ranged from 28% to 41%, for LGVs from 13% to 22%, for HGVs from 25% to 26%, buses by 24%, and motorcycles by 12%. These values for cars were similar to the reductions in fuel consumption found by Cox et al. (2020) ranging from 21% to 42%.

For cars, BEV electricity consumption was taken from Cox et al. (2018) using their parameter distribution and includes charging efficiencies and all on board energy requirements for new BEVs between 2015 and 2040. Electricity consumption for BEV LGVs and motorcycles was based upon the values used for cars from Cox et al. (2018), using the ratio of ICEV fuel consumption between these vehicle types to estimate electricity consumption for BEV LGVs and motorcycles. For HGVs and buses, BEV electricity consumption between 2020 and 2040 was taken from Sacchi et al. (2021) and Element Energy (2017), respectively.

PHEVs were modelled using the Utilisation Factor (UF) approach, where a percentage of driving is in charge depleting mode using only the electric motor, and the remaining percentage in a charge sustaining mode using a combination of the combustion engine and the electric motor. The UF gives the proportion of driving in the electric only charge depleting mode. Real world UF values in Europe have been shown to vary from 24% to 54% (Plötz et al., 2020). This European range was used in the model with a uniform distribution as there is not yet representative fleet wide data for UFs in the UK. Little published data is available for PHEV performance in hybrid drive mode, broken down by the fuel type (diesel or petrol), and so it was assumed that fuel consumption in hybrid drive mode was equivalent to that of a conventional HEV. Parameters for car electricity consumption in electric drive mode were taken from Cox et al. (2020) with LGV consumption derived in the same manner as BEVs. Electricity consumption for BEVs and PHEVs between 2010 and 2050 are illustrated in Figs. S2 to S7 in the Supplementary Material.

3.8.2. Exhaust NO_x N_2O, and $PM_{2.5}$ emissions

Emissions per kilometre of exhaust NO_x, N_2O, and $PM_{2.5}$ were assigned to each vehicle using euro standards. For HGVs, buses, and motorcycles, the emission factors were sourced from the EMEP/EEA emission inventory guidebooks using the tier 2 methodology (European Environment Agency, 2019). The methodology gives emissions per kilometre driven based the vehicle type, technology, and euro standard which are used as mean values for the parameter's normal distribution. These emission factors represent real world driving conditions and speeds across the EU and are intended for use at a national level. The guidebook gives an estimation of national level uncertainty of these emission factors, which were used to define normal distributions (European Environment Agency, 2019).

NO_x emissions for cars and LGVs were taken from Davison et al. (2021), which gives an emission factor for each euro standard for rural, urban, and motorway roads for UK specific real world conditions (rural, urban, and motorway vkm was disaggregated using data given in Department for Transport (2022b). These emission factors are given as the parameter mean with upper and lower bounds used as 95% confidence intervals of a normal distribution. Due to the real-world improvement of Euro 6 RDE vehicles (Emisia, 2020), a 75% reduction was applied to the euro 6 emission factors from Davison et al. (2021) for vehicles bought from 2019 onwards. Emission factors for exhaust $PM_{2.5}$ and N_2O for cars and LGVs were sourced from the same EMEP/EEA guidebook as the other vehicle types above.

3.8.3. Non-exhaust $PM_{2.5}$ emissions

Non-exhaust emissions from brake, tyre, and road wear were assigned by vehicle type using the parameter distributions given in the EMEP/EEA emission inventory guidebook's tier 2 method that provides specific emission factors for car technologies: ICEV, HEV, PHEV, and BEV (European Environment Agency, 2019). The possible impact of vehicle curb mass on non-exhaust emissions is investigated in a sensitivity study in section 4.4, using the curb mass-based emission factors given in OECD (2020).

3.8.4. Curb mass

The curb mass of cars and LGVs was a stochastic input to the model used for the sensitivity study on non-exhaust emissions. Curb mass for vehicles currently in the fleet was taken from the EEA CO_2 monitoring database, which gives the type-approval test weight. The population mean and standard deviation of the WLTP (Worldwide harmonised Light vehicle Test Procedure) test curb mass was used to define normally distributed parameters. The mean curb mass and standard deviation for new cars in 2019, broken down by technology, is given in Table 2. The curb mass of BEVs was found to be 21% larger than the ICEV mean, agreeing with findings in the literature (Timmers and Achten, 2016, 2018; Beddows and Harrison, 2021). As the number of BEV models on sale has not yet reached the number of ICEV models, BEV car curb mass was linearly increased up to 25% above the ICEV mean up to 2025 to match the weight increase seen for BEV equivalent make and model ICEVs (Timmers and Achten, 2018). LGV BEV mass was taken from (OECD, 2020). The remaining vehicle types did not have curb mass inputs to the model.

It is unclear how the size and weight of new vehicles will change in future, given the competing trends of larger Sports Utility Vehicles forming a larger share of sales in the UK and globally (IEA, 2021), and increasing energy density of battery technology reducing the weight required to deliver acceptable driving range. To account for this, the sensitivity study on non-exhaust emissions contains two projections for how the curb mass of cars & LGVs may change up to 2050. The first maintains current trend towards heavier vehicles, where the curb mass of cars and LGVs increase by 20% up to 2030 (2% per year), taken from the GREET model's

Table 2
EEA CO_2 monitoring data for new car sales in 2019 for the UK. The results show the mean values and standard deviation for the WLTP curb mass (kg), where the ICEVs Mean is the combined data for diesel and petrol vehicles.

Technology	N	Mean Mass (kg)	Standard Deviation	Change from ICEV Mean
Diesel	615,356	1861	304	+18%
Diesel HEV	3142	2036	378	+29%
Diesel PHEV	1069	2213	61	+40%
Petrol	1,616,847	1469	267	−7%
Petrol HEV	104,668	1609	250	+2%
Petrol PHEV	34,128	2131	356	+35%
BEV	37,727	1913	361	+21%
ICEV Mean	2,232,203	1577	328	

increase for SUVs over regular vehicles (ANL, 2019). The other forecast represents lightweighting of the fleet, reducing curb mass by 20% up to 2030 (2% per year), also taken from lightweighting estimates from GREET (ANL, 2019).

3.9. Well-to-Wheel emissions

3.9.1. Biofuels

It is required in the UK for biofuels to be blended into petrol and diesel road transport fuels under the Renewable Transport Fuel Obligation (Department for Transport, 2012). In 2020, an average of 5% ethanol is blended into petrol (E5), and 7% biodiesel is blended into diesel (B7). Corn and used cooking oil made up 54% and 77% of the feedstocks for ethanol and biodiesel, respectively (Department for Transport, 2021b). As of September 2021, petrol blended with up to 10% ethanol (E10), is available in the UK (Department for Transport, 2021a).

The future of biofuels in the UK is not clear, since increasing ethanol blends above E10 may require changes in engine standards which may take over a decade to diffuse into the market. For example, all new petrol vehicles from 2011 were required to be compatible with E10 fuel, yet it took until 2021 to introduce this fuel nationally (Department for Transport, 2021a). A uniform distribution was defined between an upper and lower bound to capture the broad range of pathways biofuel blends could take. The lower bound sees the biofuel blend proportion remain at current levels until 2050. The upper bound sees petrol reach 20% ethanol (E20) and diesel reach 15% biodiesel (B15) by 2035 and remain at this level until 2050. These limits were based on possible targets from Kampman et al. (2013), giving sufficient time for the required new vehicle technologies to diffuse into the fleet.

The fleet wide average impact of E5 and B7 biofuel blends on vehicle exhaust NO_x emissions was inherently included for passenger cars due to the use of emissions factors derived from remote sensing (Davison et al., 2021). However, other the impact of biofuel blends for other pollutants and vehicle types or for increasing biofuel blend ratios was not included as the EMEP/EEA guidebook does not contain sufficient data for this model for increasing bioethanol blends or for how biodiesel impacts emissions from post Euro 3/Euro III vehicles (European Environment Agency, 2019). This limitation of the model likely underestimates NO_x emissions as recent evidence suggests increased NO_x emissions from switching from E5 to E10 fuels (Emissions Analytics, 2020). Similarly, the EMEP/EEA guidebook estimate that increasing biodiesel blends marginally increases NOx emissions, yet may reduce $PM_{2.5}$ emissions to a greater extent (European Environment Agency, 2019).

