

Climate, air quality and health impacts of transport policies in cities

Andrea Calderon-Irazoque

Imperial College London

Centre for Environmental Policy

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Declaration of Originality

I declare that all work presented in this thesis is my own and the work of others has been properly referenced and acknowledged.

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Abstract

Environmental policies in cities have failed to effectively reduce air pollutants and greenhouse gas emissions to levels not detrimental to our environment and the health of the rapidly growing urban population. Most of the air pollutants originate from the same sources as greenhouse gases; the burning of fossil fuels and the urban transport sector are significant emitters of both. This dissertation examines the interactions between measures designed to tackle air pollution and reduce CO₂ emissions in the transport sector in cities, with London and Mexico City as case study cities.

Transport policies proposed for London by its authorities were reviewed, and from them, transport policy scenarios were developed and modelled. Technological and behavioural change transport policy scenarios were studied, including the implementation of low emission zones, vehicle electrification, reduction of car use through the promotion of active travel modes, and construction of cycle lanes. The BRUTAL sub-model of the UK Integrated Assessment Model was used to estimate CO₂ emissions and air pollutants (NO_x, NO₂, PM₁₀ and PM_{2.5}) emissions and concentrations projected to 2030. Monetised benefits for the reduction in exposure to air pollution and the offset price for CO₂ mitigation were calculated. For Mexico City, a more straightforward approach was used, assessing data from the emissions inventory to explore which strategies might be useful in reducing emissions from road transport. Health impact assessment approach was used to estimate the health impacts of air pollution exposure and physical activity in both cities.

Technological strategies are effective at reducing NO_x pollution and CO₂ emission. Behavioural change strategies yield significant reductions in particulate matter pollution. Behavioural change scenarios also deliver the most significant health benefits through an increase in physical activity. For Mexico City, the renewal of the old vehicle fleet could bring significant air pollutant emissions reductions. Future work should assess the feasibility of the scenarios.

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Chapter 1

Introduction

1.1 Research aims

Air quality pollutants and greenhouse gases (GHGs) originate from common sources: energy and industrial processes, agriculture and transport. Strategies designed to reduce GHG emissions can also affect emissions of air quality pollutants and vice versa. Thus, it is essential to identify win-win strategies that can address both environmental issues simultaneously. In this context, this research aims to use a holistic framework to identify policies that can maximise climate change mitigation and air pollution control benefits, with their corresponding health co-benefits. The objective of this dissertation is to examine how taking decisions holistically, accounting for climate, air pollution and health co-benefits could be advantageous to the decision-making process when different strategies emerge as win-win strategies.

This holistic approach is used to examine the combined effects of road transport policies for air pollution, health and carbon dioxide (CO₂) emissions. Current transport policies proposed by decision-makers to address air pollution and climate change are studied. Reducing air pollutants at the same time as GHGs results in health co-benefits through the reduction of exposure to air pollutants and further co-benefits from behavioural strategies which increase physical activity by replacing motorised transport with active travel modes (walking, cycling and public transport).

This research evaluates and compares both behavioural and technological road transport policies and focuses particularly upon how accounting for further co-benefits such as physical activity could affect what solutions emerge as the overall win-win solution. The aims of this research are addressed by considering two case study cities: London, UK and Mexico City, Mexico.

The overall aim of this dissertation is to study how decision-makers can use this holistic framework, evidence-based and thought-provoking data to help them decide on policy options, for example, when it comes to deciding between behavioural and technological approaches.

1.2 Research rationale

1.2.1 Air pollution, climate change, and health

Simultaneously, this research focuses on the interaction of strategies to reduce GHG emissions and intended to improve air quality and health. Air pollution has been identified as the single largest global environmental health risk by the World Health Organization (WHO) (WHO, 2018a). From which, exposure to particulate matter pollution alone accounts for 7.6% of global mortality (Cohen *et al.*, 2017a).

Moreover, climate change impacts such as the increase of life-threatening hot weather, severe droughts, precipitation deficits, heavy precipitation, ocean acidification, risks for some vector-borne diseases, heatwaves in cities, among others, are some of the most serious threats to the natural environment (Hoegh-Guldberg *et al.*, 2018). Both air pollution and climate change are particularly affected by the transport sector at the city level, where appropriate transport policies are required to tackle these problems while bringing health benefits to their inhabitants.

1.2.2 Transport sector

This research focuses on the transport sectors because the transport sector relies almost entirely (94%) on oil. This intense burning of fossil fuels makes the transport sector a significant emitter of air pollutants (nitrogen oxides, NO_x and particulate matter, PM), as well as a major emitter of GHGs which warm the planet and contribute to climate change. Transport accounts for half of the global energy-related NO_x emissions, one-tenth of particulate matter emissions, 14% of global GHG emissions and more than a quarter of global CO₂ emissions (IPCC, 2014a; IEA, 2016a).

Within the transport sector, this dissertation concentrates specifically on the road transport sector because road transport is by far the most significant fossil fuel consumer and consequently the largest source within the transport sector's air pollutant and GHG emissions. The road transport sector is responsible for 58% of NO_x emissions; 73% of particulate matter 2.5 micrometres (µm) or less in diameter (PM_{2.5}) emissions; and 72% of GHG emissions within the transport sector globally (Sims *et al.*, 2014; IEA, 2016a).

1.2.3 City level

The research presented in this dissertation studies cities because although they occupy just 3% of the Earth's land, they are home to 55% of the world's population, and account for 60 to 80% of the world's energy use and 75% of global CO₂ emissions, which is the most abundant GHG (IEA, 2016b; UNEP, 2019). The intense energy requirements in cities and intense burning of fossil fuels have contributed to a drastic increase in GHG emissions from cities and has caused serious air pollution problems in urban areas. The WHO estimates that 80% of all cities in the world, which are home to more than half the world's population, are exposed to harmful levels of air pollutants, which highlights the need to evaluate strategies for reducing air pollution in cities (WHO, 2016).

Specifically, this dissertation studies the road transport sector in cities because road vehicles are driven intensively in urban agglomerations, thus concentrating on harmful emissions in cities. It is estimated that road transportation in cities around the world uses nearly 40% of total global energy consumption from the transport sector (IEA, 2013). Within this sector, heavy traffic and strong dependence on fossil fuels have highly contributed to the current urban air pollution crisis and the radical increase in GHG emissions from cities (C40, 2019). Moreover, the vehicle tailpipe (from where exhaust emissions are expelled) is close to the ground, increasing people's exposure to road-transport related harmful pollutants, emphasising the need for a holistic approach when tackling GHG emissions and air pollution.

1.2.4 Transport policies in cities

It is apparent that reducing GHG emissions as well as air pollutants is essential for the implementation of appropriate transport policies. Different policies to control emissions such as air quality standards, better transport planning and public transport incentives, have helped limit emissions of air pollutants from the road transport sector in cities. However, measures to reduce emissions in cities are still failing to bring air pollution below the recommended healthy limit values in most cities (WHO, 2016). The current unsolved air pollution and climate change crisis support the motivation of this research to study win-win solutions to capitalise on environmental and health benefits and tackle these environmental issues.

Reducing emissions in the road transport sector in cities is particularly challenging due to the intense urbanisation rate that generates an increase in passenger activity. The current fast urbanisation could outweigh emissions reduced by control strategies unless transport emissions are strongly decoupled from activity growth. In this context, robust policy action and the implementation of effective policies to reduce emissions are urgently needed to protect the wellbeing of urban populations (IEA, 2016a; Sims *et al.*, 2014). This challenge demonstrates the urgent need for further research, like the one presented in this dissertation, which evaluates the most advantageous transport policies to reduce GHG emissions and exposure to air pollution.

1.2.5 Case study cities

In this dissertation, the holistic framework was addressed by assessing two case study cities: London, UK (the third-largest city in Europe) and Mexico City, Mexico (the second-largest city in Latin America) (DESA-UN, 2018). Further description of the case study cities is presented in the next chapter (section 2.5). London and Mexico City were selected because air pollution is a critical public health issue in both cities (WHO, 2016). Moreover, the road transport sector in these two cities (London and Mexico City) contributes to CO₂ emissions and air pollution in different ways, making them an interesting pair of cities to study.

In London, the road transport accounts for around a quarter (28%) of CO₂ emissions (GLA, 2017a) while in Mexico City the road transport sector accounts for the majority (74%) of CO₂ emissions (SEDEMA,

2017b). Additionally, different air pollutants affect these two cities. In London, air pollution has an important contribution from NO_x and PM (GLA, 2017a) while in Mexico City, additional to NO_x and PM, ozone pollution is a significant driver of air pollution (SEDEMA, 2018a). Additional characteristics of each city which explain why these cities were selected as case study cities are described below.

1.2.5.1 London

The implementation of effective air pollution control strategies is urgently needed in London where air pollution exceeds air quality legal limits for nitrogen dioxide (NO₂) and for particulate matter with a diameter of less than 2.5 micrometres, PM_{2.5} (EEA, 2017; GLA, 2017a). These high NO₂ pollution levels have caused the UK to face legal action (Press Association, 2016; Harvey, 2015; EC, 2010), where a significant source of such pollution in London is road transport which is responsible for half the NO_x and particulate matter emissions (GLA, 2017a).

To address the current environmental crisis, some policies at the national level, which could help improve air quality in urban areas like London have been proposed. For example, the UK is planning to ban the sale of new conventional petrol and diesel cars and vans by 2040 (DfT, 2018c). At a city level, for example, London mayors have successively implemented policies to control air pollution and reduce carbon emissions from the transport sector (TfL, 2017c; GLA, 2018a, 2010) but have failed to reduce air pollution to within legal limits (EEA, 2017). While some action has been taken to limit NO_x and PM emissions from vehicle exhausts (tailpipe emissions), the measures to limit average CO₂ emissions per km driven across the vehicle fleet have not been sufficient to meet decarbonisation objectives (Pye *et al.*, 2015).

Additionally, London is an excellent location for studying strategies to reduce air pollution and CO₂ emissions for the transport sector because the city has solid historic air pollution data records and solid emissions inventories. Additionally, there is useful data on traffic flows, vehicle fleet compositions, mobility, health and population (KCL, 2018).

1.2.5.2 Mexico City

Mexico City is an exceptional city to study road transport policies. This is due to the enormous urbanisation in the last decades, which has caused a tremendous increase in the vehicle motorisation rate. Since the nineties, Mexico City's urban population has grown by 850% (DESA-UN, 2018) and the vehicle motorisation rate increased from 0.09 to 0.3 vehicles per person in the same period (UN-Habitat, 2012; SEDEMA, 2017a). Moreover, today Mexico City is the fifth largest urban agglomeration in the world (DESA-UN, 2018).

This massively accelerated urbanisation has been chaotic, unplanned and significantly detrimental to the environment, causing a drastic increase of GHG and air pollutant emissions in the city (UN-Habitat, 2012; Molina & Molina, 2004). In addition to the enormous urbanisation, Mexico City's topography has intensified its air pollution issues. Mexico City lays in the valley of Mexico basin, and due to wind patterns and thermal inversions, pollutants become trapped.

These factors (urbanisation and topography) contributed to an air pollution crisis in the city until the point where in 1992 Mexico City was named the most polluted city on the planet by the United Nations (UN). Since then, several policies such as the requirement of catalytic converters in vehicles, lead removal from fuels, relocation of industries, public transport incentives, among others, have helped improve air quality and reduce GHG emissions. Nevertheless, the implemented policies have not been enough to mitigate the air pollution-related health risks in the city.

Today, Mexico City exceeds WHO air quality limits by an average of 30% for NO₂ (annual mean limit of 40 µg/m³), by 130% for PM_{2.5} (annual mean limit 10 µg/m³) and by 117% for ozone (8-hour mean limit of 100 µg/m³) (SEDEMA, 2018a; WHO, 2006). As such, it is apparent that this poor air quality has dramatically affected the health of Mexico City's citizens (Cifuentes *et al.*, 2001b; Bell *et al.*, 2006; Romieu *et al.*, 1996). For this reason, it is critical to study which road transport policies can bring health benefits for the reduction of air pollution and CO₂ emissions.

Furthermore, differently to the air pollutant dynamics in other European cities like London, ozone is a major air pollutant in Mexico City. Road transport is a significant contributor of precursor pollutants of ozone such as NO_x (road transport accounts for 87%) and CO (road transport accounts for 86%) (SEDEMA,

2017b). In addition to that, road transport is also a significant GHG emitter, responsible for 74% of CO₂ emissions. In the climate change arena, Mexico City has had active participation in international climate action programs and forums (C40, 2016) in which studies like the one presented in this dissertation are greatly needed.

1.3 Critical assessment of previous studies

Given the importance of concomitantly studying climate change and air pollution strategies in the two case study cities, London and Mexico City, relevant previous studies are presented in this section. Previous studies have shown that actions to mitigate GHG emissions have significant global benefits for air pollution control and health (Rafaj *et al.*, 2013; Riahi *et al.*, 2012; Field *et al.*, 2014; West *et al.*, 2013; McCollum *et al.*, 2013; Bollen, Hers & van der Zwaan, 2010) (refer to section 2.7 for more details). Studies focusing on the regional or national level, have also predicted substantial benefits from climate action on air pollution reduction and health (Amann *et al.*, 2011; van Vuuren *et al.*, 2006; Markandya *et al.*, 2009; Haines *et al.*, 2009; Smith *et al.*, 2016; Clarke *et al.*, 2014; ApSimon *et al.*, 2009).

Global and regional scale studies usually evaluate the effect of GHG emissions and air pollutant mitigation strategies for all energy sectors (refer to section 2.7 for more details). Fewer studies at these scales (global and regional) (Takeshita, 2012) have shown the benefits of GHG mitigation strategies on air pollutant emissions specifically for the road transport sector. Particularly at the city level, studies have shown that transport policies which promote low-carbon technologies, an increase of fuel efficiency, and introduce vehicle emission control technologies can reduce both GHG and air pollutants simultaneously (Chavez-Baeza & Sheinbaum-Pardo, 2014; Liu *et al.*, 2013; West *et al.*, 2004; Dhakal, 2003).

Other studies at the city level, additional to GHG emissions (generally CO₂ emissions) and air pollution estimates, have calculated health impacts of transport policies (refer to section 2.7 for more details). Some of these studies (which include CO₂ emissions assessment) have studied health impacts of transport policies which promote active travel (walking, cycling and public transport travel) usually including health impacts related to three variables: air pollution; physical activity; and road traffic injuries (Rojas-Rueda *et al.*, 2011, 2013, 2016, 2012; Zapata-Diomedes *et al.*, 2017; Woodcock *et al.*, 2009; Maizlish *et al.*, 2013; Mueller *et al.*, 2017; Xia *et al.*, 2015; Rabl & de Nazelle, 2012).

Health impacts of air pollution exposure include estimates on changes of air pollution concentration, generally particulate matter pollution (PM_{2.5}) (for example, Woodcock *et al.*, 2009; Mueller *et al.*, 2017). Additionally, they can also include health effects of inhalation of air pollution in different modes of transport (for example, Rojas-Rueda *et al.*, 2011, 2013). To calculate these air pollution-related health impacts of transport strategies, information on air pollution concentrations is required.

In this context, air pollution concentration data have been obtained from different sources in previous studies, for example, measured concentrations from monitoring stations in the city (Rojas-Rueda *et al.*, 2011), published information on air quality concentrations and source apportionment from local authorities (de Sá *et al.*, 2017), concentrations from previous modelling exercises (Cifuentes *et al.*, 2001b, 2001a), among others. However, a limitation of these studies is that most do not include air quality modelling of air pollution scenarios. Therefore, accounting for the air pollution control potential of the evaluated transport policies and their corresponding health effects is yet to be studied.