3.9.2. Vehicle combustion fuels

Upstream Well-to-Tank (WTT) emissions per unit of final fuel consumed by vehicles are taken from Prussi et al. (2020) for diesel, petrol, biodiesel, and ethanol, using asymmetric triangular distributions to provide parameter uncertainty (these emission factors are given in Table S2 the Supplementary Material). Prussi et al. (2020) does not include land use change within the WTT biofuel emission factors and so likely represents an underestimate of the true CO_2 emissions from biofuels. This source was selected as it provides WTT emission factors for European specific fuels enabling comparison between this study and previous work within Europe. Additionally,

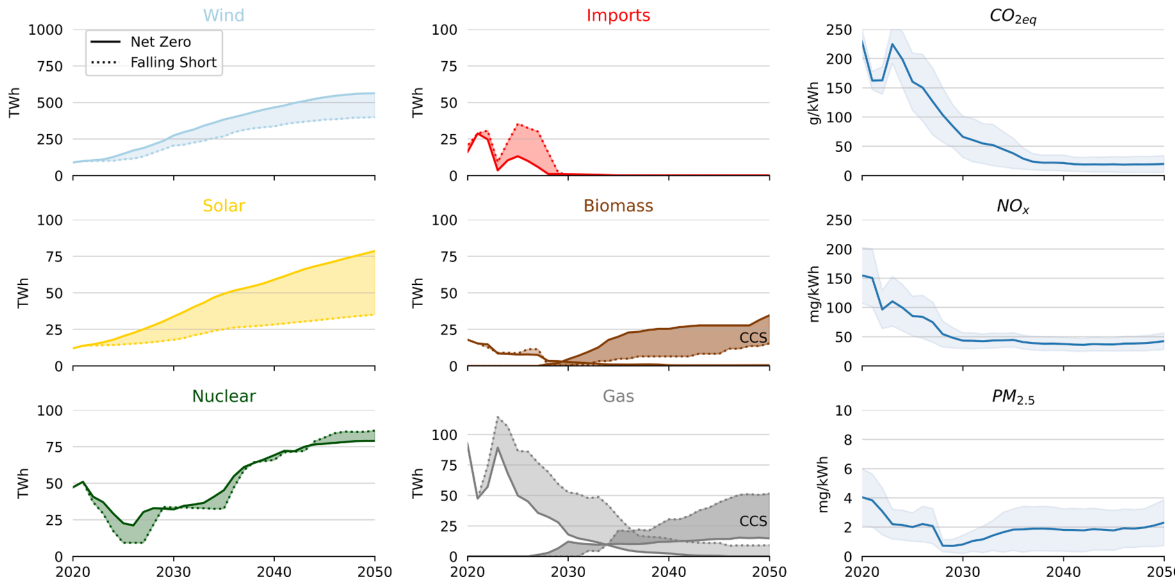

Fig. 5. Left and central panels show the range of yearly electricity generation in TWh by power plant type across the Net Zero pathway (solid line) and the Falling Short pathway (dotted line). For gas and biomass, generation with carbon capture and storage (CCS) is separated from current unabated generation and labelled in the figure. Note, wind generation's vertical axis is an order of magnitude greater than the others. Right hand panels show the resulting emission factors for the generation mix after 1000 runs, where the line shows the mean value and area marks 95% confidence intervals (including transmission and distribution losses). $CO_{2\text{-eq}}$ emissions include all WTT sources for electricity generation.

the source gives these emission factors within a WTW system boundary and so is consistent with the boundary used in this study (Prussi et al. 2020).

Tank-to-Wheel (TTW) emissions were calculated by multiplying the fuel consumed by vehicles with the corresponding fuel to CO_2 emission factor, where biofuels were considered to have no TTW CO_2 emissions following UNFCCC carbon accounting guidelines. These TTW emissions were then added to the WTT emissions to calculate total WTW emissions.

A fuel balance test was conducted which found national petrol and diesel fuel consumption calculated by the model was within + 6% to −8%, respectively, between 2015 and 2019 using historical UK data (see Supplementary Material Fig. S13).

3.9.3. Electricity generation

Previous stock flow models have used projections of the CO_2 emission intensity of electricity to determine the emissions resulting from the use of EVs (Brand et al., 2020; Craglia and Cullen, 2020b). This is a transparent and simple method but is not possible for air pollutant emissions as projections of the emission intensity for air pollutants are not typically available. Therefore, a novel approach was adopted in the model to allow for the inclusion of air pollutant emissions.

Two electricity generation pathways were taken from the National Grid's Future Energy Scenarios (FES) for 2022 (National Grid, 2021). The first pathway, Falling Short, outlines a scenario where net-zero goals are not met, with more natural gas generation and imported electricity from Europe. The second pathway is the mean of the three net-zero pathways in the FES, with higher wind, solar, nuclear, and biomass generation. This pathway is termed here as the Net-Zero pathway. The yearly output of each power plant type in TWh for each pathway is given in Fig. 5.

Power plant types in the generation mix that do not contribute a significant proportion: coal, hydro, and municipal solid waste (MSW) are not included in Fig. 5. The output from these three power plant types were assumed equal across pathways. The UK government has pledged to phase out coal by 2024, and so coal output is linearly reduced from 5 TWh to 0 between 2020 and 2024. Hydro is assumed to stay at present output, 3.6 TWh, until 2050, and MSW was assumed to stay at current output levels to the grid at 4 TWh.

To capture the uncertainty of the future generation mix, the model samples a generation mix for each model run using a uniform distribution between the Falling Short and Net-Zero pathways. The sample chooses a point between the two pathways that was constant across all plant types, thus preserving the generation mix share between the two pathways in each model run. The sampled generation mix is then used to calculate the emission intensity of electricity using emission factors defined with normal distributions. The mean emission factor values were derived from the UK's NAEI using the methods from Mehlig et al., 2021b with relative air pollutant emission factor uncertainties taken from van Harmelen et al. (2011), and are given in Table S3 in the Supplementary Material. Natural gas CCS plants were assumed to have post-combustion technologies using the mean emission factors and parameter uncertainties from van Harmelen et al. (2011). Biomass CCS emissions were assumed to increase to the same extent as those of post-combustion coal CCS emissions. Negative CO_2 emissions from biomass CCS plants were not included due to the difficulty of attributing the activity leading to the sequestered emissions. Including negative emissions in this context would imply that driving more would sequester more CO_2. However, electricity demand from other sectors, wider goals to sequester emissions, and other exogenous factors to the vehicle fleet will influence the installed capacity and output of future biomass CCS plants, and so negative emissions were considered out of scope of this analysis. Next, the emission intensity of electricity was adjusted using transmission and distribution losses of 7.5% (Staffell, 2017). And finally, supply chain CO_2 and CH_4 emissions were included for fuels consumed in power plants enabling the full WTW emission system boundaries for $CO_{2\text{-eq}}$ (Schlömer et al., 2014; Balcombe et al., 2017) (see Supplementary Material section 3). The resulting emission intensities for $CO_{2\text{-eq}}$, NO_x, and $PM_{2.5}$ from electricity generation are given on the right-hand panels of Fig. 5.

4. Scenarios

Three scenario set are used with the fleet stock-flow model; these scenario setsinvestigate i) the choice between vehicle technologies, ii) how quickly these technologies are adopted, and iii) changing transport demand effecting how these vehicles are used. These three scenario sets are compared against a 'Current Policies' (CP) scenario. The CP scenario represents a pathway that meets the government's ICEV ban dates in the Transport Decarbonisation Plan (Department for Transport, 2021c) combined with the government's corresponding forecasted growth in vkm (Department for Transport, 2022c). Hydrogen fuel cell EVs (FCEVs) were not considered in this analysis; this vehicle technology likely has a role in the future UK fleet and is a topic for future work (Staffell et al., 2019; Element Energy, 2020; Haugen et al., 2021; Tol et al., 2022).

The CP scenario was compared to other scenarios that vary a single model input in isolation. The CP scenario reaches 100% BEV and PHEV new sales market share in 2030 for cars, LGVs, and motorcycles, followed by buses in 2035 and HGVs in 2040. Car and LGV PHEVs are assumed to have a 5-year grace period between 2030 and 2035. The BEV and PHEV uptake rates for cars and LGVs are taken from the balanced pathway from the UK's Climate Change Committee's net-zero report (CCC, 2020), with PHEV sales extended to 2035 to align with the 2021 Transport Decarbonisation Plan. BEV uptake for HGVs and buses follows the rates in Element Energy (2020), where FCEV sales were transferred to BEVs.

4.1. Vehicle technology mix

Two scenarios were modelled to compare the fleet wide performance of ICEVs and HEVs to BEVs. These two scenarios shift all sales to either ICEV or HEV technologies, with all other model inputs held equal to the CP scenario. These two scenarios are labelled as

"ICEV" and "HEV", respectively; using this naming convention the CP scenario could be interpreted as a 'BEV' scenario. Figures giving the relative sales mix for each scenario are given in Figs. S8 to S10 in the Supplementary Material.

4.2. EV uptake rate

Two scenarios were compared to the CP scenario to observe the impact of an EV uptake that exceeds or misses the ICEV ban dates. The first captures the case where all the ICEV bans in the CP scenario are missed by 5 years, where BEV and PHEV car and LGV sales reach 100% in 2035 and other vehicle types 5 years later than in the CP scenaro. This scenario is termed 'CP + 5 Years'. The second captures a significantly more ambitious scenario where all the ICEV bans are reached 5 years ahead of the CP scenario, reaching 100% BEV and PHEV sales in 2025, similar to the rate of rapid EV uptake observed in Norway (Hill, 2022). This scenario is termed 'CP-5 Years'. The uptake rates for cars for each EV uptake scenario is illustrated in Fig. 6, with Figs. S8 to S10 in the Supplementary Material giving equivalent uptake rates for all vehicle types.