Fewer studies evaluating transport policies in cities have included (additionally to CO₂ emission assessments) estimations of the health impacts, accounting for the air pollution control potential of the evaluated transport policies using air quality modelling techniques (Woodcock *et al.*, 2009; Xia *et al.*, 2015; Rojas-Rueda *et al.*, 2012; Grabow *et al.*, 2012; Maizlish *et al.*, 2013). From these studies, some (Grabow *et al.*, 2012; Rojas-Rueda *et al.*, 2012; Xia *et al.*, 2015) have only evaluated behavioural change transport strategies which shift motorised travel (for example, travel by car) to active travel modes (walking, cycling and public transport).

To the best of my knowledge only (Woodcock *et al.*, 2009; Maizlish *et al.*, 2013) have evaluated technological change transport strategies (e.g. introduction of low-carbon vehicles) together with behavioural change strategies. These studies assessed CO₂ emissions, including air quality modelling, to estimate the air pollution control potential of the evaluated theoretical transport policies and their corresponding health impacts. However, Woodcock *et al.*, 2009, and Maizlish *et al.*, 2013, do not include technological change scenarios developed from the real transport policies proposed by the city authorities. Also, they do not include potential harms from travellers' inhalation of air pollution; they only look at general population exposures.

Therefore, although previous studies have greatly enriched the knowledge on this area of study, there is a current need to study technological and behavioural change strategies which relate and are informed from actual transport policies proposed by city governments which is the research aim of this dissertation. Evaluating the impacts of these transport policies in the more holistic way including their effects on CO₂ emissions reduction, their impact on air pollution control and quantifying their health co-benefits will help decision-makers to choose and to allocate funds for the implementation of the transport strategies which maximise benefits to improve the lives of the urban population.

1.4 Research objectives

To address the research aim of this dissertation, and identify real policies that have the potential to impact GHG emissions, air pollution and health together, maximising benefits in cities (London and Mexico City as case study cities), and contribute to the research area, a series of research objectives were defined and are presented below.

1. Review and identify proposed transport policies (technological and behavioural policies) which have been implemented or proposed in London and Mexico City to reduce GHG emissions, control air pollution and improve health.
2. Develop technological and behavioural change transport policy scenarios built from the review of proposed transport policies identified in London and Mexico City.
3. Develop a modelling framework to assess the impacts on CO₂ emissions and air pollution of the defined transport policy scenarios in London and Mexico City.
4. Translate the transport policy scenarios into inputs for the CO₂ emissions and air pollution modelling (or assessment) framework, defining the travel patterns associated with the transport policy scenarios.
5. Use the CO₂ emissions and air pollution modelling framework to project and estimate the impacts on CO₂ emissions, air pollutant emissions, and air pollutant concentrations (when possible) associated with the transport policy scenarios.
6. Develop a health impact assessment framework to model the health impacts of the transport policy scenarios using the travel patterns defined for the scenario and the modelled output air pollutant concentrations (when possible).
7. Identify how the transport policy scenarios can tackle climate change (through CO₂ emissions reduction), air pollution and improve health, maximising synergies and minimising trade-offs to find win-win solutions from the holistic framework developed.

The research methods developed to address each one of these research objectives are described in detail in chapter 3.

1.5 Research scope

1.5.1 Transport policies

Implemented, proposed or projected road transport policies addressing climate change, air pollution and health in London and Mexico City, as well as environmental trends were used to define the transport policy scenarios. To study the broadest spectrum of transport policies, both technological and behavioural change transport policies were taken into consideration. These categories have been used in previous studies to evaluate the impacts of transport strategies in a more comprehensive way, with an environmental focus (Kollamthodi & Watkiss, 2005; Sims *et al.*, 2014) and also including a health perspective (Woodcock *et al.*, 2009).

As such, the transport policy scenarios studied in this dissertation were divided into two categories, technological and behavioural change transport policy scenarios, according to their policy intervention approach:

- Technological change policy scenarios included technical measures often including physical changes to the vehicle (e.g. vehicle retrofitting or a switch to electric vehicles).
- Behavioural change policy scenarios included non-technical measures (e.g. mode shift from motorised vehicles to walking, cycling, and public transport).

1.5.2 Air pollutants

This dissertation studied outdoor air pollution, focusing on the two main categories of air pollutants linked to road transport which have significant health impacts: nitrogen oxides (NO_x) and particulate matter (PM). Explicitly, particulate matter of 10 micrometres or less in diameter (PM₁₀), particulate matter of 2.5 micrometres or less in diameter (PM_{2.5}), nitrogen oxides (NO_x) and nitrogen dioxide (NO₂). These pollutants were selected because transport is the largest source of NO_x pollution in cities and the world and is an important contributor to PM emissions at the local and global level. More specifically, within the transport sector, the road transport sector is the main source of NO_x emissions (58%) and PM emissions (73% of PM_{2.5} emissions) (Sims *et al.*, 2014; IEA, 2016a).

For every transport policy scenario, emissions as tonnes per year (t/y) were assessed for each air pollutant: PM₁₀, PM_{2.5}, NO_x and NO₂. Tailpipe emissions (or exhaust emissions) were calculated for the four pollutants. Additionally, a novelty of this research is that non-tailpipe (non-exhaust) particulate matter emissions, PM₁₀ and PM_{2.5}, were also estimated. The PM non-exhaust emissions sources accounted for in this research were: tyre wear and brake wear.

The key importance of accounting for non-exhaust emissions when doing traffic air quality management has been highlighted in previous studies which have found that more than half of total PM emissions originate from non-exhaust emissions sources (Ketzler *et al.*, 2007; Bukowiecki *et al.*, 2010; Timmers & Achten, 2016). A limitation of this dissertation, as it will be discussed later in section 3.3.1, is that non-exhaust emissions from road abrasion and resuspended road dust particles were not accounted for. Previous studies have shown that resuspended particles can be a significant source of traffic PM non-exhaust emissions (Bukowiecki *et al.*, 2010; GLA, 2017a).

1.5.2.1 Air pollution exposure

To estimate the health effects of exposure to air pollution, air pollutant concentrations in micrograms per cubic meter (µg/m³) were calculated for each transport policy scenario for London. Background concentrations, as well as population-weighted mean concentrations (PWMC), were modelled (refer to

section 3.3.1.2 for details). Although during my PhD, concentration maps for the four pollutants were studied, in this dissertation, particular attention to PPMC maps for PM_{2.5} and NO₂ is given for each transport policy scenario in order to estimate the health impacts. Health impacts for air pollution exposure for changes in air pollution concentrations and for air pollution inhalation in travellers were assessed.

Health impacts associated with the exposure to PM_{2.5} and NO₂ were therefore estimated. Particulate matter, in particular PM_{2.5}, is the air pollutant with the most robust quantifications of exposure and its effects on health available (de Nazelle *et al.*, 2011). Long-term exposure to PM_{2.5} has a strong association with increased mortality and morbidity from cardiovascular and respiratory disease resulting in shortened life expectancy (Cohen *et al.*, 2017b).

In addition to PM_{2.5}, the health effects of long-term exposure to NO₂ were also estimated. For NO₂, there is less robust quantification of health risks than for PM_{2.5}. However, a positive association between several causes of death and exposure to NO₂ has been found (Jerrett *et al.*, 2013; Fischer *et al.*, 2015; Beelen *et al.*, 2014; Crouse *et al.*, 2015a). The importance and rationale for including health impacts related to NO₂ in this dissertation is because NO₂ may reflect better the spatial distribution of traffic-related pollution as suggested in previous studies (Crouse *et al.*, 2015a).

1.5.3 Greenhouse gases

Referring now to climate change gases, the GHG assessed in this dissertation was CO₂ given that this gas is the most abundant anthropogenic GHG that affects the Earth's radiative balance by warming the planet (IPCC, 2013). Moreover, the road transport sector accounts for most CO₂ emissions (74%, 5.8 Gt CO₂ in 2016) from the transport sector globally (IEA, 2019). Direct or tailpipe CO₂ emissions and indirect CO₂ emissions from the generation of electricity to power electric vehicles were calculated for each transport policy scenario.

1.5.3.1 Indirect emissions

For the technological transport policy scenarios which evaluated the inclusion of electric vehicles in the vehicle fleet, the indirect CO₂ emissions generated during the generation of electricity needed to power the vehicle, were estimated. Indirect CO₂ emissions were accounted for because GHG emissions, in contrast to air pollutant emissions, are problematic for warming at the global level.

Indirect air pollutant emissions emitted in power plants outside the city limits, while generating electricity to power electric vehicles, affect the local air pollution near the power plant but not necessarily impact the local air pollution in the cities. An additional complication of quantifying indirect emissions is that they change over time with the evolution of the energy mix and capacity off renewables. Therefore, indirect air pollution emissions generated in the power plants were out of the scope of this study. A life-cycle assessment of CO₂ emissions and air quality of the transport policy scenarios is suggested as an area for further research.

1.5.4 Health impacts assessment

Finally, but central to the holistic frame of this dissertation, the health impacts of all-cause mortality were assessed for two domains: exposure to air pollution (PM_{2.5} and NO₂) and physical activity. These two domains were chosen because air pollution and physical activity are two domains with significant impacts on mortality as well as the ones with most robust exposure-health quantifications data available (de Nazelle *et al.*, 2011). It is important to note that a limitation of this study is not accounting for road traffic injuries. Studies have shown that road traffic injuries have a high impact on mortality (Rojas-Rueda *et al.*, 2011; Maizlish *et al.*, 2013; Woodcock *et al.*, 2009; de Sá *et al.*, 2017; Mueller *et al.*, 2015).

1.6 Thesis structure

To accomplish the research objectives depicted in Section 1.4, and to contribute to the analysis of win-win strategies for tackling climate change and air pollution whilst procuring health benefits for citizens, this dissertation is presented in seven chapters. Chapters 1 and 2 introduce the research aims and rationale, providing the necessary background information and a review of previous studies, introducing the rationale for the methods of this research. Chapter 3 presents a detailed and complete description of all the methods used in this dissertation. Chapters 4 and 6 are the results chapters of the London and the Mexico City assessments. Finally, Chapter 7 presents the discussion and the holistic integration of results for London and in Mexico, together with a comprehensive comparison of the two cities studied and presents concluding remarks.

1.6.1 Chapter 1 Introduction

Chapter 1 presents the research aims, motivation and rationale, an overview of previous studies to set the scene to present the research objectives of this dissertation and research scope. In the end, this chapter presents the structure of the thesis.

1.6.2 Chapter 2 Background and literature review

Chapter 2 provides background information on air pollution, climate change, the road transport sector and related abatement technologies, including a summary of associated health impacts and relevant characteristics of the two case study cities. This is followed by a review of previous studies on climate change and air pollution synergies and trade-offs at different scales. A description of methods used in previous studies is also included, and the rationale for choosing the UKIAM model is presented.

Furthermore, this chapter presents a review and discussion of previous studies focused on the study of climate, air pollution and health impacts of transport strategies in cities.

1.6.3 Chapter 3 Methods

Chapter 3 presents the complete methodological approaches used in this dissertation. The transport policies from which the transport policy scenarios are built in London and Mexico City are defined. The CO₂ emissions and air pollutants modelling framework is presented. The UKIAM-BRUTAL model used for the London case study is described, including a discussion on the UKIAM-BRUTAL model's uncertainties. Then, the emissions assessment approach for Mexico City is described. Then, the translation of the transport policy scenarios as inputs for the modelling framework is presented and followed by the health impact modelling framework description and discussion, including the description of the sensitivity analysis performed.

1.6.4 Chapter 4 CO₂ emissions and air quality modelling of transport policy scenarios in London

Chapter 4 presents and discusses the CO₂ emissions and air pollutants modelling results of the transport policy scenarios evaluated for London.

1.6.5 Chapter 5 Health impact assessment modelling of transport policy scenarios in London

Chapter 5 presents and discusses the health impact assessment modelling results of the transport policy scenarios for London.

1.6.6 Chapter 6 CO₂ and air pollution emissions evaluation and health impact assessment modelling of transport policy scenarios in Mexico City

Chapter 6 presents and discusses the CO₂ emissions and air pollutants assessment results and the health impact assessment modelling results of the transport policy scenarios for Mexico City.

1.6.7 Chapter 7 Discussion

Chapter 7 focuses on the discussion and the holistic integration of results for London and in Mexico, discussing the main findings of the research, together with a comprehensive comparison of the two cities studied (London and Mexico City) and presents concluding remarks.

Chapter 2

Background and literature review

2.1 Overview

This chapter presents background information on air pollution, climate change, health impacts and the road transport sector, followed by a literature review on previous studies addressing climate and air quality issues in transport policies. This chapter describes in detail the core concepts used in this research and presents the environmental context, which in turn motivates and highlights the need for research such as this PhD dissertation.

This chapter starts (section 2.2) by describing the two most adverse environmental issues of our time, which are the focus of this dissertation: climate change and air pollution. The definition of these environmental issues is included together with the description of the most abundant air pollutants, and greenhouse gases (GHG) emitted from the road transport sector, which will be the focus of this research as described in Chapter 1.

Other air pollutants and GHG which are regulated by health authorities (World Health Organisation, WHO) or included in climate change agreements, are also briefly described to include a complete picture of the environmental issue. A review of air quality legislation and climate change international agreements and frameworks are also explained. At the end of this section (2.2), links between air pollution and climate change are revised to highlight the importance of addressing these two environmental issues together.

Following the review on air pollution and climate change-related topics, this chapter presents in section 2.3, a review of the road transport sector. In this section (2.3) the vehicle categories used in this dissertation are described, and different abatement technologies and strategies to reduce emission from the road transport sector are reviewed. This section contains essential information to understand the technicalities of some of the transport measures assessed in this dissertation.

The next section, section 2.4, reviews the health impacts of air pollution. The core part of this research is assessing the health impacts of transport strategies motivated by the urgency of improving health in polluted cities. This section will detail the current knowledge, which states how poor air quality is damaging the health of the inhabitants of cities and the world. This section (2.4) also includes a brief review of climate change impacts to illustrate how this environmental issue is also a threat to health.

Section 2.5 presents characteristics of the two case study cities, London and Mexico City, including information on demographics, road transport, transport modes, and CO₂ emissions and air quality emissions. Reviewing the current environmental conditions of the two case study cities allows them to be used as a reference for future transport strategies and assess possible impacts.

The following sections in this chapter, sections 2.6 and 2.7, focus on the review of the literature, presenting the analysis of previous studies assessing climate and air quality impacts. Section 2.6 outlines the different modelling approaches used in previous studies to address climate and air quality measures, describing their policy applications. Importantly, subsection 2.6.6 presents the rationale for the choice of model in this dissertation, after a discussion on previous modelling tools used. Section 2.7 discusses previous studies and existing research on climate, air quality and health impacts of abatement measures in cities to explain the current position and portray how this dissertation fits in the present research and which gaps in the literature are being covered.

2.2 Air pollution and climate change

2.2.1 Air pollution

Air pollution refers to the alteration of the air in the atmosphere by the introduction of substances or energy forms (heat, noise, radioactivity) in a way that the altered atmosphere poses harm to humans, biological systems, materials or the atmosphere itself (Godish, 2003). Contamination or pollution of the atmosphere occurs because of natural processes (volcanic activity, forest fires) as well as anthropogenic.

2.2.1.1 Air pollutants

Air pollutants are emitted from a variety of sources, including transportation, fuel combustion, industrial processes, power generation, household heating and lighting, and waste disposal, among others (Figure 2.1). The most abundant air pollutants emitted from the transport sector are: nitrogen oxides (NO_x), particulate matter (PM), Carbon monoxide (CO), and volatile organic compounds (VOCs) as precursors of ozone (O_3) (coloured in green) are described below. Other air pollutants (Sulphur dioxide, SO_2) which are regulated by the WHO are also included. The following description of air pollutants is based on (Colls, 2002; Godish, 2003).

2.2.1.1.1 Nitrogen oxides (NO_x)

Nitrogen oxides (NO_x) are a mixture of gases composed of oxygen and nitrogen. The two principal oxides of nitrogen are nitric oxide (NO), and nitrogen dioxide (NO_2), $\text{NO}_x = \text{NO} + \text{NO}_2$. NO, which is a colourless and odourless gas, is a primary pollutant formed from reactions of nitrogen and oxygen in the air and the nitrogen in fuels. Fuel combustion produces a mixture of primary NO and NO_2 . Oil and coal nitrogen

content varies from 0.5% to 1.5%. NO₂, which is a yellowish, corrosive and toxic gas with a pungent and irritating odour, is both a primary and a secondary pollutant. A small proportion is primary NO₂ formed from the nitrogen in fuels and emitted through the vehicle's tailpipe. The remaining secondary NO₂ is created in the atmosphere. Ozone (O₃) can oxidise NO to produce NO₂ and O₂ ($\text{NO} + \text{O}_3 \rightarrow \text{NO}_2 + \text{O}_2$). During daylight, the NO₂ absorbs radiation and decomposes back to NO and O₃ ($\text{NO}_2 + h\nu (\text{O}_2) \rightarrow \text{NO} + \text{O}_3$), reversing the reaction and settling in equilibrium. Global NO_x emissions were estimated at 107 Mt in 2015, 50% of which, came from the transport sector (Figure 2.1) (IEA, 2016a).

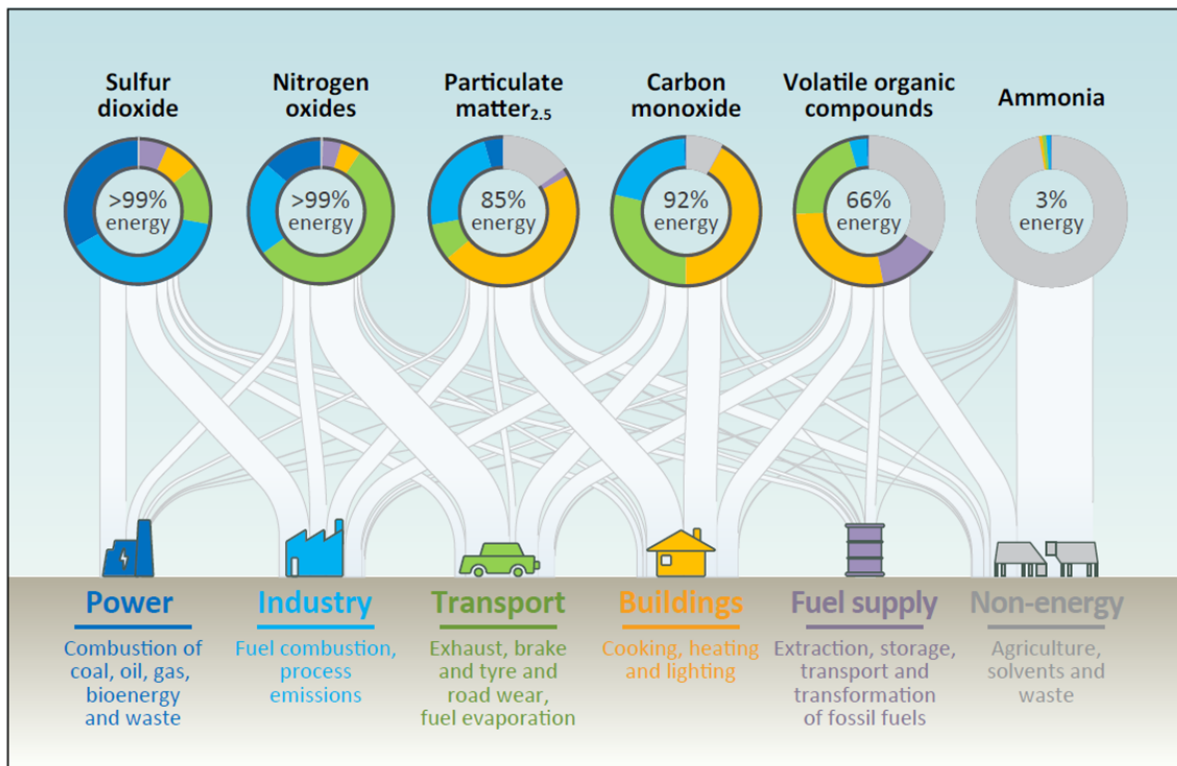


Figure 2.1 Selected air pollutants and their sources at the global level (IEA, 2016a). The transport sector contribution to air pollutant emissions is coloured in green and so is the most abundant pollutant.

2.2.1.1.2 Particulate matter (PM)

Particulate matter (PM) is formed from solid and liquid substances (also known as aerosols) that vary in size, from nanometres (nm) (10^{-9}) to micrometres (μm) (10^{-6}). Particulate matter can be classified according to its size. Particles with a diameter of $10\ \mu\text{m}$ or smaller are referred to as PM_{10} . The coarse fraction of PM_{10} is usually cited as particles with a diameter between $2.5\ \mu\text{m}$ and $10\ \mu\text{m}$. PM_{10} include pollen, mould spores and coarse dust from construction. Particulate with a diameter of $2.5\ \mu\text{m}$ or less μm are referred to as $\text{PM}_{2.5}$ and are usually called the fine particle. $\text{PM}_{2.5}$ include black carbon (pure carbon or soot and primary particles, and secondary particles formed by chemical interactions in the atmosphere) and smog. Particulate matter with a diameter of less $0.1\ \mu\text{m}$ are known as ultrafine particles and include black carbon.

Airborne particulates can be primary (released directly from the source) or secondary (formed in the atmosphere from chemical reactions) and come from natural and anthropogenic sources. Components and associated sources of primary particulate matter include the following (Figure 2.2): (i) Sea salt (NaCl). (ii) Black carbon produced from incomplete combustion of fossil fuels. (iii) Trace metals (lead cadmium, nickel, chromium, zinc, manganese) usually at very low concentrations generated from an industrial process or during the abrasion process from vehicle brakes and tyre wear. (iv) Mineral components (aluminium, silicon, iron) from coarse construction dust or wind-dust.

Components and sources of secondary particulate matter include (Figure 2.2): (i) Sulphate from the oxidation of SO_2 into the atmosphere. (ii) Nitrate from the oxidation of NO_x and reaction with ammonia (NH_3) emitted in agriculture (Figure 2.1). (iii) Water. (iv) Secondary organic aerosol which comes from the oxidation of volatile organic compounds (VOCs), particularly from biogenic VOCs. SO_2 , NO_x , NH_3 and VOCs are precursors of secondary particulate matter.

Particulate matter emission in the transport sector can be classified as exhaust or non-exhaust. Exhaust emissions refer to the emissions that come out directly from the vehicle tailpipe to the atmosphere. Non-exhaust emissions come from sources such as tyre wear, brake wear and road surface wear (other potential sources are clutch wear, engine wear or from corrosion of other vehicle components) (Barlow J. *et al.*, 2007). More than 50% of global particulate matter emissions come from the residential (buildings) sector, the industry and transport sector are the second and third most important emitters worldwide (Figure 2.1).

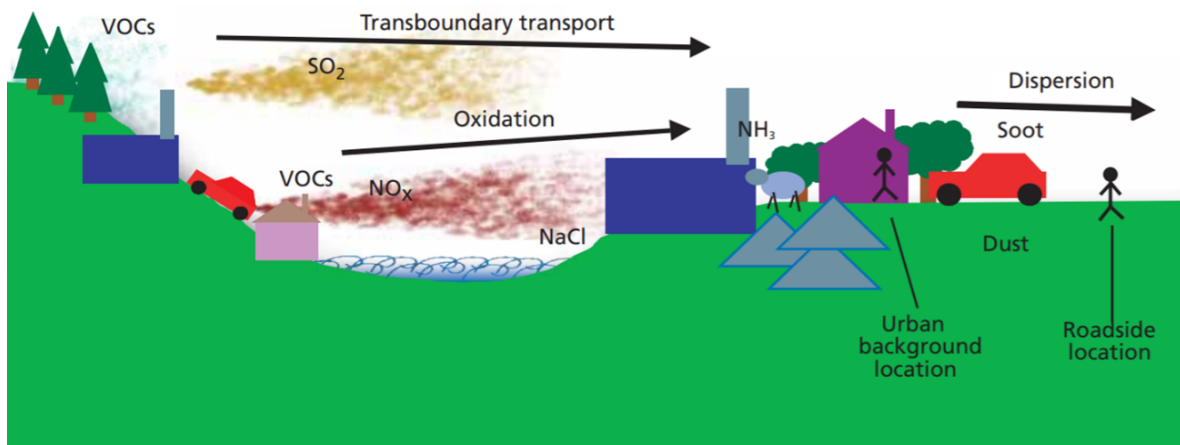


Figure 2.2 Sources of particulate matter (PM) (AQEG, 2005).

2.2.1.1.3 Carbon monoxide (CO)

Carbon monoxide (CO) is a colourless, odourless gas that comes from incomplete fuel combustion, industrial processes and biomass burning. CO is oxidised in the troposphere (depth of troposphere is 10 to 12 km) and is an important ozone (O₃) precursor. Road transport (mostly petrol vehicles) and combustion in the residential sector are significant sources of CO pollution at the global level (Figure 2.1).

2.2.1.1.4 Ozone (O₃)

Ozone (O₃) (a pale blue gas with a pungent odour) mainly occurs (90%) in the stratosphere (heights 10 to 30 km) in the region also known as the ozone layer. Ozone in the stratosphere is produced from the photochemical reaction with oxygen molecules.

However, low level or tropospheric ozone is an atmospheric pollutant important for human health, crops and ecosystems. Tropospheric ozone is a secondary pollutant which is produced during a photochemical reaction. The photochemical reaction occurs when sunlight oxidises carbon monoxide (CO) or volatile organic compounds (VOCs) (Figure 2.1), in the presence of NO_x. VOCs sources include solvent use, combustion in road transport and the energy sector. NO_x, CO, and VOCs are considered as ozone precursors. The time scale of the formation of ozone can take hours, days or even longer (AQEG, 2009).

In rural areas where fewer sources of NO (less road traffic), the NO₂ is usually considerably higher than the NO. A higher level of NO₂ acts as a precursor of ozone ($\text{NO}_2 + h\nu (\text{O}_2) \rightarrow \text{NO} + \text{O}_3$). In cities where NO_x emissions (mostly NO) are higher, ozone reacts with NO to form NO₂ ($\text{NO} + \text{O}_3 \rightarrow \text{NO}_2 + \text{O}_2$). Then, there is generally lower ozone in urban areas than in rural areas. Reduction in NO_x (and a decrease in NO) emissions in urban areas over the last 10 to 15 years have led to an increase of ozone in cities (AQEG, 2009).

2.2.1.1.5 Sulphur dioxide (SO₂)

Sulphur dioxide (SO₂) is a colourless gas with a pungent odour which is a primary pollutant (emitted directly from a specific source). Sulphur dioxide plays a role in forming winter-time smog. Sulphur dioxide emissions come from natural sources (like volcanos) and mainly from anthropogenic sources which account for more than 70% of SO₂ global emissions (Colls, 2002). Most of the sulphuric anthropogenic emissions come from the combustion of fossil fuels. All fossil fuels contain sulphur (oil and coal can contain between 0.1% and 4%) which is released as sulphur dioxide during combustion. The energy (power) sector and the industrial sectors are the most significant emitters of SO₂ accounting for 45% and 30%, respectively, of the 80 Mt emitted in 2015 globally (Figure 2.1) (IEA, 2016a).

2.2.1.2 Air pollution legislation in Europe

The Convention on Long-range Transboundary Air Pollution (LRTAP) of the United Nations Economic Commission for Europe, signed in 1997, was the first international treaty to deal with air pollution in a large region (UNECE, 2018). The Convention has been extended by eight protocols containing legally binding targets for emission reductions.

The 1999 Gothenburg Protocol to Abate Acidification, Eutrophication and Ground-level Ozone (Gothenburg Protocol) is the latest Protocol of the Convention. It includes specific national emission ceilings for sulphur dioxide, nitrogen oxides, ammonia, and volatile organic compounds. The revised Gothenburg Protocol, which is not yet in force, would be the first binding agreement to include emission reduction commitments for fine particulate matter including the short-lived climate pollutant black carbon (or soot) as a component of particulate matter (UNECE, 2018).

Similar emission limits (ceilings) have been implemented in Europe under the National Emission Ceilings Directive (2001), which was adopted in the UK as the National Emission Ceilings Regulations 2002, and covers SO₂, NH₃, VOCs, NO_x, PM_{2.5} (Defra, 2019e). These are annual limits, but there are short term limits too, e.g. 50 µg/m³ as a daily limit not to be exceeded more than 35 times per year; and 200 µg/m³ as an hourly limit for NO₂.

Additionally, in Europe, the 2008 Ambient Air Quality Directive sets legally binding limits for concentrations of particulate matter (limiting annual concentration of PM₁₀ to 40 µg/m³ and of PM_{2.5} to 25 µg/m³) and nitrogen dioxide (limiting annual concentration of NO₂ to 40 µg/m³) (Defra, 2019e).

Another essential legislation that governs air pollutant emissions in the European Union (EU) is the Euro Standards. The European emission standards (Euro standards) (Table 2.2) is the legislation which defines exhaust emissions limits for road transport vehicles in the European Union (EU). There are Euro standards in place for cars, vans, heavy-duty vehicles (coaches, buses, trucks), and mobile machinery. For each vehicle type, different standards apply. The emissions limits are set in the European Union directives for the following pollutants: carbon monoxide (CO), total hydrocarbon (THC), non-methane hydrocarbons (NMHC), nitrogen oxides (NO_x) and particulate matter (PM) (Table 2.2).

Vehicles are tested for compliance with emissions standards in standardised laboratory tests. However, emissions in real-world driving conditions are known to behave differently (O’Driscoll *et al.*, 2016). To address the discrepancy with real driving emissions, the EU has introduced real driving emissions (RDE) testing using portable emissions measurement systems for emissions vehicle testing, in the Euro 6d-Temp (Sept 2019) (Table 2.2).

However, the RDE testing was implemented with a conformity factor that allows flexibility for compliance with the emission limits. With the current conformity factor of 2.1 for NO_x, new diesel cars will be permitted to emit 2.1 times the current type-approval limit in the RDE test. By 2020 the conformity factor is supposed to be 1.5 for NO_x (EC, 2019).

The EU also established carbon dioxide (CO₂) fleet average emissions targets for road transport vehicles in EU Regulation 443/2009 (EU, 2009) (Table 2.1). Passenger cars have an average emission target value of 95 g CO₂ per km by 2020.

Table 2.1 Average CO₂ emissions targets as set in EU Regulation 443/2009 (EU, 2009).

Vehicle type	Year	Fleet average emissions targets (grams of CO ₂ per km)
Passenger cars	Current	130
	2020	95
Light commercial vehicle	Current	175
	2020	147

Table 2.2 European emission standards for passenger cars (European Commission, 2019).

Tier	Date	Engine type	Carbon monoxide (CO)	Total hydrocarbons (THC)	Non-methane hydrocarbons (NMHC)	Oxides of nitrogen (NOx)	Hydrocarbons and oxides of nitrogen (THC+NOx)	Particulate matter (PM)	Number of particles (PN)
	and EU directive		g/km	g/km	g/km	g/km	g/km	g/km	No./km
Euro 1	Jan-93	Diesel	2.72 (3.16)	-	-	-	0.97 (1.13)	0.14 (0.18)	-
	91/441/EEC	Petrol	2.72 (3.16)	-	-	-	0.97 (1.13)	-	-
Euro 2	Jan-97	Diesel	1	-	-	-	0.7	0.08	-
	94/12/EC	Petrol	2.2	-	-	-	0.5	-	-
Euro 3	Jan-01	Diesel	0.66	-	-	0.5	0.56	0.05	-
	98/69/EC	Petrol	2.3	0.2	-	0.15	-	-	-
Euro 4	Jan-06	Diesel	0.5	-	-	0.25	0.3	0.025	-
	98/69/EC	Petrol	1	0.1	-	0.08	-	-	-
Euro 5a	Jan-11	Diesel	0.5	-	-	0.18	0.23	0.005	-
	715/2007/EC	Petrol	1	0.1	0.068	0.06	-	0.005	-
Euro 5b	Jan-13	Diesel	0.5	-	-	0.18	0.23	0.0045	6×10^{11}
		Petrol	1	0.1	0.068	0.06	-	0.004	-

Table 2.2 (Continued) European emission standards for passenger cars (European Commission, 2019).