4.3. Transport demand

The two sets of scenarios described above used the same transport demand as in the CP scenario. A third set of scenarios was created to observe the impacts of changing vkm with the same fleet of vehicles as the CP scenario. A high demand scenario, termed 'CP High VKM', takes the upper forecast of vkm from the Department for Transports National Road Traffic Projections (2022) which encapsulates the potential rebound effects of BEVs where transport demand increases due to lower vehicle running costs, causing only BEV vkm to increase for cars, LGVs, HGVs, and motorcycles (Department for Transport, 2022c). A low demand scenario, 'CP Low VKM', combined the vkm forecast used in the CP scenario with the reductions in vkm given by the CCC in their Tailwinds net-zero pathway. This forecast is based on socio-economic measures such as increasing active travel, increasing car occupancy, and changes in home working that result in vkm reductions for cars, LGVs and motorcycles that is met equally by vehicle technologies (Climate Change Committee, 2020). These scenarios are summarised in Tables 3 to 6, where Table 4 gives the total vkm for the CP scenario by vehicle type, and Table 5 and Table 6 give the changes in vkm for the CP Low VKM and CP High VKM scenarios respectively .

5. Results

This section gives results for each of the three scenario sets in turn, followed by five sensitivity studies addressing assumptions on non-exhaust emissions, vehicle curb mass, electricity generation, survival-age rates, and mileage-age rates. The results given below show median results from 1000 runs of the model and are given with 5th and 95th percentile values in brackets.

5.1. Vehicle technology mix

Fig. 7 gives the CO_{2eq}, NO_x and $PM_{2.5}$ emission trends for the three technology mix scenarios. The upper left panel of Fig. 7 shows that by 2050 both ICEV and HEV scenarios reduced annual WTW CO_{2eq} emissions by 20% (14% – 26%) and 31% (26% – 35%),

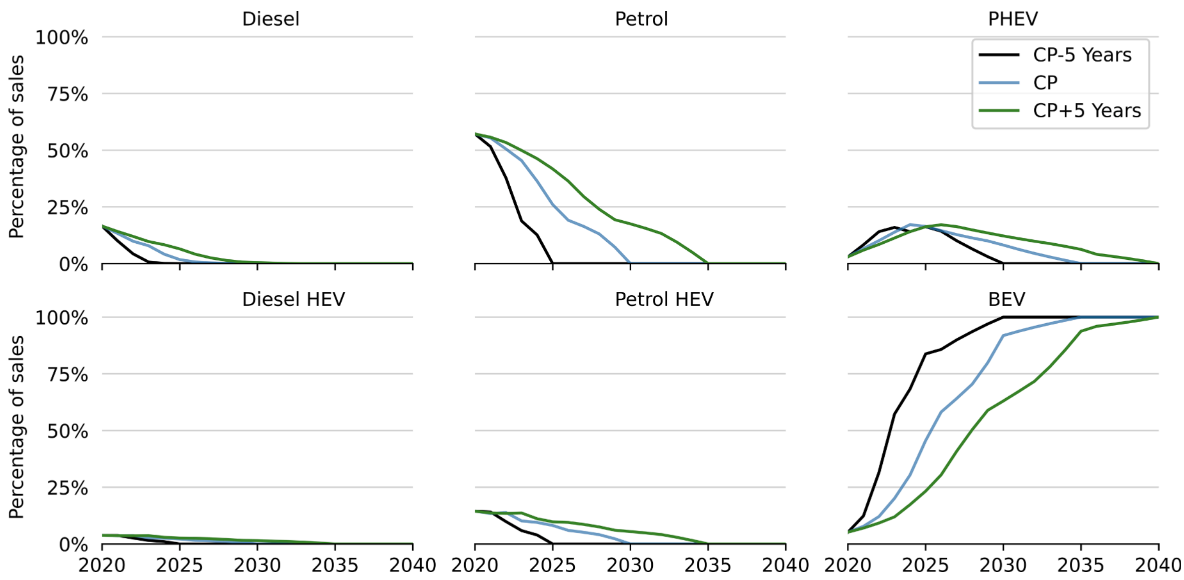

Fig. 6. The percentage of car sales across vehicle technologies, where colour shows the different scenario for the set of EV uptake scenarios. CP shows the current government targets with CP-5 Years and CP + 5 Years showing if these targets are exceeded or missed by 5 years, respectively.

Table 3
Summary of scenarios.

Scenario	Description
CP	The UK government's current policies, where new BEV sales increase to achieve the ICE ban dates and with transport demand steadily increasing as given in Table 4 under the CP columns.
ICEV	Only new sales of ICE vehicles, with the same transport demand as CP.
HEV	A quick transition from new ICEV sales to only new HEVs sales (5 years to 100% market share), with the same transport demand as CP.
CP-5 Years	As CP, with EV uptake rates achieving the ICE bans 5 years early.
CP + 5 Years	As CP, with EV uptake rates achieving the ICE bans 5 years behind.
CP High VKM	As CP, with transport demand growing due rebound effects of EVs.
CP Low VKM	As CP, with transport demand decreasing due to socio-economic measures.

Table 4
Annual vkm for each vehicle type between 2019 and 2050 for the CP scenario.

	Billion vkm per year				
	Car	LGV	HGV	Bus	Motorcycle
2019	423	86	28	4	4
2030	454	98	30	4	5
2040	472	101	31	4	5
2050	482	103	32	4	5

Table 5
Change in annual vkm for the CP Low VKM scenario, where the change in vkm is met equally across all vehicle technologies due to behavioural changes affecting transport demand, taken from the tailwinds scenario from the Climate Change Committee (2020).

	Change in vkm per year (equally distributed across vehicle technologies)				
	Car	LGV	HGV	Bus	Motorcycle
2019	0%	0%	0%	0%	0%
2030	−16%	−4%	0%	0%	−16%
2040	−25%	−4%	0%	0%	−25%
2050	−34%	−4%	0%	0%	−34%

Table 6
Change in annual vkm for the CP High VKM scenario, where the change in vkm is met entirely by BEVs due to changes in running costs increasing vkm, taken from the vehicle-led decarbonisation scenario from the Department for Transport (2022c).

	Change in vkm per year (from BEVs alone)				
	Car	LGV	HGV	Bus	Motorcycle
2019	0%	0%	0%	0%	0%
2030	+6%	+5%	0%	0%	+6%
2040	+12%	+26%	+2%	0%	+12%
2050	+14%	+44%	+2%	0%	+14%

respectively, when compared to emissions in 2019. During the same period, the Current Policy scenario, CP, reduced WTW CO_{2eq} by 98% (97% − 99%), down to 3.4 MT (1.5 MT – 4.9 MT). The decreases in WTW CO_{2eq} emissions occur across scenarios despite overall vkm increasing by 15%. The lower left panel in Fig. 7 shows that the cumulative WTW CO_{2eq} emissions by 2050 for the CP scenario was under half of those of the ICEV and HEV scenarios. Light-duty vehicles (cars, LGVs, and motorcycles) produced 78% of WTW CO_{2eq} emissions in 2019 which reduced to 64% by 2050; emissions from heavy-duty vehicles (HGVs and buses) grew from 22% to 36% of CO_{2eq} WTW emissions by 2050 (see Fig. S14 in the Supplementary Material for disaggregation of CO_{2eq} emissions by vehicle type).

The right-hand panels in Fig. 7 show that the short-term change up to 2030 for NO_x and $PM_{2.5}$ emissions is similar across the three scenarios. After 2030 the scenarios diverge, with the CP scenario tending towards zero vehicle NO_x emissions by 2050 with a remaining 6.1 kT (4.4 kT – 7.7 kT) coming from power stations. Whereas by 2050, the NO_x emissions from ICEV and HEV scenarios reach 75.3 kT (70.9 kT – 80.2 kT) and 33.3 kT (31.5 kT – 35.1 kT), respectively. In 2050, vehicle and power station $PM_{2.5}$, emissions reach 11.4 kT (9.9 kT – 13.0 kT), 11.0 kT (9.7 kT – 12.4 kT) and 9.4 kT (8.1 kT – 10.8 kT) for the ICEV, HEV and CP scenarios, respectively.

5.2. EV uptake rate

Fig. 8 shows that the median annual WTW CO_{2eq} emissions for the EV uptake scenarios converge by 2050, with the CP-5 Years and