Tier	Date (First Registration) and EU directive	Engine type	Carbon monoxide (CO)	Total hydrocarbons (THC)	Non-methane hydrocarbons (NMHC)	Oxides of nitrogen (NOx)	Hydrocarbons and oxides of nitrogen (THC+NOx)	Particulate matter (PM)	Number of particles (PN)
		g/km	g/km	g/km	g/km	g/km	g/km	g/km	No./km
Euro 6	Sep-15	Diesel	0.5	-	-	0.08	0.17	0.0045	6×10^{11}
		Petrol	1	0.1	0.068	0.06	-	0.0045	6×10^{11}
Euro 6b	Sep-15	Diesel	0.5	-	-	0.08	0.17	0.0045	6×10^{11}
	459/2012/EC	Petrol	1	0.1	0.068	0.06	-	0.0045	6×10^{11}
Euro 6c	Sep-18	Diesel	0.5	-	-	0.08	0.17	0.0045	6×10^{11}
		Petrol	1	0.1	0.068	0.06	-	0.0045	6×10^{11}
Euro 6d- Temp	Sep-19	Diesel	0.5	-	-	0.08	0.17	0.0045	6×10^{11}
		Petrol	1	0.1	0.068	0.06	-	0.0045	6×10^{11}
Euro 6d	Jan-21	Diesel	0.5	-	-	0.08	0.17	0.0045	6×10^{11}
		Petrol	1	0.1	0.068	0.06	-	0.0045	6×10^{11}

2.2.2 Climate change

Climate change is defined by the Intergovernmental Panel on Climate Change (IPCC) as the “change in the state of the climate that can be identified by changes in the mean and the variability of its properties, and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forcings such as modulations of the solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or land use” (Allwood *et al.*, 2014).

The anthropogenic influence on the climate is clear. Recent anthropogenic emissions of greenhouse gases (GHG) are the highest in history and have led to unprecedented atmospheric GHG concentrations “in at least the last 800,000 years. Their effects, together with those of other anthropogenic drivers, have been detected throughout the climate system and are extremely likely to have been the dominant cause of the observed warming since the mid-20th century” (IPCC, 2014a). “Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed, the amounts of snow and ice have diminished, and sea level has risen” (IPCC, 2014a).

2.2.2.1 Greenhouse gases

Greenhouse gases (GHG) are gaseous constituents of the atmosphere that warm the surface of the planet by absorbing outgoing thermal infrared radiation and emitting some of the radiation back toward the surface. This property causes the greenhouse effect that is essential to life on Earth. Some GHG are natural, but others are partially or entirely anthropogenic (Allwood *et al.*, 2014). “Annual anthropogenic GHG emissions have increased by 10 Gt CO₂eq (carbon dioxide equivalent) between 2000 and 2010, with this increase directly coming from (Figure 2.3) energy supply (47%), industry (30%), transport (11%) and buildings (3%) sectors (medium confidence). Accounting for indirect (off-site) emissions raises the contributions of the buildings and industry sectors” according to the IPCC (IPCC, 2014a).

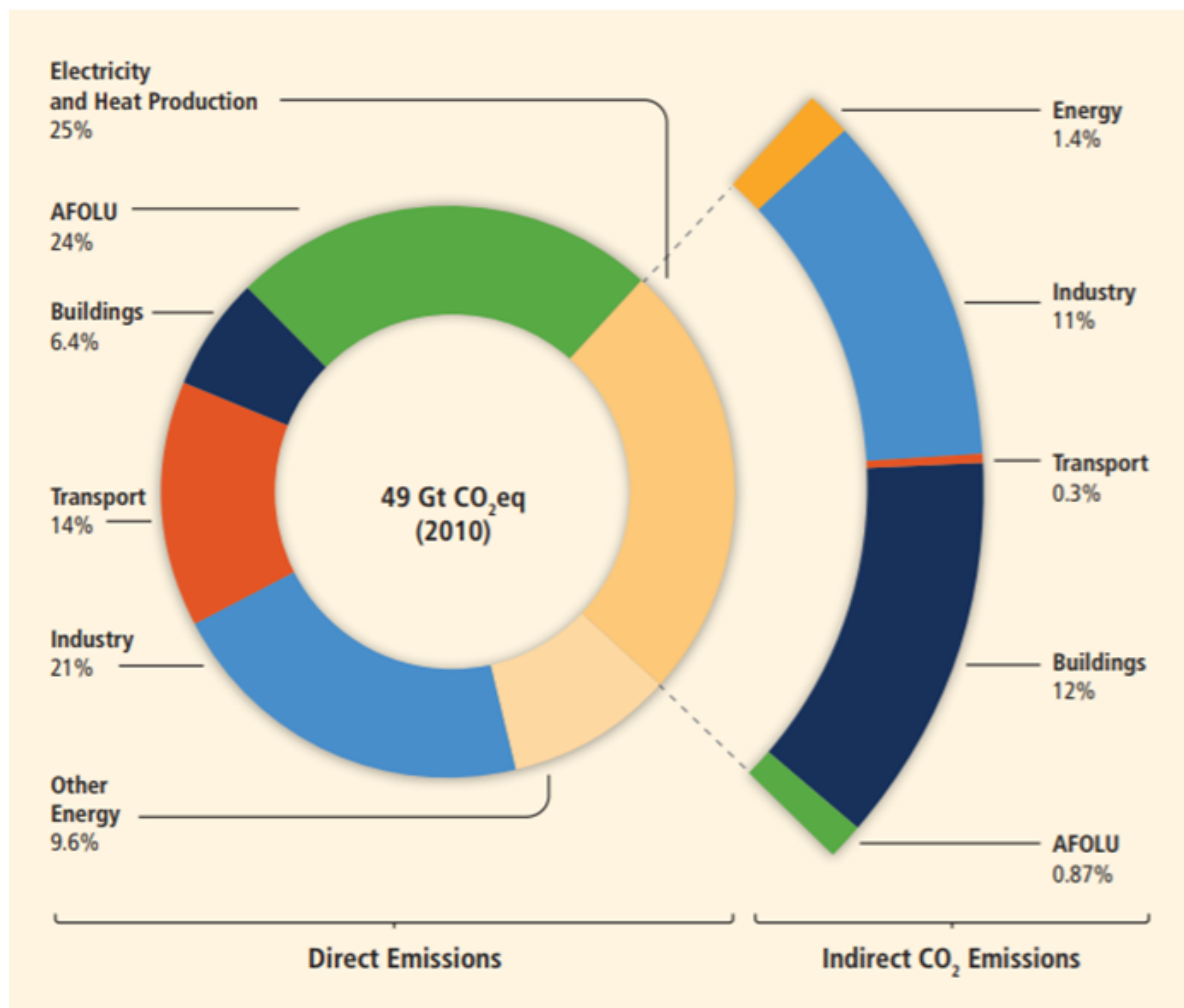


Figure 2.3 Global anthropogenic GHG emissions (Gt CO₂eq (carbon dioxide equivalent) per year) by economic sector (IPCC, 2014a).

Note: Direct emissions are on-site emissions from the source. Indirect emissions are not on-site emissions, for example, emissions from electricity generation. AFOLU: Agriculture, Forestry and Other Land Use.

2.2.2.1.1 Carbon dioxide (CO₂)

Carbon dioxide (CO₂) is the most abundant greenhouse gas (GHG) on the planet, accounting for close to 80% of GHG emissions globally. As a result, CO₂ was chosen as the GHG studied in this research. CO₂ is a naturally occurring gas, produced in aerobic biological processes and combustion and is required by plants during photosynthesis. CO₂ is also the principal anthropogenic GHG produced by the burning of fossil fuels, industrial processes (e.g. cement production) and land-use change (e.g. deforestation). Pre-industrial (1850) CO₂ concentrations varied around 280 ppm (parts per million) (IPCC, 2014a).

Today, CO₂ concentrations have risen to 411 ppm (1.5 fold), the highest concentrations in 650,000 years (NASA, 2019). Global anthropogenic CO₂ emissions today are around 40 Gt per year (in contrast to approx. 2 Gt per year in 1850). Human activities are estimated to have caused approximately 1.0 °C of global warming above pre-industrial levels (Masson-Delmotte *et al.*, 2018).

2.2.2.1.2 Other greenhouse gases

The primary greenhouse gases in the atmosphere are water vapour (H₂O), carbon dioxide (CO₂), nitrous oxide (N₂O), methane (CH₄) and ozone (O₃). CO₂ is not the only GHG that is currently on the rise. CH₄ and N₂O have also drastically increased as a result of human activities, primarily agriculture. CH₄ accounts for 16% of annual anthropogenic GHG emissions and N₂O accounts for 6.3% of GHG emissions. There are human-made greenhouse gases in the atmosphere. For example, halocarbons like chlorofluorocarbons (CFCs). Fluorinated gases account for 2% of GHG emissions.

2.2.2.2 Climate change international agreements and frameworks

The international body that facilitates intergovernmental climate change negotiations is the United Nations climate change secretariat was established in 1992 when countries adopted the United Nation Framework Convention on Climate Change (UNFCCC) (UNFCCC, 2019). The most relevant treaties outlined by the UNFCCC secretariat to respond to the threat of climate change are the Kyoto Protocol (adopted in 1997) and the Paris Agreement (adopted in 2015).

The Kyoto Protocol is an international agreement which sets internationally binding emission reduction targets for greenhouse gases. Additional to national measures, the Kyoto Protocol offers some market-based mechanisms to help countries meet their objectives:

- The International Emissions Trading allows countries which have reduced emissions by more than that which they committed to, to sell this excess capacity to countries which have not met their emission reduction targets.
- The Clean Development Mechanism allows a country to implement an emission-reduction project in developing countries.
- The Joint Implementation will enable countries to earn emission reduction units (ERUs) from an emission-reduction or emission removal project in another party.

To date, 192 countries are parties to the Kyoto Protocol, the US and Canada have withdrawal from the Protocol. One of the commitments established in the Protocol is to reduce GHG emissions by at least 18% below 1990 levels during the period from 2013 to 2020. The Kyoto Protocol applies to the following greenhouse gases: carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF₆), and nitrogen trifluoride (NF₃) (UNFCCC, 2012).

In December 2015 Parties to the UNFCCC reached the Paris Agreement which aims to keep the global temperature rise this century well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5 °C (UNFCCC, 2019). The Paris Agreement entered into force on 2 November 2016.

Countries that joined in the agreement are, overall, responsible for at least 55% of total GHG emissions. The Paris Agreement requires Parties to align to their National Determine Contributions (NDCs) which set national targets to reduce GHG emissions. To date, the Paris Agreement has 185 Parties. In June 2017 Donald Trump, president of the US, announced the US withdrawal of the agreement that cannot be effective until November 2020.

Cities have shown strong leadership on climate change action (C40, 2019). The number of cities that have agreed to follow voluntary frameworks that provide technical and political assistance to reduce GHG emissions has increased to thousands of cities in the world in the last decade. Some of the most influential city frameworks and agreements are C40 Cities Climate Leadership Group (C40), the Cities for Climate Protection (CCP) Campaign, the European Covenant of Mayors, and the US Conference of Mayors Climate Protection Agreement (Seto & Dhakal, 2014; Bulkeley *et al.*, 2011).

2.2.3 Links between air pollution and climate change

Climate change and air pollution are intrinsically linked. In the following section, details of this intrinsic link between climate change and air pollution are presented to support the motivation of this research to use a holistic framework. GHG and air pollutant emissions originate from common sources (combustion, industrial processes, transport and agriculture) (IPCC, 2013; Unger, 2012).

The burning of fossil fuels produces air pollutants that contribute the most to both local and transboundary air pollution problems as well as a significant fraction of GHG. For example, the combustion of coal produces CO₂ emissions (which is the most abundant GHG) and releases SO₂, NO_x, and PM emissions (which are air pollutants). The burning of natural gas, additional to CO₂ emissions, generates NO_x emissions. In the road transport sector, for example, the burning of diesel and petrol fuels emits CO₂ emissions and large quantities of NO_x.

There are multiple interactions (sharing common sources) of air quality on climate change and vice versa. Thus, efforts to reduce GHGs have the potential to improve air quality and measures addressing these environmental issues should be studied under one common holistic framework.

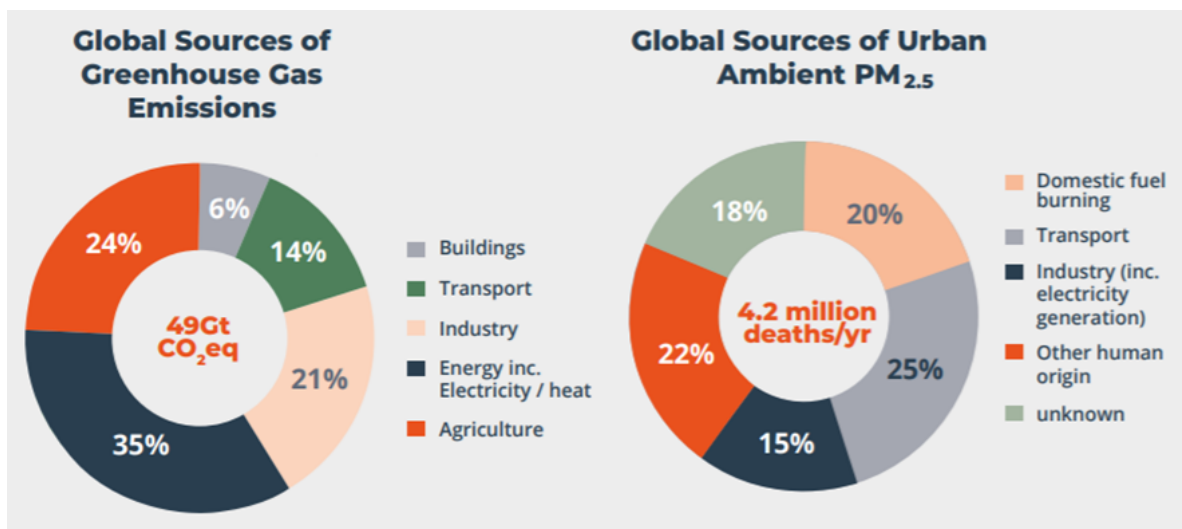


Figure 2.4 Main sources of greenhouse gas emissions and urban ambient air pollution (IPCC, 2014b; WHO, 2018b).

2.2.3.1 Atmospheric impacts of air pollutants on climate change

The most important air pollutants which affect the climate through their interaction with the Earth's radiation budget are tropospheric ozone (O₃) and particulate matter aerosol including sulphate, nitrate, black carbon and secondary organic aerosol (SOA) (Unger, 2012). Radiatively active air pollutants (O₃, sulfate, nitrate, BC, SOA) are referred to as the short-lived climate forcers (SLCFs) because they have shorter atmospheric life than CO₂. Besides, CH₄ is included as SLCF because of its role as an O₃ precursor. These air pollutants influence regional and global climate in complex feedbacks.

Some pollutants cause warming (absorbing aerosols) while others generate cooling (reflective aerosols) by scattering solar radiation back to space. Sulphates and nitrates are mostly reflective aerosols producing a cooling effect in the atmosphere. While black carbon, which is an absorbing aerosol, and ozone have a warming impact on the atmosphere. The increase in tropospheric ozone from air pollution (NO_x, CO and VOC precursors) is a significant greenhouse gas forcing increasing warming on the planet. (ApSimon *et*

al., 2009; Air Quality Expert Group, 2007; Climate & Clean Air Coalition, 2014; Kirtman *et al.*, 2013; Unger, 2012).

The climate effects of atmospheric aerosols are uncertain, but all models agree that the net global impact of aerosol in the atmosphere is cooling, by a potentially large amount (Andreae, Jones & Cox, 2005). This cooling effect has ‘protected’ the Earth from the global warming effect created by anthropogenic emissions of GHG (Ramanathan & Feng, 2008; Hansen & Hansen, 2004; Unger, 2012; Andreae, Jones & Cox, 2005).

It has been estimated that the net effect of these radiatively active air pollutants has cooled the planet, reducing the surface temperature by - 1.3 °C (Ramanathan & Feng, 2009). The effective (absolute) increase in global temperature from the emissions of GHG (not accounting for the cooling effect created by air pollutants) has caused a surface warming of 2.4 °C (1.6 °C to 3.6 °C) (Ramanathan & Feng, 2009).

The impacts of air pollution on climate change described above relate to the long-range pollution transport of air pollutants at a regional and global scale, highlighting how air pollution is not just a local urban issue. Air pollution, concentrated in mega-city hot spots, is transported across continents and oceans resulting in the formation of extended air pollution clouds which can span over entire oceans and continents (Ramanathan & Feng, 2009).

These large air pollution clouds contain aerosols which can absorb or reflect sunlight. Mostly, these large air pollution clouds absorb sunlight producing a cooling effect (when aerosols take cloud droplets and reflect radiation). However, sometimes these clouds can also enhance warming (due to black carbon aerosols) (Ramanathan & Feng, 2009). According to (Ramanathan & Feng, 2009) the global cooling effect of this extended air pollution may have masked as much as 47% (20% to 80%) of the global warming by greenhouse gases.

A large reduction of cooling air pollutants without a comparable reduction in GHG emissions may lead to a warming of the planet (Unger, 2012; Jacobson & Streets, 2009). Following emission trajectories from the IPCC, Jacobson & Streets, 2009, modelled two scenarios: a ‘clean or low-carbon’ scenario which had a high proportion of clean energy and achieved steep reductions of global CO₂ emissions by 2020, 2050 and 2100, and a less ambitious with a lower percentage of clean technology in the energy mix scenario and smaller reduction of CO₂ emissions.

However, although one scenario was “cleaner” than the other, the “cleaner” scenario enhanced global warming more than the less ambitious scenario because in the less ambitious scenario more significant warming was masked by the increase of reflective aerosol particles. One slows warming but increases particles, whereas the other reduces particles but speeds up warming. This result implies that neither scenario is entirely beneficial.

Efforts to control air pollution may reduce the cooling effect and enhance the surface warming, highlighting the urgency to reduce GHG emissions as well. Thus, efforts to reduce GHGs and air pollution must be made under one common framework. The ideal policy then is to minimise warming gases, and both warming and cooling particles simultaneously (Unger, 2012; Jacobson, 2009; Ramanathan & Feng, 2009).

2.2.3.2 Climate change and air pollution disparities

An important difference between climate change and air pollution is the temporal and spatial scales. Air pollution is a local, urban, national, regional and global issue while climate change is a global one. Benefits of air pollution control can be wider than cities reducing local emissions and are usually more certain than climate change benefits. They occur close to where pollutants are being measured and reduced. Benefits from climate change mitigation are global, long-term, and more uncertain. For this reason, mainly local authorities currently address air pollution control measures while climate change mitigation actions play an essential role in international negotiations (Swart *et al.*, 2004; Barker *et al.*, 2007).

Another disparity is the different use of different metrics to measure climate and air pollution impacts (McCollum *et al.*, 2013). For example, among others, climate change impacts can be evaluated using the following metrics: (i) The probability of limiting global temperature rise to 2 °C above pre-industrial levels. (ii) The Global Warming Potential (GWP) which measures how much energy the emissions of one tonne of gas will absorb over a given period, relative to the emissions of one tonne of CO₂. (iii) The Global Temperature change Potential (GTP) which quantifies the temperature change after the time that the gas has been emitted, also relative to CO₂. (iv) Costs assessment.

Climate change impacts metrics are often discordant with metrics for air pollution and health impacts. Air pollution and health impact metrics, among others, often include the following: (i) Number of premature deaths. (ii) Years of Life Lost (YLL) due to premature mortality in the population. (iii) Years Lost due to Disability (YLD) for the exposed population. (iv) Disability-Adjusted Life Year (DALY) which can be thought of as one lost year of healthy life and is calculated as the sum of YLL plus YLD. (v) Costs assessment.

In the political arena, climate change and air pollution are discussed separately. Climate change subjects are internationally considered in the United Nations Framework Convention on Climate Change (UNFCCC). At the same time, air pollution topics are discussed in separate institutions, mainly local but also in international forums such as the United Nations Economic Commission for Europe's task-force on Long-Range Transboundary Air Pollution (UNECE- LRTAP) (Bollen *et al.*, 2009).

Moreover, measures to mitigate climate change and air pollution are typically chosen to address each problem exclusively and separately. Some policies entail trade-offs. For example, some actions for air pollution control, such as end-of-pipe technologies result in small increases in carbon dioxide emissions (CO₂) due to the rise in fuel consumption.

Ways to reduce GHG emissions such as CO₂ Capture and Storage (CCS) technologies installed in power plants, do not address emissions of air pollutants (Bollen *et al.*, 2009; ApSimon *et al.*, 2009; Air Quality Expert Group, 2007; Oxley *et al.*, 2012). Another example of the trade-offs between air pollution and climate change is illustrated by the example of choosing a diesel or a petrol vehicle. If the objective is to reduce NO_x emissions and improve air quality, one will choose a petrol car. However, petrol cars emit more CO₂ than diesel cars. Thus, if the objective is to reduce CO₂ emissions to meet climate change mitigation targets, one would choose a diesel car.

2.3 Transport

In the previous section, it was shown how the transport sector is a significant emitter of both air pollutants and GHG. Thus, addressing air quality and climate change issues with a holistic framework for the transport sector can be particularly beneficial and was part of the motivation for this research. This section provides the required information for the reader to understand how the transport policy scenarios in this research were built.

The definitions of the vehicle categories used in the transport policy scenarios are presented here, as well as the explanation of how conventional internal combustion vehicles and non-conventional electric vehicles work. In addition, some of the abatement technologies and strategies used and considered that require a technological definition because they are part of some of the transport policy scenarios of study, are also described in this section. Discussion on alternative abatement strategies and other abatement measures including in the transport policy scenarios of study are presented in the following chapter.

2.3.1 Vehicle categories

Road transportation can be categorised by the source of transportation (vehicles carrying passengers or vehicles carrying goods), by the size of the vehicle (light-duty vehicles like passenger cars and vans or heavy-duty vehicles like trucks, buses, and coaches) or by the engine type (diesel, petrol, electric). The vehicle categories used in this research are the following: (i) motorcycles, (ii) cars, (iii) buses, (iv) coaches, (v) light goods vehicle (LGV) (mass not exceeding 3.5 tonnes), and (vi) heavy goods vehicle (HGV) (mass over 3.5 tonnes).

2.3.1.1 Conventional vehicle technologies: Diesel and petrol engines

The internal combustion engine (ICE) is the most common vehicle engine today. An ICE is a heat engine that converts thermal and chemical energy to mechanical energy through the combustion of a fuel that is oxidised by air. ICE can generate ignition of the fuel either by spark ignition (as in petrol engines) or by compression ignition (as in diesel engines).

Diesel engines work by injecting the diesel fuel into a highly air-compressed chamber to allow the fuel to ignite. The heat generated during the air compression, together with the injection of fuel is enough to initiate the combustion process. The compression level in diesel engines is usually twice as much as in petrol engines. If the diesel fuel is not well mixed with air during combustion, then the combustion is incomplete, which results in the formation of particulates. A diesel vehicle engine typically operates at a thermal efficiency of 30%.

The cetane number is an indicator of the combustion speed and compression needed for ignition of fuel. The cetane number is an inverse function of the ignition delay. The cetane number relates to the time between the initial injection of the fuel and the start of the combustion. In a diesel engine, the higher the cetane number, the shorter the ignition delay periods are, and the better the combustion is. Fuels with lower cetane number have longer ignition delays. Generally, diesel engines can operate with cetane numbers around 50. In the European Union, the established standard for diesel fuel is a cetane number of 51.

Petrol engines, contrary to diesel ones, take in a mixture of petrol and air and compress it, then the fuel mix is ignited by a spark. This process is able to occur because petrol fuel is much lighter than diesel fuel and quickly evaporates to mix more efficiently than diesel with air in the combustion chamber. This is why combustion in a petrol engine is usually more complete than in a diesel engine and generates fewer particles than diesel combustion. A petrol vehicle engine typically operates at a thermal efficiency of 20%.

The octane number relates to the compression of the fuel needed before ignition in the engine. The higher the octane number is, the more compression the fuel can endure before igniting and the better the petrol fuel burns within the engine. Petrol engines ignite the compressed mixture of air and fuel. Thus, the high compressibility of the fuel matters mainly for petrol engines. The most common type of octane rating

worldwide is the Research Octane Number (RON). The RON generally varies between 90 and 100 in different countries.

In contrast with petrol engines, diesel engines do not compress the air-fuel mix; instead, they compress the air and then inject the fuel. Therefore, fuel compressibility is important for petrol engines but not for diesel engines. Therefore, fuels with a high octane number and low cetane number are suitable for petrol engines. In contrast, fuels with small octane number and high cetane numbers are best for diesel engines.

Although diesel and petrol fuels have similar calorific values (energy per unit of mass) diesel fuel is denser than petrol, and thus contains more energy by volume. As a result, less diesel fuel is required to produce the same amount of energy. For this reason, diesel vehicles emit less CO₂ than petrol vehicles. However, the high temperatures needed in the diesel combustion produce more NO_x, which is formed at higher temperatures. Therefore, diesel vehicles emit more NO_x than petrol vehicles. The difference in emissions makes a trade-off between diesel and petrol cars that will be studied in this research. Moreover, as mentioned above diesel engines emit more PM than petrol engines, which explains why particle filters (which will be defined in the following section) have only been fitted to diesel vehicles and have not been fitted to petrol vehicles.

2.3.2 Abatement technologies and strategies

2.3.2.1 Hybrid and electric vehicles

Hybrid and electric vehicles use electric motors that convert electrical energy into mechanical energy. Most electric motors work through the interaction between the motor's magnetic field and the electric currents to generate a rotational force (torque). Electric motors can be powered by direct current (DC) or by alternating current (AC). Batteries are common sources of DC power, and the power from the grid is AC power.

2.3.2.1.1 Hybrid electric vehicles (HEVs)

Hybrid electric vehicles (HEVs) are powered by an internal combustion engine (like diesel or petrol vehicles) in combination with an electric motor which uses energy stored in batteries. HEVs have lower tailpipe emissions than conventional diesel or petrol vehicles. Available HEVs in the market include Ford Fusion Hybrid, Honda Insight, Hyundai Ioniq, Toyota Prius, among others (EERE, 2017). The different categories of HEVs are discussed below.

- Mild hybrid vehicles or micro hybrids use a battery and an electric motor together with the internal combustion engine, but these two power sources cannot be used independently. Thus, a mild hybrid vehicle cannot run on all-electric mode.
- Full hybrid vehicles can use together or independently the internal combustion engine and the electric motor to power the vehicle. Thus, a complete hybrid vehicle can run on just the internal combustion engine, the batteries (all-electric) or a combination. These types of vehicles which can run in all-electric mode are called zero-emissions capable. The zero-emissions capable vehicles are not zero-emission vehicles because they emit tailpipe emission when powered by the combustion engine. Full hybrid vehicles have larger batteries and more powerful electric motors than mild hybrid vehicles (EERE, 2017).

2.3.2.1.2 Plug-in hybrid electric vehicles (PHEVs)

Plug-in hybrid electric vehicles (PHEVs) are powered by an internal combustion engine and an electric motor which uses energy stored in batteries. PHEV can be plugged-in and recharged using electricity from the grid. PHEVs can be powered by electricity, making them zero-emissions capable vehicles. Usually, the internal combustion engine runs when the battery is mostly depleted, during rapid acceleration, or when intensive heating or air conditioning is required.

PHEVs usually have larger batteries than HEVs. Commercially available PHEVs include Honda Clarity PHEV, Hyundai Ioniq Plug-in Hybrid, Mitsubishi Outlander PHEV, Toyota Prius Prime, Audi A3 e-tron, BMW 530e, among others. There are also light-duty PHEVs commercially available (EERE, 2017).

Hybrid vehicles can have a series or a parallel configuration to combine the power from the electric motor and the internal combustion engine. In parallel hybrids, both the electric motor and the internal combustion engine drive the wheels. Series hybrids use only the electric motor to drive the wheels, and the internal combustion engine is used to generate electricity for the motor. The most common HEVs are parallel hybrids. PHEVs can be configured in parallel and series. Series PHEVs are often referred to as extended-range electric vehicles (EREVs) (EERE, 2017).

2.3.2.1.3 All-electric vehicles (EVs)

All-electric vehicles (EVs) or battery electric vehicles (BEVs) only have an electric motor and a battery, and they derive all their power from electricity stored in the batteries pack. When depleted, the batteries are recharged using grid electricity, either from a wall socket or a dedicated charging unit. Since EVs does not have an internal combustion engine, EVs are known as zero-emission vehicles because they do not produce tailpipe emissions; they do not have a tailpipe.

However, EVs do emit non-tailpipe emissions, and pollutants are also emitted during the electricity generation required to power EVs. EVs convert about 59% to 62% of the electric energy from the grid to power the vehicle, in contrast with diesel or petrol vehicles which only convert about 20% to 30% of the energy stored in the fuel to power the vehicle (EERE, 2017). Commercially available EVs models include Audi e-tron, BMW i3, Ford Transit Van/Wagon, Hyundai Kona Electric, Nissan Leaf, Tesla Model S, Fiat 500e, among others. Both heavy-duty and light-duty EVs are commercially available (EERE, 2017). Discussion on all-electric vehicles will be included in the next chapter.

2.3.2.1.4 Fuel cell electric vehicles (FCEVs)

Fuel cell electric vehicles (FCEVs) are powered by hydrogen. The fuel cells generate electricity from hydrogen that may be generated onboard (by reforming natural gas, methanol, ammonia, or other hydrogen-containing fuel), or produced externally and stored onboard after refuelling. FCEVs produce no tailpipe emissions except water vapour and are more efficient than the conventional internal combustion engine

vehicles. Car manufacturers offer a limited number of FCEVs, including the Hyundai Nexo, Honda Clarity and Toyota Mirai (EERE, 2017).

Deep decarbonisation studies indicate that significant penetration of electric vehicles in the fleet is needed (and is a determining factor) to achieve the sustainable development goal and limit the rise of global temperature to two degrees or less (two-degree target) (Pye *et al.*, 2015; IEA, 2018b). The same studies indicate that the electricity would need to be generated by clean sources. The International Energy Agency predicts that around 900 million electric cars would be needed by 2040 for the transport sector to be in line with the two-degree target (today there are 3 million electric cars in the world) (IEA, 2018b, 2018a).

2.3.2.2 Emissions control technologies

Control technologies needed to comply with stringent emissions standards for tailpipe emissions are widely available. Control technologies usually depend on controlling the air-fuel mix and catalytic treatment. Tailpipe emissions are heavily dependent on emissions control technologies.

2.3.2.2.1 Two-way catalytic converter

A two-way catalytic converter is a device that converts toxic exhaust gases from an internal combustion engine into less toxic pollutants by two oxidation reactions. (i) Oxidation of CO to CO₂. (ii) Oxidation of unburnt hydrocarbons to CO₂ and water. A two-way catalytic can be installed in diesel cars at an estimated cost of \$116 to \$350.