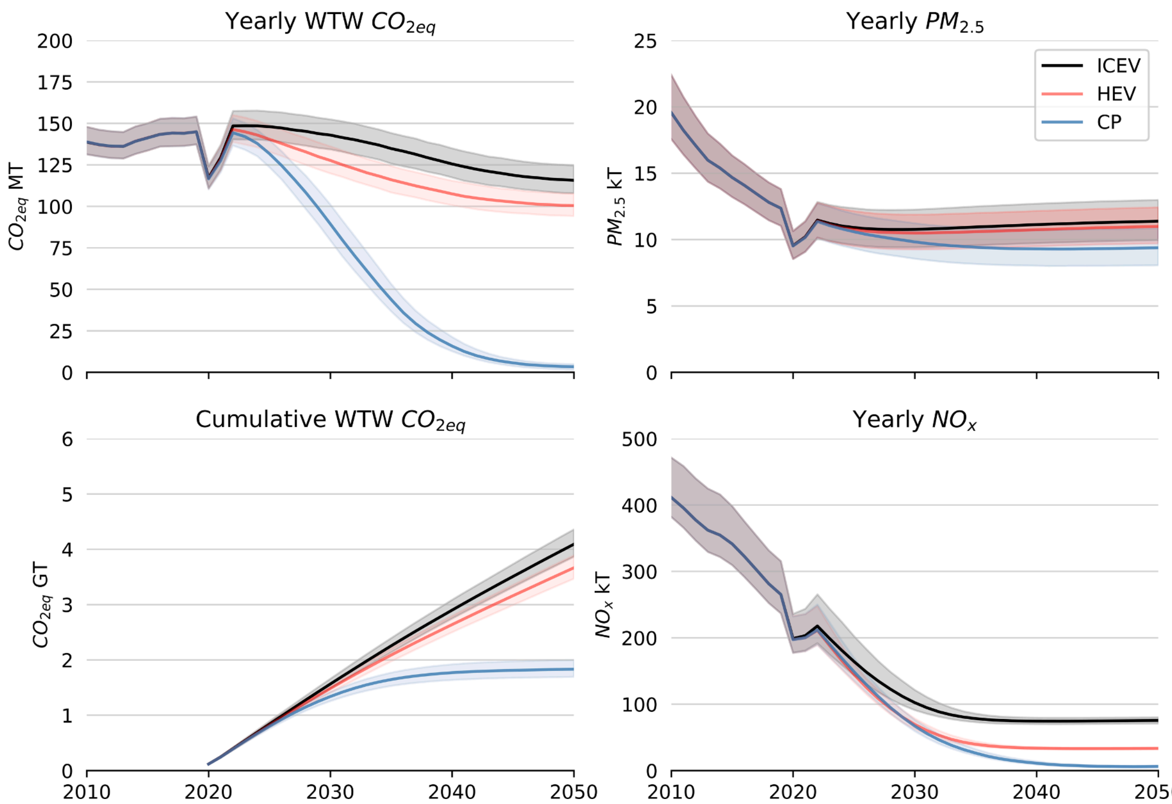

Fig. 7. Emissions from power stations and vehicles from 2010 to 2050 for the CP, ICEV, and HEV scenarios. Clockwise from top left: yearly WTW CO_{2eq} emissions from all sources; yearly vehicle and power station $PM_{2.5}$ emissions; yearly vehicle and power station NO_x emissions; cumulative WTW CO_{2eq} emissions from all sources starting from 2020. Colours give the different scenarios; solid lines show the median of 1000 runs, and the shaded areas give the 5th to 95th percentiles.

CP + 5 Years ranging between 2.9 MT (1.2 MT – 4.5 MT) to 5.2 MT (3.3 MT – 7.1 MT). These results show that the difference in annual WTW CO_2 emissions between the EV uptake rate scenarios is small, suggesting that all there is little difference between these scenarios when considering yearly CO_{2eq} WTW emissions in 2050. On the other hand, cumulative WTW CO_{2eq} emissions diverge after 2030, reaching between 1.55 GT (1.42 GT – 1.69 GT) and 2.16 GT (2.00 GT – 2.34 GT) by 2050 for the CP-5 Years and CP + 5 Years, respectively. This difference of 0.61 GT between the CP-5 Years and CP + 5 Years scenarios can be approximated as a 61 MT (or 3.3%) increase or decrease in cumulative WTW CO_{2eq} emissions to 2050 for every year the CP policy targets are missed or exceeded, respectively. For air pollutant emissions, the rate of EV uptake had a negligible impact on emissions, with all scenarios following the same trajectory within their uncertainty bounds, with the exception of the CP + 5 Year scenario having marginally higher NO_x emissions in the 2030 s.

Fig. 9 shows electricity generation emissions in isolation for the three EV uptake scenarios. Yearly power station WTW CO_{2eq} emissions peak between 2025 and 2035, and are highest for CP-5 Years, as the decarbonisation of the generation mix lags behind the uptake of electric vehicles. In the central CP scenario, emissions reach a maximum of 4.1 MT of CO_{2eq} per year, less than 3% of current total road sector emissions. For the CP scenario, NO_x emissions from electricity generation grew to exceed vehicular sources by 2040, whereas $PM_{2.5}$ emissions from electricity generation do not exceed 3% (2% – 5%) of vehicular sources by 2050, due to non-exhaust emissions. Fig. 8 and Fig. 9 indicate that the relative uncertainty of electricity generation emissions was larger than other emission sources, but the absolute emissions were smaller than the other sources.

5.3. Transport demand

The top left-hand panel of Fig. 10 shows that from 2019 yearly WTW CO_{2eq} emissions for the transport demand scenarios decline at a similar rate towards 2050, with CP Low VKM declining the fastest and CP High VKM declining the slowest. By 2050, the cumulative WTW CO_{2eq} emissions range from 1.72 GT (1.60 GT to 1.87 GT) to 1.84 GT (1.70 GT – 2.00 GT) for the CP Low VKM and CP High VKM scenarios, respectively. Transport demand scenarios have a negligible impact on vehicular NO_x emissions, whereas for $PM_{2.5}$ emissions a greater effect is seen, with emissions of 7.5 kT (6.6 kT – 8.5 kT) and 11.0 kT (9.5 kT – 12.7 kT) for the CP Low VKM and CP high VKM scenarios, respectively.

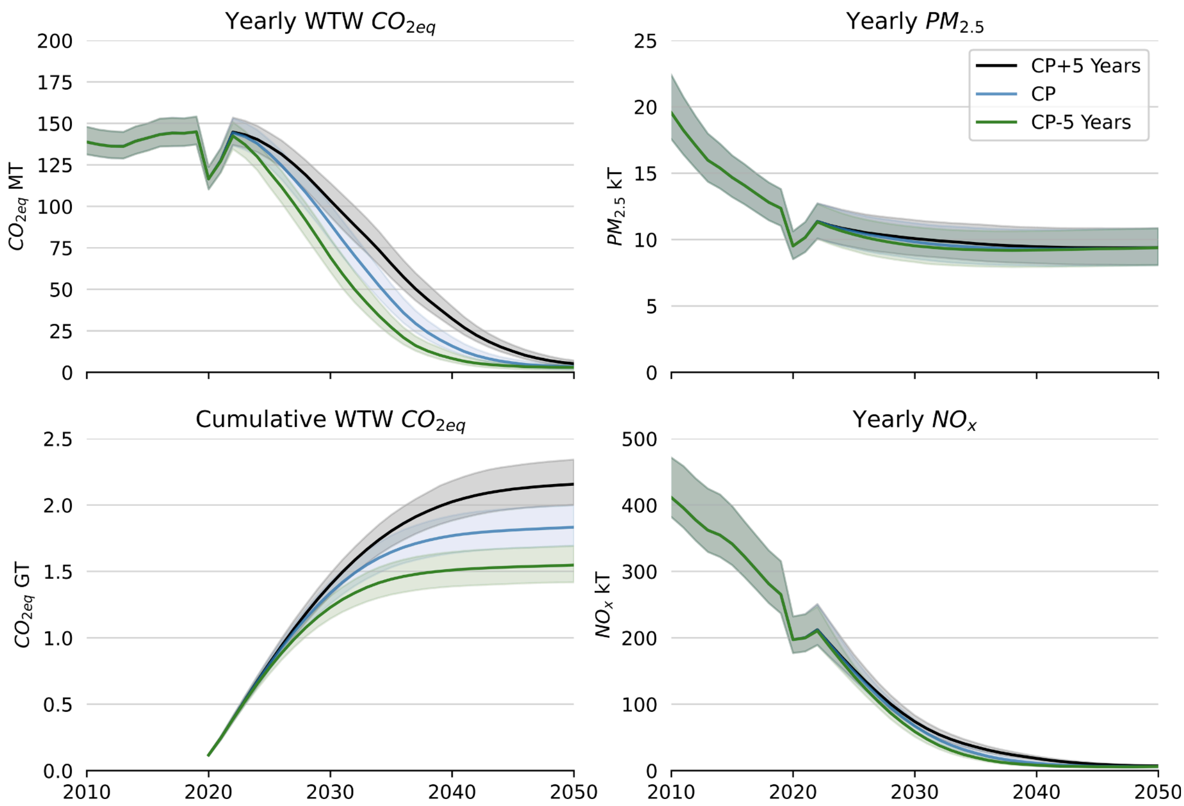

Fig. 8. Emissions from power stations and vehicles from 2010 to 2050 for the CP, CP + 5 Years, and CP-5 Years, scenarios. Clockwise from top left: yearly WTW CO_2 emissions from all sources; yearly vehicle and power station $PM_{2.5}$ emissions; yearly vehicle and power station NO_x emissions; cumulative WTW CO_2 emissions from all sources starting from 2020. Colours give the different scenarios; solid lines show the median of 1000 runs, and the shaded areas give the 5th to 95th percentiles.

5.4. *Sensitivity studies*

Five sensitivity studies were conducted to address key assumptions made in the model regarding non-exhaust emissions, vehicle curb mass, electricity generation, survival-age rates, and mileage-age rates.

5.4.1. *Evs and non-exhaust emissions*

The vehicle technology scenarios (ICEV, HEV, and CP) were run with two sets of non-exhaust emission factors. The first uses the emission factors outlined in section 3.8.3 *Non-exhaust $PM_{2.5}$ emissions*, using the methodology given in EMEP/EEA guidebook that do not include a direct relationship between vehicle curb mass and emission rates (European Environment Agency, 2019). The second adopts new emission factors from OECD (2020) for cars and LGVs that are functions of vehicle curb mass. These functions are given in Equation S1 and S2 in the Supplementary Material section 2.4. Fig. 11 shows the $PM_{2.5}$ emissions from the two methods, split by scenario and by source. Emissions calculated with the OECD factors remain similar between the technology scenarios, but have higher uncertainty, especially in the CP scenario due to the compounding emission factor and vehicle curb mass parameter uncertainty. The OECD factors suggest that overall vehicular $PM_{2.5}$ emissions will increase from 2030 onwards in line with growth of overall vehicle kilometres driven. The lower plots of Fig. 11 show that for the CP scenario, tyre wear will become the leading non-exhaust emission source for both methods.

5.4.2. *Vehicle curb mass*

The non-exhaust emission factors from OECD (2020) that are functions of curb mass were used again in a second sensitivity study observing how these $PM_{2.5}$ emissions may change under different scenarios of vehicle size. Two scenarios based upon the CP scenario were modelled where the curb mass of cars and LGVs were increased or decreased by 20, where this change was taken from the GREET model using the curb mass differences between SUVs, regular cars, and lightweight cars. Fig. 12 shows the $PM_{2.5}$ emissions for these two sensitivity scenarios alongside the CP scenario, where $PM_{2.5}$ emissions may change by ± 15% depending on the trajectory of vehicle size. The results given in Fig. 12 also highlight the uncertainty of this projection, with $PM_{2.5}$ emissions ranging 7.2 kT between the 5th and 95th percentiles across both curb mass sensitivity study scenarios.

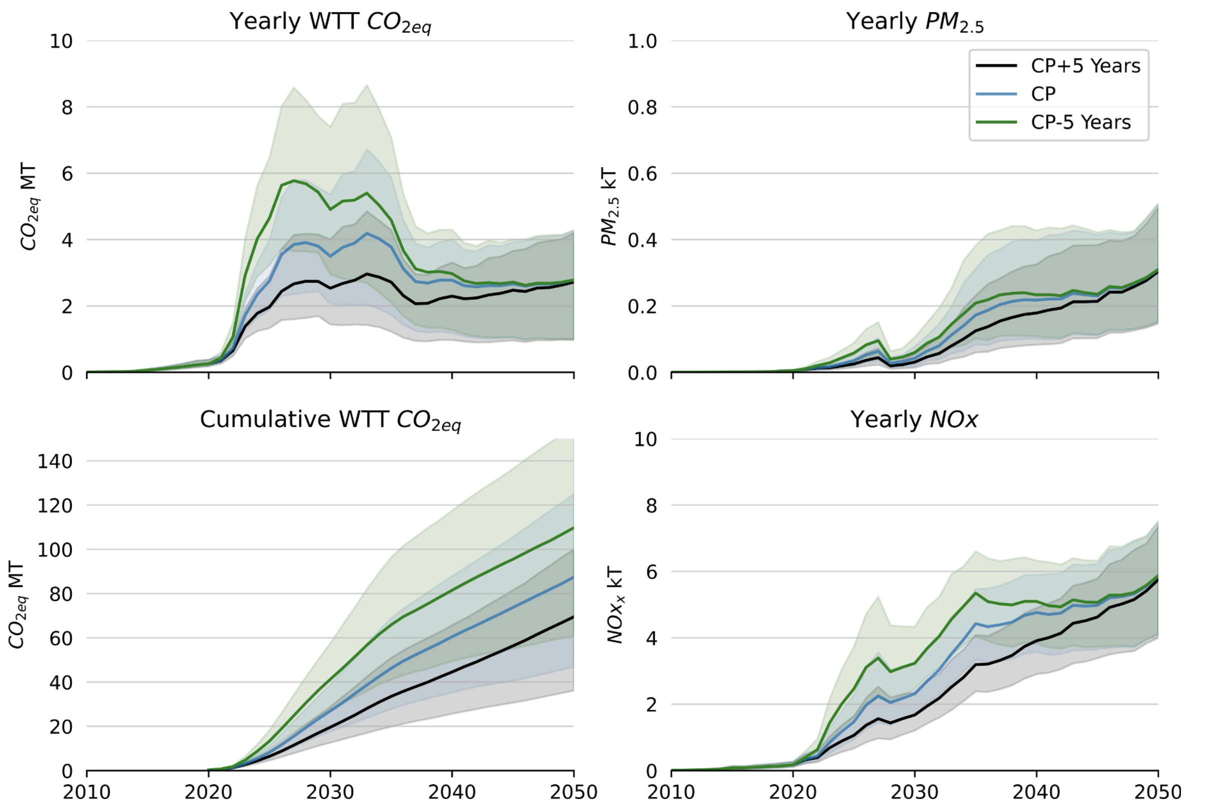

Fig. 9. Emissions from power stations from 2010 to 2050 for the CP, CP + 5 Years, and CP-5 Years scenarios Clockwise from top left: yearly WTT CO_{2eq}; yearly power station $PM_{2.5}$ emissions; yearly power station NO_x emissions; cumulative WTT CO_{2eq} emissions starting from 2020. Colours give the different scenarios; solid lines show the median of 1000 runs and the shaded areas give the 5th to 95th percentiles.

5.4.3. *Electricity generation*

In the results presented above, electricity generation was handled by using a sampled generation mix between two pathways. Here the two pathways, Falling Short (FS) and Net-Zero (NZ), are used as fixed inputs to the model with all other parameters held equal to the CP scenario, thus isolating the impact of these two pathways compared to the CP scenario. The WTT emissions from electricity generation for the FS and NZ pathways are shown in Fig. 13 alongside the CP scenario, which averages the two. The difference in electricity generation emissions between the two pathways is significant for CO_{2eq}, with SP reaching over twice the cumulative WTT CO_{2eq} emissions as NZ by 2050. The difference in electricity generation cumulative WTT CO_{2eq} emissions between the pathways reaches 77 MT by 2050, which amounts to a 4.2% change when considering all WTW CO_2 sources. This relatively small impact of the future generation mix on cumulative WTW CO_2 emissions from all sources confirms previous work for the UK (Craglia and Cullen, 2020b). Similarly, uncertainty of the future generation mix does not significantly affect air pollutant emissions. Power station NO_x emissions remain relatively consistent between FS and NZ scenarios, whereas power station $PM_{2.5}$ emissions range from between 2.5% and 4.1% of total $PM_{2.5}$ emissions by 2050 for the FS and NZ scenarios, respectively.

5.4.4. *Survival-age rates*

A sensitivity study was conducted to observe the impact of the model assumption that median vehicle lifetimes and survival-age rates remain constant from 2019 up to 2050. This sensitivity study observed the impact on the model if the current trend of longer lasting vehicles continues. To do this, the historical growth rate of vehicle lifetime of 2% per year on average for cars, LGVs, rigid HGVs, and buses was used to extend the survival-age curves of these vehicle types. This growth in vehicle lifetime was applied over 15 years, extending vehicle lifetimes by 30%. These extended survival-age curves were applied to all vehicle registration years to provide the largest effect to model results. The CP scenario was run with these extended survival-age rates and the results are presented in Fig. 14 alongside the CP scenario. The results given in Fig. 14 indicate that longer vehicle lifetimes may increase WTW CO_{2eq} and NO_x emissions up to 2050 and 2040, respectively. By 2050 cumulative WTW CO_{2eq} emissions for the sensitivity study increased by 0.14 GT or 8% over the CP scenario.

5.4.5. *Mileage-age rates*

The model assumed mileage-age rates for HEVs, PHEVs, and BEVs, followed the current milage-age rates of ICEVs in the fleet. Whereas recent evidence from the MOT data used to derive these ICEV mileage-age rates shows that the current generation of BEV and