2.3.2.2.2 Three-way catalytic converter (TWC)

A three-way catalytic converter (TWC) is a device that converts toxic exhaust gases from an internal combustion engine into less toxic pollutants by a three-way oxidation-reduction reaction. (i) Reduction of

NO_x into N₂. (ii) Oxidation of CO to CO₂. (iii) Oxidation of unburnt hydrocarbons to CO₂ and water. TWCs are used in petrol vehicles.

Diesel cars cannot use TWCs because diesel engines function under lean engine operation where there is an excess of oxygen in the chamber, so the oxidation reaction is favoured versus the reduction reaction that reduces NO_x. For this reason, petrol vehicles NO_x tailpipe emissions are lower than diesel vehicles NO_x tailpipe emissions. The estimated cost of complying with Euro 6 and having one fitted, is in the range of \$362 to \$416 for a four-cylinder petrol engine (Yang *et al.*, 2015; IEA, 2016a).

2.3.2.2.3 Lean NO_x trap (LNT)

Lean NO_x trap (LNT) is a device designed to adsorb NO_x to reduce exhaust emissions from the internal combustion engine. NO_x is absorbed in a lean engine reaction which burns the fuel with an excess of air in the ICE. LNT has approximately 70% to 90% efficiency. The physical size of LNT limits NO_x storage capacity. LNT has an estimated cost of around \$320 to \$509 (Yang *et al.*, 2015).

2.3.2.2.4 Selective catalytic reduction (SCR)

Selective catalytic reduction (SCR) is a device used to reduce NO_x to nitrogen and water in the presence of ammonia. SCRs have up to 95% NO_x conversion efficiency. SCR can be combined with LNT in a unit to allow higher NO_x conversion efficiencies. The ammonia synthesised by LNT reacts with NO_x in the SCR, and care is necessary to avoid emissions of excess ammonia. The estimated cost is \$418 to \$494 (Yang *et al.*, 2015).

2.3.2.2.5 Exhaust gas recirculation (EGR)

Exhaust gas recirculation (EGR) works by recirculating a fraction of exhaust gas to the combustion chamber. This dilutes the O₂ in the incoming air stream and provides gases to act as absorbents of combustion heat to reduce temperatures and reduce the exhaust NO_x.

NO_x is produced when mixtures of nitrogen and oxygen react with high temperatures in the combustion chamber. An advantage of EGR is that it can be used in combination with other control technologies. EGRs tend to be used in conjunction with SCR. EGR is widespread in those vehicles complying with Euro 3 to Euro 6. An estimated cost for EGR is \$142 to \$160 (Yang *et al.*, 2015).

2.3.2.2.6 Particulate filters (DPF and GPF)

Particulate filters (DPF and GPF) are devices designed to remove particulate matter from the exhaust gases in diesel and petrol engines. Diesel particulate filters (DPF) are the most common and have shown high efficiency by filtering most particles. However, there is some evidence that DPFs emit a significant amount of particulate matter during regeneration (i.e. when burning off the accumulated particulate) at high temperatures (Giechaskiel *et al.*, 2017). The estimated cost on the market today for a DPF is \$640 to \$2,500, and the estimated cost of GPF is \$57 to \$184 (Brussels *et al.*, 2011; AM, 2018).

Emission control devices such as diesel particulate filters and selective catalytic reduction have been shown to produce an increase in CO₂ emissions (Sims *et al.*, 2014).

2.3.2.3 Emissions control strategies

The Euro standards define the limits for exhaust emissions of new vehicles for NO_x, PM, and CO in Europe. New vehicles are laboratory tested to comply with emissions standards.

Low emission zones are delimited areas where the most polluting vehicles are restricted or charged with a fee to improve air quality. Exhaust emissions standards are used to set the emissions limits of vehicles entering low emissions zones.

Policies such as the low emission zones usually require vehicles to use one of the emissions control technologies described above. Low emission zones have been implemented in some cities around several countries in Europe (Belgium, Germany, Netherlands, Sweden, Denmark, Italy and the UK, among others) (CLARS, 2017). However, different studies (O'Driscoll *et al.*, 2016; Kousoulidou *et al.*, 2013) have shown that real-world emissions often exceed the emissions standard limits in real-world driving conditions.

2.4 Health Impacts

The core part of this research is to account for the impacts of the transport policies of study on health. Thus, this section is intended to present an overview of the health impacts of air pollution, including the quantified effect of air pollution in the global population. Also, the World Health Organisation (WHO) Air Quality Guidelines are reviewed because concentrations resulted from the assessment of the transport policy scenarios will be compared with these air quality guideline levels. The WHO interim target values are also included in the description of the effects of air pollution on health in very polluted places, like Mexico City. A detailed description of selected relative risk functions and other health impact parameters are discussed in the following chapter.

Moreover, the health effects of climate change are reviewed to show how climate change is also significantly affecting human health. Although climate change effects are not accounted for in this dissertation, it is essential to show the current understanding of the relationship between climate change and health. Not accounting for the health effects of climate change is a limitation of this study embodied by the difficulty of accounting for these impacts, as will be discussed below.

2.4.1 Air pollution and health

Air pollution is the leading environmental cause of premature death in the world. It is estimated that air pollution was responsible for 6.5 million premature deaths in 2015, 11.5% of total global mortality (Table 2.3) (Landrigan *et al.*, 2018; Prüss-Üstün *et al.*, 2016).

Global Burden of Disease (GBD) studies estimate mortality and morbidity due to air pollution from (i) Ambient particulate matter pollution measured as the annual average daily exposure to outdoor PM_{2.5} (µg/m³). (ii) Household air pollution from solid fuels estimated as the annual average daily exposure to household concentrations of PM_{2.5} from solid fuel use (coal, wood, charcoal, dung, and agricultural

residues). (iii) Ambient ozone pollution as the exposure to seasonal (3 months) hourly maximum ozone concentrations, measured in ppb (Forouzanfar *et al.*, 2016). Of the three, the most significant health impacts are due to PM_{2.5} outdoor concentrations (4.2 million deaths estimated), and household air pollution (4.3 million deaths estimated) according to WHO estimates (Landrigan *et al.*, 2018).

The most robust evidence on health effect is from studies related to exposure to ambient PM_{2.5}. Long-term exposure to PM_{2.5} has a strong association with increased mortality and morbidity from cardiovascular and respiratory diseases which shorten life expectancy (Cohen *et al.*, 2017b). Cardiovascular and respiratory disease associated with exposure to indoor and outdoor PM_{2.5} pollution includes the following: ischaemic heart disease (accounts for 34% of deaths), chronic obstructive pulmonary disease (25% of deaths), lower respiratory infections (11% of death) and tracheal, bronchial, and lung cancer (7% of deaths).

The International Agency for Research on Cancer (IARC) unanimously classified outdoor particulate matter air pollution as carcinogenic to humans classing it as an IARC Group 1. This classification means that there is sufficient evidence of carcinogenicity in humans (Loomis *et al.*, 2013).

Clinical and experimental studies suggest that particulate matter pollution increases the risk of cardiovascular disease by provoking the following conditions: (i) Atherosclerosis: arteries become clogged with plaques which cause the arteries to harden and narrow, restricting the blood flow and oxygen supply to vital organs. (ii) Increasing oxidative stress: an imbalance between free radical activity (which help fight pathogens) and antioxidant activity. (iii) Increasing insulin resistance, causing endothelial (membrane responsible for maintaining vascular tone and regulate oxidative stress) dysfunction, and augmenting propensity to coagulation (Pope, 2015; Landrigan *et al.*, 2018).

Recent evidence suggests that there may exist an association between PM_{2.5} pollution and non-communicable (chronic) diseases including diabetes (Meo *et al.*, 2015), decreased cognitive function (Casanova *et al.*, 2016; Heusinkveld *et al.*, 2016), and premature birth and low birth weight (Malley *et al.*, 2017; RCP, 2016). The challenges for future reductions in the number of diseases attributable to air pollution are substantial.

Table 2.3 Global estimated deaths (millions) due to air pollution risk factors from the Global Burden of Disease study in 2015 (Forouzanfar *et al.*, 2016) versus WHO data (Prüss-Üstün *et al.*, 2016), (Landrigan *et al.*, 2018)

Air pollution	Global Burden of Disease study (95% CI)	WHO (95% CI)
	Global estimated deaths (millions)	Global estimated deaths (millions)
Total	6.5 (5.7 – 7.3)	6.5 (5.4 – 7.4)
Household air	2.9 (2.2 – 3.6)	4.3 (3.7 – 4.8)
Ambient particulate	4.2 (3.7 – 4.8)	3.0 (3.7 – 4.8)
Ambient ozone	0.3 (0.1 – 0.4)	-

2.4.1.1 Air quality guidelines

The World Health Organisation has issued Air Quality Guidelines that provide concentration limit values for key air pollutants that represent a health risk (Table 2.4). The Guidelines apply worldwide and are based on expert evaluation of current scientific evidence for particulate matter (PM), ozone (O₃), nitrogen dioxide (NO₂) and sulphur dioxide (SO₂). In 2016, 91% of the world's population was living in places where the WHO air quality guidelines levels were not met.

In addition to guideline values, interim targets are given for each pollutant (Table 2.5). These are proposed as incremental steps in a progressive reduction of air pollution and are intended for use in areas where pollution is high.

Table 2.4 WHO Air Quality Guidelines (WHO, 2006).

Time frame	Fine particulate matter (PM _{2.5})	Coarse particulate matter (PM ₁₀)	Ozone (O ₃)	Nitrogen dioxide (NO ₂)	Sulphur dioxide (SO ₂)
	Concentrations (µg/m ³)				
	(µg/m ³)	(µg/m ³)	(µg/m ³)	(µg/m ³)	(µg/m ³)
Annual mean	10	20	-	40	-
24-hour mean	25	50	-	-	20
8-hour mean	-	-	100	-	-
1-hour mean	-	-	-	200	-
10-minute mean	-	-	-	-	500

Table 2.5 WHO air quality guidelines and interim targets for particulate matter: annual mean concentrations (WHO, 2006).

Interim target	PM _{2.5}	PM ₁₀	The basis for the selected level
	Annual mean concentrations (µg/m ³)		
IT-1	35	70	These levels are associated with about a 15% higher long-term mortality risk relative to the AQG level.
IT-2	25	50	These levels lower the risk of premature mortality by approximately 6% [2–11%] relative to the IT-1 level.
IT-3	15	30	These levels reduce the mortality risk by approximately 6% [2–11%] relative to the IT-2 level.
Air quality guideline (AQG)	10	20	These are the lowest levels at which total, cardiopulmonary and lung cancer mortality have been shown to increase with more than 95% confidence in response to long-term exposure to PM _{2.5}

2.4.2 Climate change and health

Climate change can affect human health, both directly and indirectly (Table 2.6). Direct effects include increasing incidences of respiratory and cardiovascular disease. Indirect effects are challenging to evaluate because they are the result of long causal pathways (WHO, 2018b).

The highest anticipated threat to health from climate change is malnutrition, and the young and the elderly will be particularly affected. Climate change effects on nutrition include lower nutrient quality of crops ‘hidden hunger’ (Calderon Irazoque, 2014); Reduction of the diversity of food; Impacts on water and sanitation; affect food security (food availability, access, use and stability); and affect food safety from extreme events. For example, rising temperatures can increase the levels of pathogens in food (such as ciguatera in fish) and in the increase of pathogens spread from livestock (WHO, 2018b).

The spread of infectious diseases is increasing as a result of climatic changes. For example, the density attributed to the mosquitoes responsible for the transmission of dengue fever has risen by approximately 10% since the 1950s (Watts *et al.*, 2018). Climate change can also cause non-communicable diseases such as mental illness after extreme weather events, climate-related displacement, immigration and loss of culture can be lifelong (WHO, 2014).

The impacts of climate change on vulnerable infrastructure can increase health risks. For example, more extreme storms and flooding can affect energy distribution and result in contamination of water. Health facilities are sensitive to extreme weather events, rises in sea-level in coastal locations and increasing demand as a result of hazards (WHO, 2018b; Watts *et al.*, 2018).

“The impacts of climate change on health are strongly influenced by individual and population factors, including age (children and the elderly are often at higher risk) and gender. For example, during droughts, women and children in developing countries are often the worst affected, as a consequence of their respective roles in household decisions, and tasks such as water collection. In contrast, male farmers are disproportionately likely to commit suicide during droughts” (WHO, 2014). Understanding gender differences in vulnerability, roles and capacity are essential to design effective, equitable climate adaptation programmes (Field *et al.*, 2014).

The poorest and most vulnerable populations will be the most affected by climate change impacts. Even if low and middle-income countries have contributed the least to GHG emissions, their communities will bear

the most onerous burden of climate-related health impacts. It is essential to address such inequities to reduce vulnerability, build resilience and prevent more significant unfairness as a result of climate change (Field *et al.*, 2014).

Table 2.6 Direct and indirect health impacts for exposure to climate change events (WHO, 2018b).

Climate change event	Health impact
<i>Direct</i>	
Extreme weather events (droughts, floods, heatwaves, storms and wildfires).	Respiratory and cardiovascular disease, heatstroke, injuries and allergies.
Exposure to higher temperatures.	Mental illness.
<i>Indirect</i>	
Climate variation, extremes events and rises in sea-level.	Malnutrition, food and water insecurity, the spread of infectious diseases, the spread of waterborne infectious diseases.
Rising temperatures, floods and droughts.	Food insecurity.
	Food safety.
Societal responses to climate change.	Population displacement, forced migration and reduced access to health services.

2.5 Case study cities: London and Mexico City

This section starts by describing the rationale for studying cities in this dissertation. The level of air pollution and GHG emissions in cities in the world is discussed. Then, a description of the location, demographics, the road transport, the mobility patterns, and the CO₂ and air pollution emissions are described for the two case study cities investigated in this dissertation: London, United Kingdom (UK), and Mexico City, Mexico.

2.5.1 Rationale to study cities

According to the WHO, 80% of the urban population is exposed to a harmful level of air pollution. Meaning that in 80% of cities, there is no compliance with WHO air quality guideline levels for PM_{2.5}. Average particulate air pollution levels in many developing cities can be 4 to 15 times higher than WHO air quality guideline levels, putting many at risk of long-term health problems (WHO, 2016).

Moreover, cities play an essential role in efforts to tackle climate change. Today, more than half the world's population lives in urban areas. This unprecedented global urbanisation, projected to increase in the coming decades, has a significant effect on greenhouse gas (GHG) emissions. The growth of urban populations is correlated with an increase in income, and higher urban incomes are associated with higher consumption of energy and higher GHG emissions (Seto & Dhakal, 2014; UNDESA, 2014). Cities account for over two-thirds of the world's energy use and around 70% of global carbon dioxide (CO₂) emissions.

These alarming contribution of cities to global warming (by emitting CO₂) and the current air pollution crisis in cities motivated the focus of this research in cities.

2.5.2 London and Mexico City

The two case studies cities in this research are London, United Kingdom (UK) (Figure 2.5, Table 2.7), which is the capital of the UK and one of the largest cities in Europe, and Mexico City, Mexico (Figure 2.6, Table 2.7), which is also the capital of Mexico and one of the largest cities in the world. Mexico City's urban sprawl during the end of the last century was extensive and disorganised. Today, 20.9 million people live in Mexico City's metropolitan area. The metropolitan area of Mexico City homes more than twice the population of that which lives within the city (only 8.8 million people). London has a similar population of 8.8 million people. London's metropolitan area accounts for only 13.7 million people (Table 2.7).

London and Mexico City have similar population densities of around 6,000 persons per km² (Table 2.7). Average annual temperatures are much warmer in Mexico City, on average, 4.5 °C warmer. A significant difference between these two cities is the GDP per capita. Londoners have, on average more than three times more (3.2 times more) GDP per person than people living in Mexico City (PwC, 2009). Refer to Table 2.7.

The motorisation in London and Mexico City is similar with 2.7 and 2.3 million licensed cars, respectively. The number of licensed cars in the 8.8 million population of each city, denote a motorisation rate of 0.3 and 0.26 vehicles per person, respectively. The vehicle fuel mix is significantly different in both cities. In Mexico City, almost all vehicles are fuelled by petrol (93%). While in London just 70% of vehicles are powered by petrol and a notable number of vehicles (30%) are fuelled by diesel. This difference in vehicle fuel use will be significant when considering NO_x and CO₂ emissions later in this dissertation (Chapter 4 and Chapter 6). Refer to Table 2.7.

The mobility patterns show that in Mexico City, much more people use public transport. In Mexico City, 53% of trips are made on public transport. In London, only 28% of trips are made on public transport. People walk more in London. In London, 33% of trips are made walking. In Mexico City, only 22% of trips are made walking. The average travel time per day in both cities is around an hour (60 min). Refer to Table 2.7.

Sources of CO₂ emissions in Mexico City and London are quite different. The road transport sector in Mexico City is responsible for the vast majority of CO₂ and NO_x emissions (74% and 86%, respectively).

In contrast, the road transport sector in London accounts for only 28% of CO₂ emissions and 50% of NO_x emissions. Particulate matter emissions from the road transport sector in both cities are similar, accounting for around half of PM_{2.5} and PM₁₀ emissions. Refer to Table 2.7.

City-wide annual mean concentrations of air pollutants are considerably higher in Mexico City. NO_x and NO₂ city-wide annual mean concentrations in Mexico City are one and a half times more elevated than in London. The same pattern is observed for city-wide annual mean concentrations of particulate matter. Mexico City's PM_{2.5} city-wide annual mean concentrations are 1.6 times higher than London's. Mexico City city-wide PM₁₀ annual mean concentrations are even higher, 2.6 times higher than those observed in London. Refer to Table 2.7.

Moreover, the atmospheric dynamics and dispersion in both cities are very different. The topography of Mexico City situated in a valley promotes the occurrence of thermal inversion in which a "lid" traps all the pollution in the valley. These conditions in the Valley of Mexico City promote the production and trapping of ozone which is one of the most important pollutants threatening the health of Mexicans. In contrast, in London ozone pollution is not a threat. The different contextual conditions of these two case study cities are essential when analysing the effect of different transport policies.

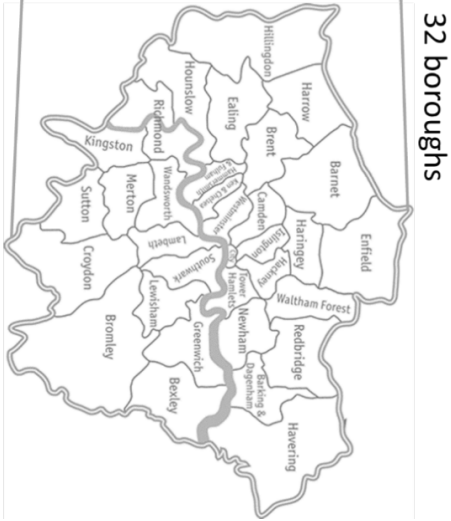
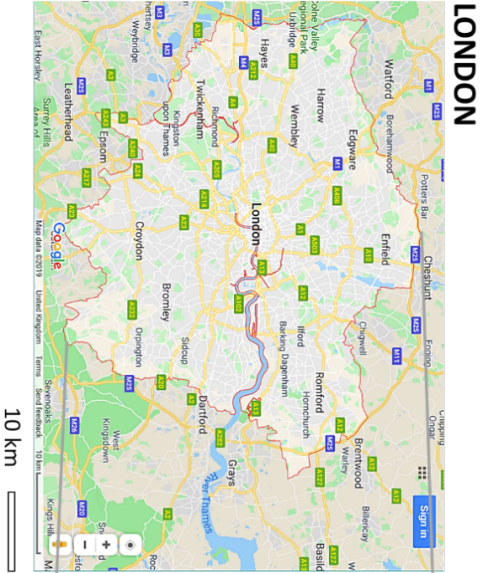
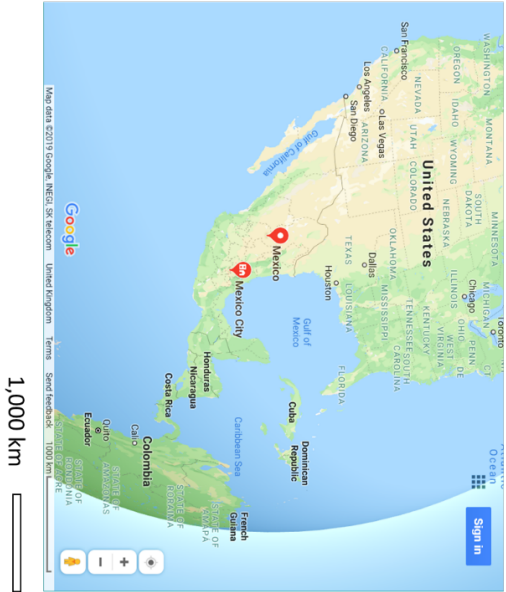
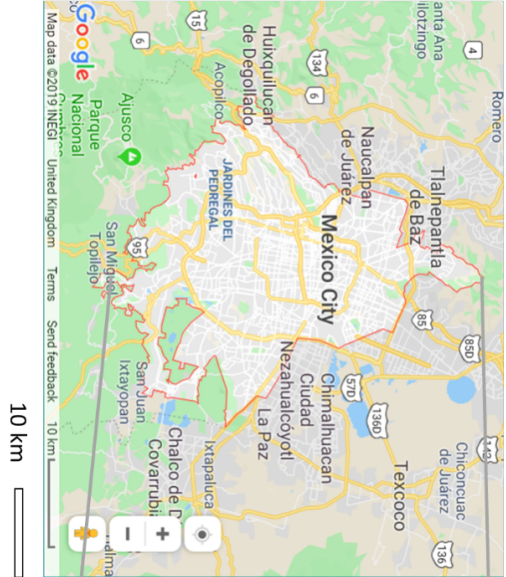


Figure 2.5 Map of the United Kingdom, London, and London's 32 boroughs (source: Google Maps).

MEXICO



MEXICO CITY



16 boroughs

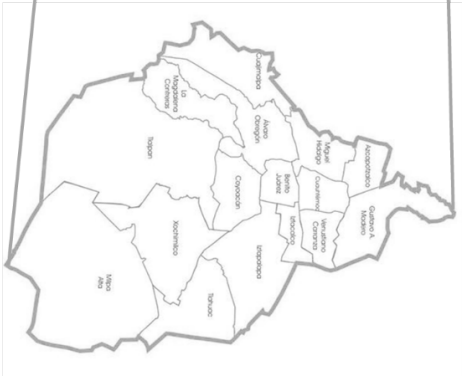


Figure 2.6 Map of Mexico, Mexico City, and Mexico City's 16 boroughs (source: Google Maps).

Table 2.7 Characteristics of London and Mexico City, the two case study cities of this dissertation.

Note: The city of London refers to the area covered in its 32 boroughs, and the city of Mexico City refers to the area covered in its 16 boroughs.

Description	London, UK	Mexico City, Mexico	Reference
Demographics			
Metropolitan area			
Metropolitan area name	London commuter belt	Metropolitan Area of the Valley of Mexico	(ONS, 2019; INEGI, 2014, 2017)
Population metropolitan area (million)	13.7	20.9	
Metropolitan area (km ²)	8,382	7,585	
City (not metropolitan area)			
Population city (million)	8.8	8.8	(ONS, 2019; INEGI, 2014, 2017) Figure 2.6 & Figure 2.6 Map of Mexico, Mexico City, and Mexico City's 16 boroughs (source: Google Maps).
Local authority districts city	32 boroughs	16 boroughs	
Area city (km ²)	1,572	1,485	
Density (persons/km ²)	5,590	6,000	(PwC, 2009)
Elevation (m)	11	2,250	
Climate	Temperate oceanic	Subtropical highland	
Average temperature (°C)	6 - 13	12 - 16	
Estimated GDP (\$ bn)	565	390	
GDP per capita (\$ k)	65.8	20.4	

Table 2.7 (Continued) Characteristics of London and Mexico City, the two case study cities of this dissertation.

Description	London, UK	Mexico City, Mexico	Reference
Road transport			
Number of licensed cars (million)	2.7	2.3	(ONS, 2019; SEDEMA, 2017a; GLA, 2017a)
<i>Metropolitan area</i>	-	5.7	
Petrol vehicles (%)	70	93	
Diesel vehicles (%)	30	7	(TfL, 2018; INEGI, 2017)
Household with a car (%)	52	53	
Mobility			
Number of trips per day (million)	18.2	17.3	(ONS, 2019; SEDEMA, 2017a; GLA, 2017a)
Transport modes (percentage by the number of trips) in the city limits: London (32 boroughs) and Mexico City (16 boroughs).			
Public transport (%)	28	53	(ONS, 2019; SEDEMA, 2017a; GLA, 2017a)
Taxi (%)	2	5	
Car (%)	35	18	
Cycle (%)	3	1	
Walk (%)	33	22	
Average daily travel time (min)	63	58	

Table 2.7 (Continued) Characteristics of London and Mexico City, the two case study cities of this dissertation.

Description	London, UK	Mexico City, Mexico	Reference
CO ₂ emissions and air quality			
CO ₂ emissions (Mt/yr)	23.6	16	(GLA, 2017a; SEDEMA, 2017b, 2018a)
<i>From road transport (%)</i>	28	74	
NO _x emissions (kt/yr)	47.7	60.9	
<i>From road transport (%)</i>	50	86	
PM ₁₀ emission (kt/yr)	4.4	10.7	
<i>From road transport (%)</i>	50	53	
PM _{2.5} emissions (kt/yr)	2.3	5.1	
<i>From road transport (%)</i>	57	56	
NO _x annual mean concentration (µg/m ³)	60	87	
NO ₂ annual mean concentration (µg/m ³)	35	52	
PM ₁₀ annual mean concentration (µg/m ³) (Including PM ₁₀ non-exhaust)	21	51	
<i>Metropolitan area (µg/m³)</i>	-	70	
PM _{2.5} annual mean concentration (µg/m ³) (Including PM _{2.5} non-exhaust)	14.2	23	
<i>Metropolitan area (µg/m³)</i>	-	30	
Ozone concentration (µg/m ³)	36 (background)	217 (8-hour mean)	

2.6 Critical assessment of previous studies: Climate and air quality modelling approaches and policy applications

Several predictive models have been made available in order to inform policy development and assist with air quality and climate assessments. Description and critical assessment of some of the most widely used models (Integrated Assessment Models (IAMs), atmospheric dispersion, semi-empirical and land use regression (LUR) models) for climate and air quality assessments are presented in this section. A description of each model's strengths, limitation and policy applications are described below.

2.6.1 Integrated Assessment Models (IAMs)

2.6.1.1 Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE)

MESSAGE is an Integrated Assessment Model (IAM) used for energy system planning, energy policy analysis and scenario development at the global level. The MESSAGE model represents the global energy system in eleven regions (including North America, Latin America & the Caribbean, Western Europe, among others) and was developed at the International Institute for Applied Systems Analysis (IIASA) (IIASA, 2018).

MESSAGE accounts for the complex energy system interconnections between these regions of the world (e.g. resource extraction, imports and exports, processes and transportation). The MESSAGE model estimates most of the greenhouse gases and other radiatively active gases: CO₂, CH₄, N₂O, NO_x, volatile organic compounds (VOCs), CO, SO₂, PM, BC, Chlorofluorocarbons (CFCs) and hydrochlorofluorocarbons (HCFCs). The MESSAGE models both the energy and non-energy sectors (e.g. deforestation, livestock, solid waste, wastewater, among others) (McCollum *et al.*, 2013).

The MESSAGE model is used in conjunction with the MAGICC (Model for Greenhouse gas Induced Climate Change) model for estimating probabilistic scenarios for climate change. To estimate regionally,

sector-based (outdoor) air pollutant emissions and pollution control costs, MESSAGE is linked to the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) (for details, please see section 2.6) air quality model (IIASA, 2018).

Other global IAMs in the same category as MESSAGE model include MERGE (Manne & Richels, 2005), IMAGE (Alcamo *et al.*, 1994), MiniCAM (Edmonds *et al.*, 1995), and GCAM, among others.

2.6.1.1.1 Strengths

The MESSAGE model provides detailed modelling of the complex interconnections in the global energy systems and the estimation of a complete list of GHG from both the energy and non-energy sectors. Analytical representations for energy supply, demand and end-use analysis, as well as “top-down” and “bottom-up” approaches, which were commonly separated, are integrated or linked within the MESSAGE model framework.

2.6.1.1.2 Limitations

The MESSAGE model is mainly focused on GHG interaction, and air pollution modelling requires the GAINS model. The modelling runs are long and use considerable time and resources. Moreover, there is an intrinsic uncertainty in future projections about global energy systems (e.g. resource extraction, imports and exports). MESSAGE is a region/global model and is not used to assess intra-urban variability or to study dynamics at the city level.

2.6.1.1.3 Policy application

The modelling framework has been used in institutions for policy assessment including, the Intergovernmental Panel on Climate Change (IPCC), the World Energy Council, the European Commission, and the Global Energy Assessment (IIASA, 2018).

2.6.1.2 Greenhouse gas Air pollution Interactions and Synergies (GAINS)

The Greenhouse – Gas Air Pollution Interactions and Synergies (GAINS) model is an Integrated Assessment Model (IAM) which explores cost-effective emission control strategies that simultaneously tackle local air quality and greenhouse gases (GHG) to maximise benefits (Amann *et al.*, 2011). The GAINS model was developed at the International Institute for Applied Systems Analysis (IIASA) and measures ten air pollutants (NO_x, PM_{2.5}, PM₁₀, SO₂, NH₃, VOC, among others) and six GHGs (CO₂, CH₄, N₂O and F-gases) (IIASA, 2018).

The GAINS model distinguishes between 165 regions, including several countries in European and provinces/states in China and India. Also, GAINS tends to be applied at a continental scale with different versions for Europe and Asia, for example. Although GAINS was developed to study the effects of GHGs and air pollutants across regions, a new version of the model called GAINS-City (Liu *et al.*, 2013) was developed to study the interactions at the city level, including intra-city variations.

2.6.1.2.1 Strengths

The GAINS model is useful for studying synergies and trade-offs between air quality and climate measures accounting for emissions and air pollutant concentrations. The GAINS model allows for a cost assessment of the emission control measures. Such costs are assessed for GHG and air pollutants, and therefore, these costs can be easily compared across the pollutants.

2.6.1.2.2 Limitations

Long modelling runs and the resolution are not specialised for the study of urban areas where decision-makers could take advantage of a synergetic approach between climate and air pollution policies. There is uncertainty on mitigation costs, technology deployment, which could affect future estimates by GAINS.

2.6.1.2.3 Policy application

The GAINS model has been broadly used for policy assessment. For example, for the revision of the Gothenburg Protocol by Convention on Long-range Transboundary Air Pollution (CLRTAP) (see section 2.1.1.2). For the negotiations under the UNFCCC, a special version of GAINS was developed to compare greenhouse gas mitigation efforts among countries (IIASA, 2018).

2.6.1.3 UK Integrated Assessment Model (UKIAM) – BRUTAL sub-model

The UK Integrated Assessment Model (UKIAM) (Oxley *et al.*, 2003) is used to investigate abatement measures in the UK modelling of projected emissions of SO₂, NO_x, NH₃ and PM₁₀/PM_{2.5} and VOCs as well as estimating pollutant concentrations and deposition of sulphur and nitrogen across the UK. The UKIAM evaluates population air pollution exposure, monetised health impacts, and also effects on the protection of natural ecosystems.