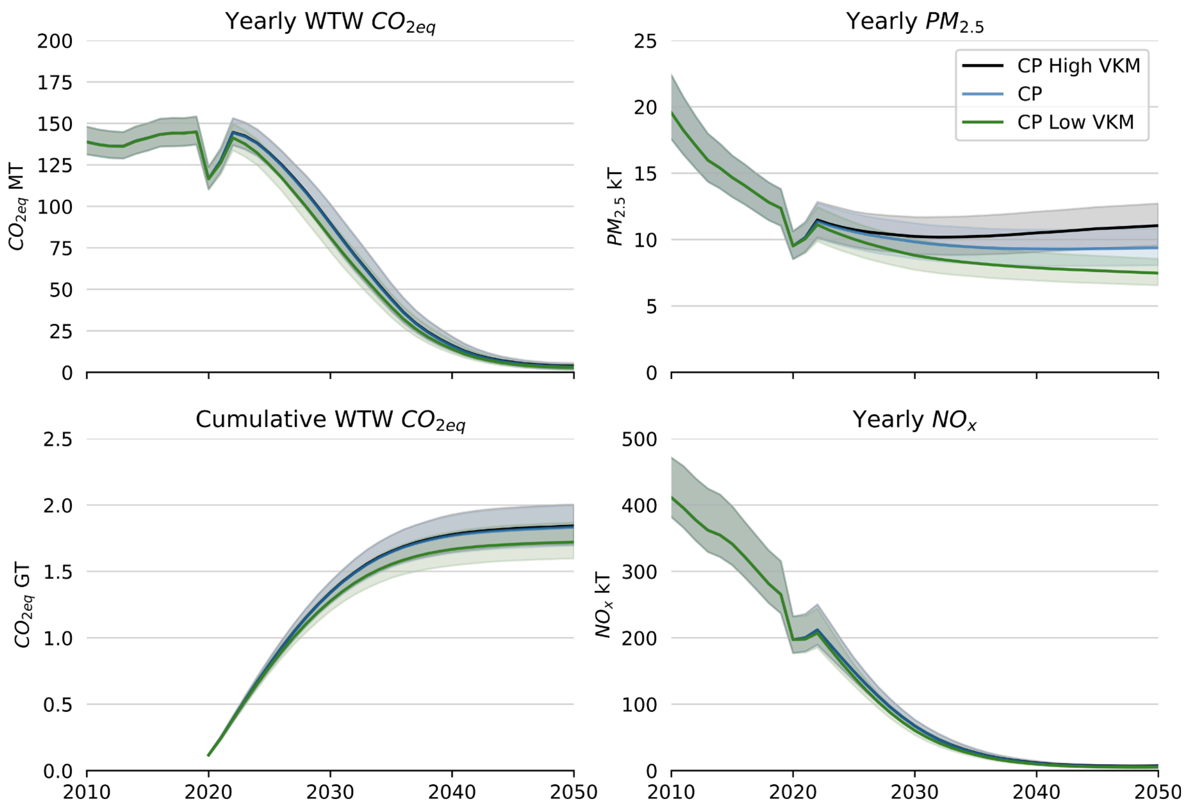

Fig. 10. Emissions from power stations and vehicles from 2010 to 2050 for the CP, CP High VKM, and CP Low VKM. Clockwise from top left: yearly WTW CO_{2eq} emissions from all sources; yearly vehicle and power station $PM_{2.5}$ emissions; yearly vehicle and power station NO_x emissions; cumulative WTW CO_{2eq} emissions from all sources starting from 2020. Colours give the different scenarios; solid lines show the median of 1000 runs and the shaded areas give the 5th to 95th percentiles.

HEV cars are not driven with the same usage patterns, with BEV mileage reducing at a faster rate than ICEVs and HEV mileage remaining higher than ICEVs as the vehicles age. A sensitivity study was conducted to observe the impact of these current mileage-age rates on model results where the CP scenario was run with the current BEV and HEV mileage-age rates. The CP scenario with these changes to mileage-age rates was found to marginally increase WTW CO_{2eq} emissions, with cumulative WTW CO_{2eq} emissions increasing by 2% by 2050. This increase was well within the uncertainty range of the model. The change in NO_x and $PM_{2.5}$ emissions for this sensitivity study was smaller than WTW CO_{2eq}; please see the Supplementary Material Fig. S14 to see the results visualised.

6. Discussion

The results presented here indicate that transitioning the UK's road transport fleet to BEVs offers substantial CO_{2eq} emission reductions even when considering the consequential emissions from electricity generation to charge those vehicles. The scale of CO_{2eq} emission reductions relies upon decarbonisation of the electricity system, but as the UK's electricity system is now on a relatively tightly-defined and ambitious decarbonisation trajectory. These results show that the UK government's goal to approach zero CO_{2eq} emissions from road transport, and so being compatible with a net zero economy by 2050, is possible through a fleet of BEVs. This finding agrees with previous work identifying the transition to BEVs is key to mitigating CO_{2eq} emissions (Hill et al., 2019; Brand et al., 2020; Craglia and Cullen, 2020b).

The results also suggest that NO_x and $PM_{2.5}$ air quality benefits of transitioning to BEVs, compared to ICEVs and HEVs, are not as strong as those for CO_{2eq} emissions and will occur closer to 2050. Vehicle NO_x emissions should decline at a similar rate with or without rapid uptake of BEVs over the next decade since the primary driver for reducing NO_x emissions is removing the oldest and most polluting vehicles from the fleet. By 2040, the removal of exhaust emissions through BEVs enables the fleet to approach zero exhaust NO_x emissions. At which point the small amount of NO_x emissions (6.1 kT) from electricity generation exceeds those from vehicle exhausts. Displacing exhaust NO_x to power stations should be carefully examined since moving pollution sources from one location to another is not a wholistic solution. That said, the order of magnitude reduction in NO_x emissions enabled by a BEV fleet and the removal of these emissions from populated urban areas will likely improve health outcomes through reduced population exposure to NO_x. For exhaust and non-exhaust $PM_{2.5}$ emissions, these results show that it is uncertain if a BEV fleet will outperform an ICEV or HEV fleet, since the difference in emissions between these fleets lies within the overall uncertainties of emission factors, specifically when

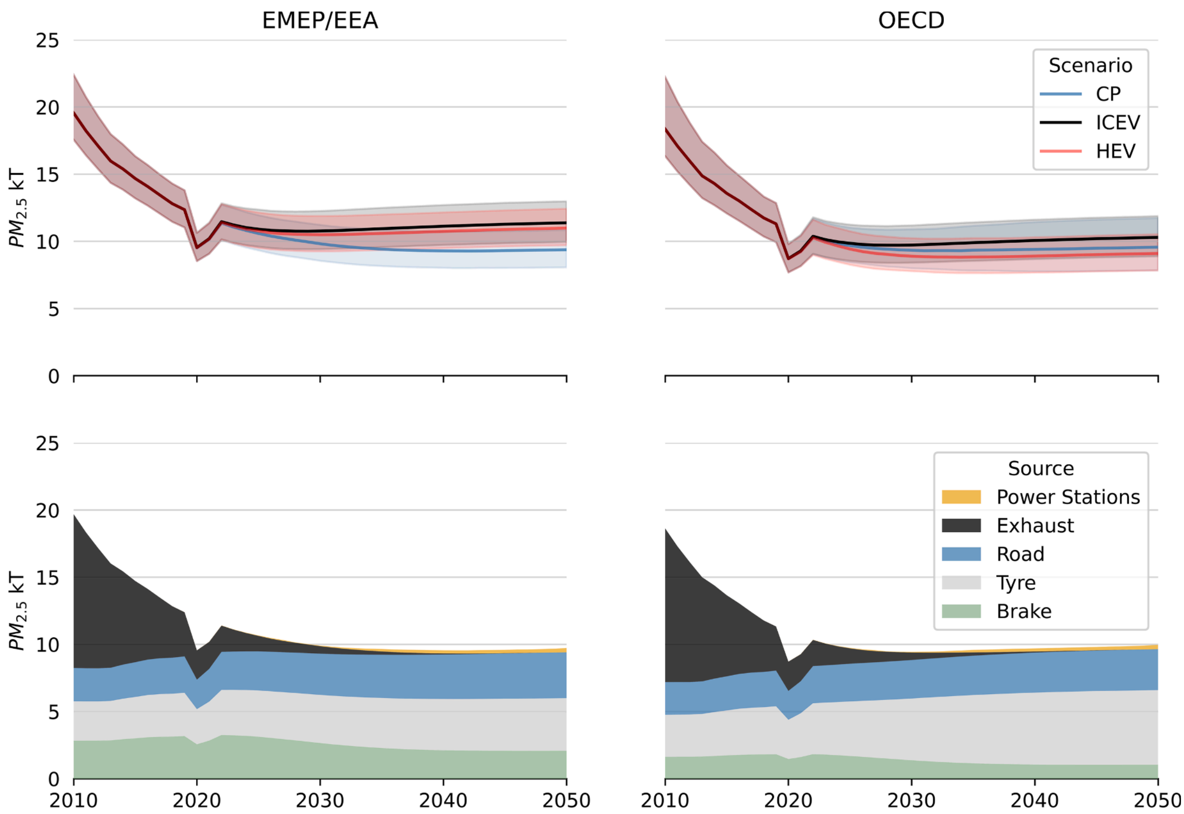

Fig. 11. $PM_{2.5}$ emissions from vehicle and power stations from 2010 to 2050. Left hand panels use EMEP/EEA non-exhaust emission factors, right hand panels use OECD non-exhaust emission factors (when applicable). Upper panels give total $PM_{2.5}$ emissions for the three scenarios, ICEV, HEV, and CP, where the solid line gives the median, and the area marks the 5th and 95th percentiles from 1000 runs. Lower panels show $PM_{2.5}$ emissions for the CP scenario, where the coloured areas show the emission source.

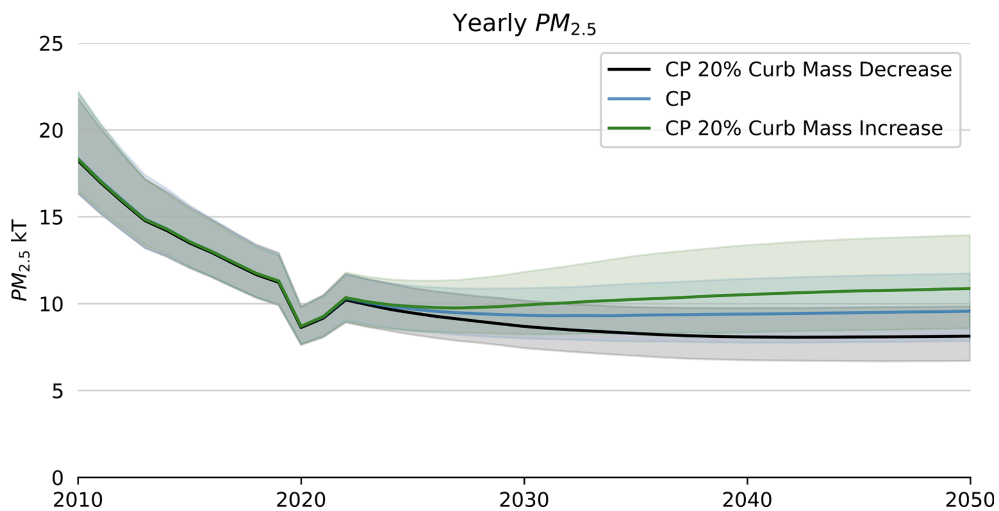

Fig. 12. $PM_{2.5}$ emissions from vehicle and power stations from 2010 to 2050 using the OECD (2020) emission factors for the CP scenario and the two curb mass sensitivity scenarios where mass was increased or decreased by 20% for cars.

considering the impact of regenerative braking and increased vehicle weight of BEVs. Indeed, these results illustrate that further research into non-exhaust emissions is required, echoing recent recommendations from the field (Air Quality Expert Group, 2019; Harrison et al., 2021).

All BEV uptake rates, missing or exceeding the government's targets by 5 years, reduced WTW CO_{2eq} emissions to between 96 and

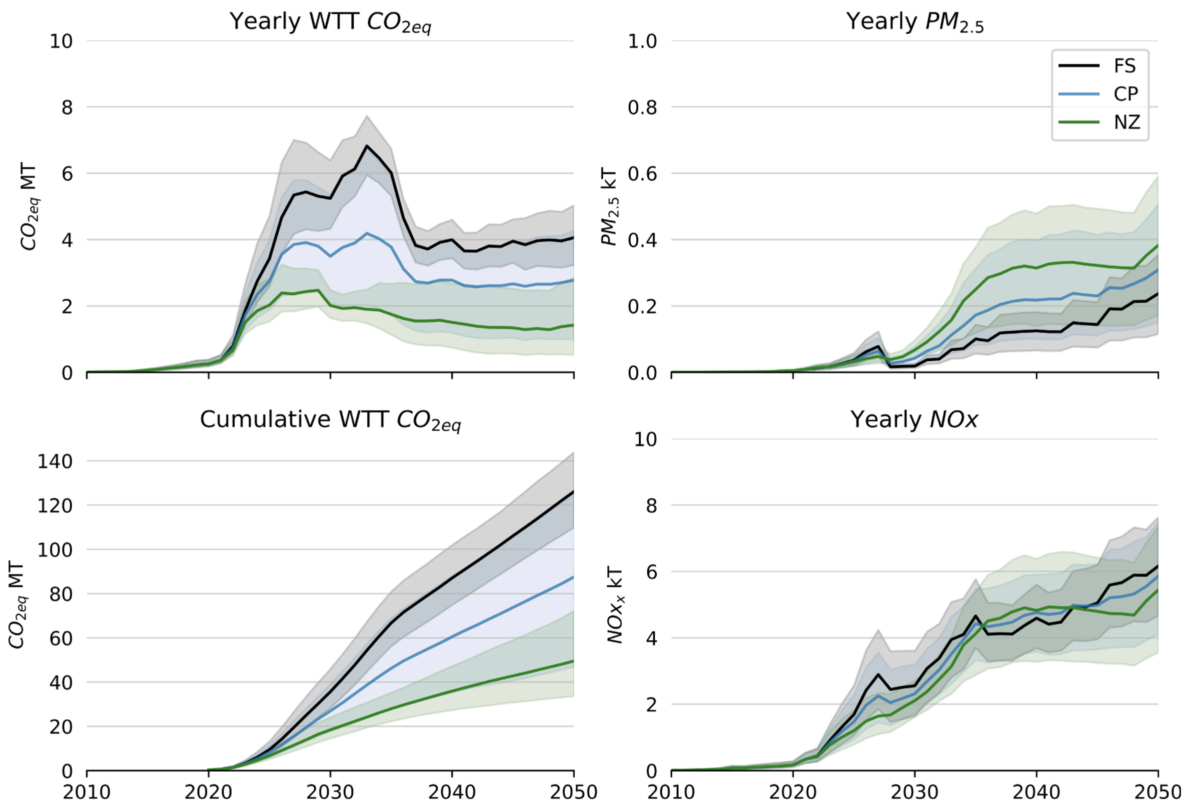

Fig. 13. Emissions from power stations due to charging EVs. Clockwise from top left: yearly WTT CO_{2eq}; yearly $PM_{2.5}$ emissions; yearly NO_x emissions; cumulative WTT CO_{2eq} emissions starting from 2020. Colours give the different scenarios; solid lines show the median of 1000 runs and the shaded areas give the 5th to 95th percentiles.

98% showing that there is little difference between these scenarios for operating WTW CO_{2eq} emissions by 2050. This result suggests that delays in meeting the ICEV ban dates may still be compatible with a net zero economy due to the small impact this ICEV target has on meeting yearly CO_{2eq} emissions by 2050 (neglecting vehicle life cycle emissions during manufacture). However, the rate of EV uptake has a large impact on cumulative CO_{2eq} emissions between 2020 and 2050. Cumulative CO_{2eq} emissions could change by 17% by 2050 for BEV uptake missing or exceeding the government's targets by 5 years. Achieving these goals early will pose many challenges, yet this result illustrates the potential benefits to achieving these goals and the potential downsides of failing to meet them. This asymmetrical result for EV uptake, where EV uptake may have small impact on yearly emissions but a large impact on cumulate emissions by 2050, opens broader policy questions on the aims of the government's Transport Decarbonisation Plan (Department for Transport, 2021a). Does the plan aim to minimise CO_{2eq} emissions? Or is the aim to *only* reach a net zero fleet by a certain year? This differentiation may relieve or exaggerate the pressure to switch to BEVs. In contrast, the speed of BEV uptake may have a negligible impact on air pollutant emissions, especially in the short term. This suggests that the current government policies for increasing BEV uptake may be beneficial for reducing cumulative CO_{2eq} emissions, but other non-technological strategies are needed to reduce NO_x and $PM_{2.5}$ emissions.

Reducing transport demand combined with a fleet of BEVs was found to yield significant reductions in non-exhaust $PM_{2.5}$ emissions in the long term. However, the same was not found for NO_x. The reason for this discrepancy between $PM_{2.5}$ and NO_x was due to the timing of the changes in transport demand. The change in transport demand used in this study gradually increased between 2020 and 2050. This change in transport demand, alongside rapid BEV uptake rate, will be too late to change vehicle NO_x emissions as these are only affected when ICEVs and HEVs are still in the fleet. The opposite effect should be expected for increases in transport demand, with $PM_{2.5}$ emissions increasing at a similar rate to vkm and NO_x emissions increasing only if the changes occur while ICEVs and HEVs are still in the fleet. Changes in CO_{2eq} emissions were not as sensitive to changes in transport demand as air pollutant emissions, largely due to the timing of the changes. The rapid uptake rate of BEVs with a similarly rapid decarbonisation of the electricity system shortens the window where changes in transport demand could have an impact on CO_{2eq} emissions. Moreover, a faster and larger reduction in transport demand was found by Brand et al. (2020) to have a greater impact on GHG and air pollutant emissions than the results found in this study (12% vs 6% for cumulative CO_2 emissions by 2050). More ambitious scenarios of road transport behavioural change in the UK have been shown to reduce pressure on other sectors in the pursuit of net zero targets (Barrett et al., 2022). These findings suggests that reducing vkm effective for reducing CO_{2eq} emissions if introduced while vehicles with exhausts are still in the feet, but further research into behavioural change's impact on air quality is needed during a rapid shift to BEVs.

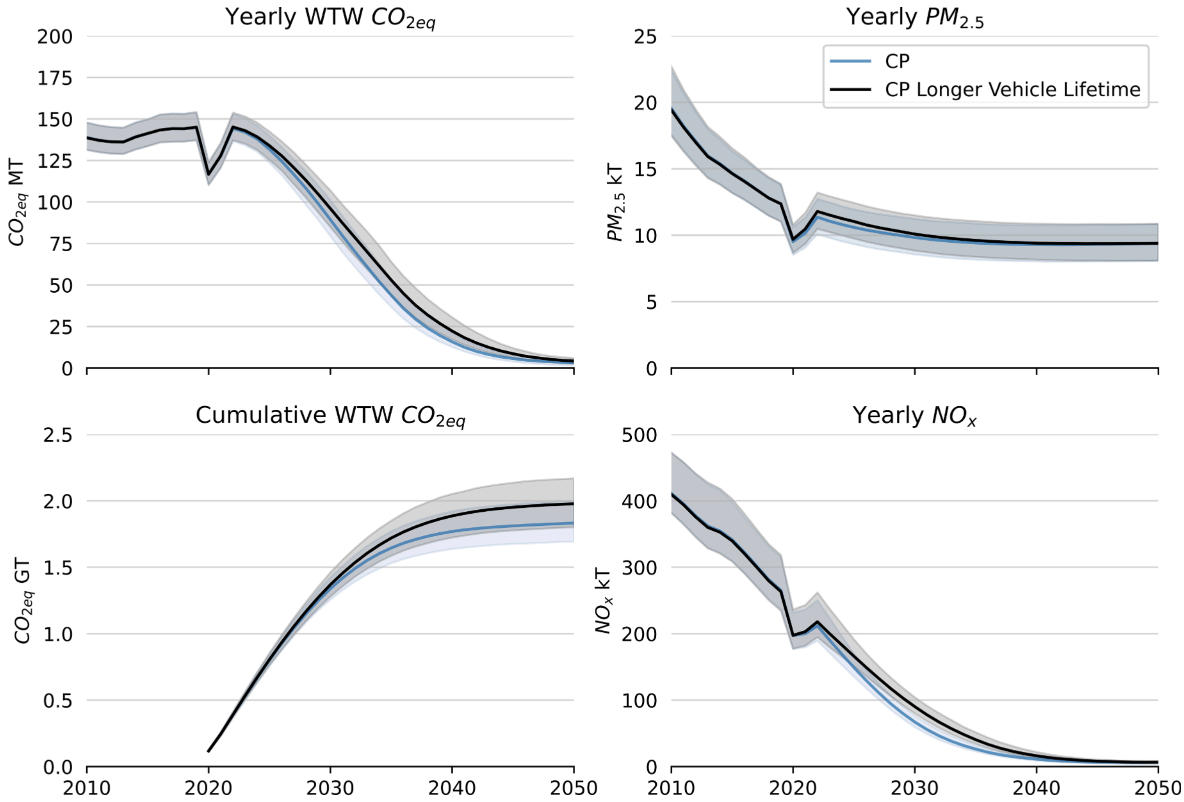

Fig. 14. Emissions from power stations and vehicles from 2010 to 2050 for the CP scenario and the CP Longer Vehicle Lifetime sensitivity study where the survival rates of cars, LGVs, rigid HGVs and buses were extended using the historical growth in vehicle lifetime. Clockwise from top left: yearly WTW CO_{2eq} emissions from all sources; yearly vehicle and power station $PM_{2.5}$ emissions; yearly vehicle and power station NO_x emissions; cumulative WTW CO_{2eq} emissions from all sources starting from 2020. Colours give the different scenarios; solid lines show the median of 1000 runs and the shaded areas give the 5th to 95th percentiles.

Throughout the results, the absolute uncertainty in NO_x emissions calculated by the model reduces over time, yet the relative uncertainty in NO_x emissions increases. This effect was due to the changing contribution of exhaust emissions and power stations emissions. Firstly, the uncertainty of the exhaust NO_x emission factors used for cars and LGVs reduces for newer euro standards, and so as the older vehicles leave the fleet the emission factors reduce to only those with the smallest uncertainties (Davison et al. 2021). For other vehicle types the relative uncertainty in the emission factors remains constant (using values form the EMEP/EEA guidebook), but the mean value of the emission factor decreases (European Environment Agency, 2019). This effectively tends the fleet towards a smaller number of emission factors with smaller uncertainties, reducing the output exhaust NO_x emission uncertainty. On the other hand, looking at the range between the ICEV and HEV scenarios suggest that if the future technology mix was a stochastic model input (opposed to current fixed input as a scenario variable), the uncertainty in NO_x emissions would indeed be increasing over time. Secondly, on a relative uncertainty basis, power station NO_x emissions were significantly more uncertain than exhaust NO_x emissions, where this can be seen in the range of results presented in section 5.1. Vehicle technology mix. For the ICEV and HEV scenarios the range between the 5th and 95th percentiles for NO_x emissions were 13% and 10% (with respect to the median value), respectively. For the CP scenario the range between the 5th and 95th percentiles for NO_x emissions was 56%. Yet due to the CP scenario having the lowest absolute NO_x emissions, the relative uncertainty appears small in the values given in the results and figures. Again, if the future technology mix was a stochastic model input, then the uncertainty in total NO_x emissions would have increased over time.

The CO_{2eq} emissions calculated in this study used the WTW system boundary and so excluded emissions included in a broader life cycle assessment (LCA). The largest of these lifecycle emissions not included in this study are vehicle and battery manufacture, which contribute a significant share of lifecycle CO_{2eq} emissions for EVs (Bieker, 2021). To estimate how the CO_{2eq} WTW results presented in this study would have been affected by the inclusion of these sources for cars, we use the vehicle and battery manufacturing emissions per vehicle from Hoekstra (2019) of 8,000 kg CO_{2eq} and 13,500 kg CO_{2eq} for ICEVs and BEVs, respectively, applying these to new vehicle sales in 2019 and 2050. In 2019, 2.4 million new ICEV cars entered the fleet (SMMT, 2020), producing 19 MT CO_{2eq}, raising WTW emissions by 21% for cars. In 2050, using the same volume of vehicle sales as 2019 but now with full market share for BEVs would produce 32 MT CO_{2eq}, raising WTW emissions by 2,000% for cars. This latter estimate for 2050 is the worst-case scenario, where vehicle and battery manufacturing does not improve from today's materials and energy requirements, or decarbonise the energy sources used. If manufacturing does fully decarbonise, Hoekstra (2019) estimates BEV vehicle and battery manufacture emissions reduce 10-fold and so reducing the emissions produced from manufacturing vehicles in 2050 to 3.2 MT CO_{2eq}. This best-case scenario for 2050 raises CO_{2eq} WTW emissions by 200%, revealing that manufacturing emissions will become the dominant LCA source with the shift to BEVs alongside a decarbonised electricity system and so will remain key area for future research.

The methods used in this study have a few notable limitations that are avenues for future work. Firstly, the model used Monte Carlo methods that assumed all parameters were independent random variables, where there will most likely be correlation between these variables. And so, the uncertainties presented these results are likely underestimates. Next, the model excluded FCEVs, due to the difficulty of projecting hydrogen production and the air pollutants and GHG emissions from the production processes, where FCEVs likely have a role in the heavy-duty fleet. And finally, the model calculates WTW CO_{2eq} emissions, excluding the emissions from manufacture. Including emissions from the full vehicle life cycle, as demonstrated for cars above, would increase emissions for a BEV fleet due to the added emissions produced during battery production and will grow in significance towards 2050.

Furthermore, this study relied upon assumptions that the current usage and lifetime of ICEVs in the fleet today, such as mileage-age rates and survival-age rates, could be applied to future EVs. The sensitivity study on longer vehicle lifetimes demonstrated that CO_{2eq} and NO_x emissions may substantially increase if ICEVs remain in the fleet longer than modelled. How these assumptions change over time with new technologies, new policies, and changing consumer behaviour is unknown. Several disruptive technologies and policies for the UK are imminent, such as the ICEV bans, changes to vehicle and fuel taxation, and connected and autonomous vehicles, that when combined may bring a transformational paradigm shift for the fleet. Future work could estimate how each of these possible factors may impact these assumptions on the current usage and lifetime of vehicles which could then be used in future fleet turnover models.

7. Conclusions

A stock-flow model for the UK road transport fleet was created to answer key questions surrounding the move away from ICEVs. The model was designed to calculate vehicle and power station CO_{2eq} emissions and air pollutant emissions on a Well-to-Well basis and to encapsulate global model uncertainty using Monte Carlo methods. The model was used to address three aspects of the transition away from ICEVs: i) the vehicle technology mix, ii) the uptake rate of this transition, and iii) how the new fleet of vehicles would be used.

The results in this study suggest that transitioning the fleet to BEVs offers substantial Well-to-Wheel CO_{2eq} emission reductions, reducing emissions by 98%, and so compatible with a net zero economy by 2050 if the existing government ICEV ban targets are met alongside the legislated decarbonisation of the electricity system. When transitioning the fleet to BEVs, cumulative WTW CO_{2eq} emissions by 2050 were sensitive to the ICEV ban date. However, if the goal is only to reach net zero CO_{2eq} emissions across the economy by 2050, there appears to be flexibility in the uptake rate of BEVs, where ICEV ban delays of up to 5 years may still be compatible with the broader net zero economy wide target.

A rapid transition to BEVs may not substantially impact air pollutant emissions of NO_x and $PM_{2.5}$ in the short term. NO_x emissions will decline with or without BEVs up to 2030 due the removal of the oldest ICEVs from the fleet. Beyond 2030, BEVs offer substantial improvements over a HEV or ICEV fleet even when considering electricity generation emissions. For $PM_{2.5}$, non-exhaust sources remain a key issue for all vehicle technologies up to 2050. BEVs are unlikely to change the total amount of non-exhaust emissions, and mostly affect the composition of sources. However, this finding is highly uncertain due to the underlying emission factors and the opposing effects of regenerative breaking reducing brake wear and increased vehicle weight increasing tyre wear.

Changes in transport demand when transitioning to a fleet of BEVs, from increases in demand due to vehicles having lower running costs or from reductions in demand due to societal changes, may occur too late too significantly affect vehicular exhaust emissions. Therefore, efforts to reduce transport demand may require greater urgency for these measures to meaningfully impact exhaust emissions. However, in the long-term changes in transport demand will still significantly impact non-exhaust $PM_{2.5}$ emissions.

Overall, these findings illustrate that the rapid uptake of EVs has the potential to decarbonise the transport sector before 2050 while significantly reducing emissions of NO_x. The decarbonisation of the electricity system enables this, where GHG and air pollutant emissions from power plans supplying BEVs remain small throughout the transition when compared to exhaust emissions. The key remaining environmental externality of the transport sector will continue to be $PM_{2.5}$ air pollution due to non-exhaust emissions from BEVs. Reductions in vehicle kilometres driven may be able to mitigate a portion of non-exhaust emissions but is expected to come into effect too late to impact exhaust emissions.

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CRediT authorship contribution statement

Daniel Mehlig: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Iain Staffell:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Marc Stettler:** Supervision, Conceptualization, Writing – review & editing. **Helen ApSimon:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

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