This model combines sector-specific emissions as well as long-range atmospheric transport. The UKIAM includes the Abatement Strategies Assessment Model (ASAM) module which estimates the imported contribution; information from sophisticated dispersion models (Fine Resolution Atmospheric Multi-pollutant Exchange (FRAME) model and the EMEP model) is required.

The UKIAM has a high-resolution urban sub-model called BRUTAL (Oxley *et al.*, 2009) which investigates the urban transport dynamics with the capacity of evaluating not only technological but also, behavioural changes in the transport sector. BRUTAL models transport emissions resulting from variations in the vehicle mix and vehicle flows on different roads, including the spatial distribution (Oxley *et al.*, 2009). BRUTAL is a sub-model within UKIAM modelling road transport across the UK road network.

UKIAM is the UK Integrated Assessment Model (IAM) bringing together imported contributions (ASAM sub-model) shipping and other UK sources including road transport from BRUTAL to produce maps of pollutant concentration and deposition, and derive resulting effects on human health and ecosystems.

Please note that a detailed description of the UKIAM-BRUTAL model is presented in Chapter 3.

2.6.1.3.1 Strengths

The model is unique in combining contributions from the continental to the local street scale. The model accounts for long-range air pollution, modelling the effect of transboundary influences, which is particularly important for the analysis of PM pollution. The BRUTAL sub-model of the UKIAM treats road transport on a bottom-up approach across the road network.

The BRUTAL sub-model is quick to run with run times of around 30 minutes, making it ideally suited for the analysis of a variety of scenarios. The UKIAM model evaluates air pollution exposure as well as monetised health impacts. It is also capable of modelling roadside concentrations across the whole of the UK and calculating the peak of local concentrations in urban street canyons. The UK has been established for the UK but could in principle be applied to other countries if the equivalent data was available.

2.6.1.3.2 Limitations

The BRUTAL sub-model of the UKIAM estimates only annual average, relies on the definition of traffic flow data and future projections, which is uncertain. The model does not estimate hourly concentrations or the effects of diurnal variations in traffic on population exposure. The resolution of the model could be a limitation in some studies. UKIAM comes down to a 1x1 km resolution for urban background, and also considers one road in each grid-square selected with the highest emissions. Another limitation is that, like GAINS, it scales source contributions linearly to represent the effect of emission reductions without including for the non-linearity of chemistry in producing secondary PM.

2.6.1.3.3 Policy application

The UKIAM model is one of the models used by the UK Department for Environment Food & Rural Affairs (Defra). The UKIAM was one of the two models used for Defra's recently published report on 'Assessing progress towards WHO guideline levels of PM_{2.5} in the UK' (Defra, 2019c). The UKIAM model is also used to support Defra in addressing compliance with the Gotenburg protocols and the NECD. It has also been used toward assessing air pollution benefits of UK scenarios for the UK Committee on Climate Change.

2.6.2 Atmospheric dispersion models

2.6.2.1 Community Multiscale Air Quality (CMAQ)

The Community Multiscale Air Quality (CMAQ) model (EPA, 2019) is a sophisticated atmospheric dispersion model which combines meteorological models to model atmospheric and weather dynamics, emission models to model anthropogenic and naturally-occurring emissions and air chemistry-transport models to model atmospheric dynamics of air pollutants under variable conditions. The CMAQ model was developed by the United States Environmental Protection Agency (EPA) to provide comprehensive estimates of ozone, particulates, toxics, and acid deposition.

2.6.2.1.1 Strengths

CMAQ's ability to accept inputs from a variety of meteorological and emission models has facilitated the use of this model for different contexts and countries in the world (like UK and Mexico) despite not being designed specifically for those countries, meaning that it can be relatively easily adapted. CMAQ's capacity for coupling with other models like the Atmospheric Dispersion Modelling System (ADMS) (will be introduced in section 2.6.2.2) has important benefits when modelling, for example, ozone across the urban and regional scale.

2.6.2.1.2 Limitations

The complexity of the model and the extensive meteorological data demand, considerably increase the running times to days or weeks. Long-running times are inconvenient when analysing a large variety of different policy measures because modelling could take up considerable time and resources (Williams & Barrowcliffe, 2011).

2.6.2.1.3 Policy application

The CMAQ model was used to support the Clean Air Act and the development of the National Ambient Air Quality Standards in the United States of America (EPA, 2019). Among others, the Ministry of the Environment of Mexico City uses CMAQ to evaluate their air quality policies (SEDEMA, 2015).

2.6.2.2 Atmospheric Dispersion Modelling System (ADMS)

The Atmospheric Dispersion Modelling System (ADMS) is a dispersion model used to model air quality concentrations at a high spatial resolution across urban areas, accounting for the impacts of buildings, complex terrain, coastlines and variations in surface roughness (CERC, 2019). The ADMS model was developed by Cambridge Environmental Research Consultants (CERC) and had different specialised software, relevant to this study is ADMS-Urban model which is specific to air quality management in urban areas and cities and captures street scale resolution including road networks and street canyons.

Although ADMS does not model GHG, it utilises the Emissions Inventory Toolkit (EMIT) to calculate air pollutants and GHG emissions (including NO_x, PM and CO₂) urban areas for the dispersion modelling with ADMS-Urban. EMIT uses the UK Department for Environment, Food & Rural Affairs (Defra)'s Emission Factor Toolkit (Defra, 2019d). EMIT and ADMS-Urban allow source apportionment analysis, which quantifies the contributions from particular road vehicles such as diesel cars to emissions and concentrations (CERC, 2019). ADMS-Urban has been coupled with regional models, such as CMAQ, to evaluate the effect of pollutants on a longer scale range.

2.6.2.2.1 Strengths

High spatial resolution, concentrations are calculated for individual receptors and are thus geographically specific (to better than the nearest 0.1 m), allowing detailed concentration patterns near sources to be shown. Moreover, concentrations are modelled on hour by hour basis using the regional meteorological data set. There are options to apply diurnal, weekly and monthly profiles to the emissions or detailed hour-by-hour profiles for a full year (Williams & Barrowcliffe, 2011).

2.6.2.2.2 Limitations

The model does not have the capability to model the contribution of distant sources; it does not model regional concentrations. However, this can be overcome by using monitoring data to determine regional background or by nesting ADMS within a regional model like CMAQ. The run time can be long (days) when used to model a large area in detail (Williams & Barrowcliffe, 2011).

2.6.2.2.3 Policy application

ADMS-urban has been widely used in environmental decision making in urban areas. Among others, ADMS-urban has been used in the UK for the review of Local Air Quality Management programs; also Defra UK has used it for the assessment of proposals concerning Heathrow Airport which were submitted to the Department for Transport; it has also been used by policymakers in China to plan large-scale developments for the 2008 Olympics (CERC, 2019).

2.6.3 Semi-empirical models

2.6.3.1 Pollution Climate Mapping (PCM) model

The Pollution Climate Mapping (PCM) model is a semi-empirical, geographical information system (GIS) based model, used by Department for Environment, Food and Rural Affairs (Defra), UK (Defra, 2019a) and driven by the National Atmospheric Emissions Inventory (NAEI). The PCM model is a semi-empirical model calibrated to match measurements. The PCM consists of modules which provide concentrations of different air pollutants across the UK (including NO_x, NO₂, PM₁₀, PM_{2.5}, SO₂, CO, benzene and ozone) at a 1x1 km grid resolution.

The PCM model is also used for scenario assessment and population exposure calculations to assist policy developments. Roadside concentrations are based on an empirical approach with concentrations defined as being 4 m from the kerb. The model produces annual mean concentrations and shorter period concentrations relying on empirical relationships. The model uses source-footprints pre-calculated with ADMS (Williams & Barrowcliffe, 2011).

2.6.3.1.1 Strengths

It provides concentrations for all relevant air pollutants, and it is consistent with other measurements. It can incorporate improved science as it develops, e.g. the relationship between changes in emissions of secondary inorganic aerosol precursors and the resulting PM components. It can provide projections of future concentrations, including the PM_{2.5} exposures. It is fast to run, which makes it suited to scenario testing (Williams & Barrowcliffe, 2011).

2.6.3.1.2 Limitations

An important limitation of PCM is its uncertainty over future projections because it is calibrated annually to the current year's measured concentrations. Moreover, since the outputs of PCM are determined primarily by the NAEI, the results in terms of past and future trends are only as good as the emission estimates that are in the inventories. This can be problematic since, in the PCM, the roadside concentrations are obtained from an empirical relationship between measured levels and emission estimates (Williams & Barrowcliffe, 2011).

2.6.3.1.3 Policy application

The PCM is the model used by Defra to provide required annual compliance reports and assessments of future policy options by the EU Air Quality Directive.

2.6.3.2 ERG-Toolkit

The ERG-Toolkit is a semi-empirical model used to predict annual mean concentrations of NO₂, NO_x, PM₁₀ and PM_{2.5}, explicitly developed for London by King's College London University. The ERG-Toolkit outputs have a high spatial resolution, especially near to roads. The model splits the road network into 10 m grids. The model uses ADMS roads to model the concentration in roads and within street canyons. The conversion of NO_x to NO₂ is based on an empirical relationship (KCL, 2019).

2.6.3.2.1 Strengths

The model is relatively quick (hours) to run. The use of monitoring data to define the regional background is an advantage in that it improves the accuracy of the total modelled concentrations (Williams & Barrowcliffe, 2011).

2.6.3.2.2 Limitations

The model does not predict hourly concentrations. The empirical relationship to derive NO₂ from the NO_x does not allow for varying primary NO₂ proportions in the emissions. The reliance on monitoring data to define regional background is a disadvantage for the modelling of future scenarios, as there is no deterministic basis for projecting the measured regional background. The model has only been applied to London. (Williams & Barrowcliffe, 2011).

2.6.3.2.3 Policy application

The ERG-Toolkit has been used to provide air quality and emissions information to London policymakers at the Greater London Authority and Transport for London. The model has been used extensively in the Mayors Air Quality Strategy (KCL, 2019).

2.6.4 Land-use regression models

Land-use regression (LUR) models combine measured air pollutant values at a number of locations (~20 to 200) (from monitoring stations, for example) with predictor variables used to define sources and patterns of air pollution (e.g. land cover, traffic flow) and in this way predict pollution levels at unsampled locations in the study area. LUR utilises simple linear regression, but for the generation of predictor variables and the application of the model, both geographic information system (GIS) and statistical packages are required (Morley & Gulliver, 2018).

LUR models have been used to model annual mean concentrations of NO₂, NO_x, PM_{2.5}, BC and VOCs in different settings, mostly in European and North-American cities (Hoek *et al.*, 2008). LUR models are not well fitted for modelling background concentration at a national or regional scale because LUR models cannot model the secondary formation of pollutants or deposition. For this reason, previous studies have coupled LUR models with satellite-derived and chemical transport model data to estimate air-pollution exposure in larger regions, for example, in Europe (de Hoogh *et al.*, 2016).

LUR models are frequently used for epidemiological studies to statistically link the long-term effects of air pollution at a fine spatial scale to specific diseases. Epidemiological studies require a representative air pollution exposure estimate for a defined time period, usually for many thousands of individuals. The use of portable personal monitoring devices would often be preferred to overexposure modelling, but this has the limitation of being restrictively expensive and time consuming for larger studies of long-term health effects. As a result, modelling tools, such as LUR models and the models described in the above sections, are used to predict exposure at desired locations (Morley & Gulliver, 2018).

2.6.4.1 Strengths

LUR models use empirical data from actual air pollution measures from monitoring stations which is an advantage versus more deterministic models. LUR models have been shown to perform better or equivalent to conventional dispersion models when modelling spatial variation of air pollution in urban areas. LUR models require less detailed input data and are a computational power with less time-consuming modelling runs than conventional dispersion models (Hoek *et al.*, 2008).

2.6.4.2 Limitations

The main limitation of LUR is that it requires a network of fixed-site air pollution monitors to derive the model; monitoring data is often not available in some developing cities. Most LUR models are built for one specific city, and transferability to other locations is difficult. The main limitations of the model used in this dissertation are that it is not useful for policy development since future predictions cannot be modelled.

2.6.4.3 Policy application

LUR models have been frequently used in epidemiology studies for health impact assessments which inform health air quality guidelines such as those from the WHO (discussed in section 2.6.3). However, for this dissertation, LUR models are not useful since future scenarios cannot be modelled.

2.6.5 Discussion

The different models, presented in the section above, were evaluated in order to choose the most appropriate model for addressing the objectives of this dissertation. The model requirement for this dissertation was the following: The model of choice needed to cover both GHGs and air quality pollutant emissions. The model of choice was required to assess future scenarios at the city scale (in particular for London). The model of choice was required to give pollutant concentrations that could be used for estimating impacts on health.

The range of model evaluations presented above covers different spatial scales (from urban to global), different pollutants and different methodological approaches. An advantage of integrated assessment models (IAMs) to address the objectives of this dissertation is that these types of models, like the GAINS model, have been built specifically to investigate air pollution and climate abatement measures from a holistic perspective. Although some of these IAMs were developed to model the regional and global scales (e.g. GAINS, UKIAM), some of these models have evolved to cover the urban and intra-urban variability.

For example, Liu *et al.*, 2013, developed the urban-scale version of the GAINS model (originally a regional model), the GAINS-city model and has used it to study air pollutants and GHG control measures in Beijing, China (their results will be discussed in section 2.7). The UKIAM model which broadly speaking could be seen as a national-scale version of the GAINS model, also developed a sub-model called BRUTAL which models road transport within UKIAM nationally from the road network, this being an important urban source.

The detailed treatment of road transport in the BRUTAL sub-model is useful to study technical and non-technical strategies at the city level. The BRUTAL sub-model captures the transport sector dynamics, incorporates the long-range pollution contribution from the UKIAM and is being combined with treatment of other UK sources and imported contributions within UKIAM. Moreover, the CMAQ model has been coupled with ADMS to combine regional and urban-scale analysis (King's College London, 2018).

There are also some similarities between models of different categories (IAM, dispersion models, semi-empirical). For example, the UKIAM, which is an integrated assessment model, estimates background concentrations at a 1 km² resolution and considers roadside contributions as a separate addition, as well as the PCM model which is semi-empirical.

Nevertheless, UKIAM is a more deterministic model. Moreover, some models (e.g. UKIAM and ADMS) have evolved to widen their modelling focus and integrate an additional assessment of GHG emissions. Some other models, like LUR models, are specifically for air pollution exposure analysis with no module for GHG emissions analysis. Some models have been specifically designed for a city, for example, the ERG Toolkit, the BRUTAL model and most of the LUR models. In contrast, some other models, like CMAQ and ADMS, are more flexible and can adapt to different contexts being used in different countries and cities.

Importantly, the aim of the study determines the adequacy of the model of choice. Models with quick running time unsophisticated computational requirements like the UKIAM (which runs in minutes) and the ERG Toolkit (which runs in hours) are better choices of models when the study aims to investigate a wide variety of different policy measures or scenarios.

More extended running time models like CMAQ and ADMS could prove not so convenient since longer running times are considerable (sometimes hours/days) and can often require other resources. However, for studies which require urban details, for example, studying the effect urban construction profile in pollution dynamics or the study of air pollution exposure, ADMS or LUR models would be adequate models to use, respectively. However, LUR models can not be used for modelling future situations or abatement scenarios.

2.6.6 Rationale for the choice of model in this dissertation

After consideration of the different models presented, the UKIAM model was chosen as an adequate model to address the objectives of this dissertation for the following reasons:

- The UKIAM model allows for the analysis of GHG emissions and air pollutant emissions and concentrations.
- The UKIAM model is a policy model used for Defra, and it has been subject to detailed inter-comparison with other models against measurements and critical review by the UK Air Quality Expert Group.
- The BRUTAL sub-model of the UKIAM model captures the transport dynamics of one of our case study cities, London, allowing us to estimate the CO₂ emissions and air pollution changes for the application of different policies.
- The BRUTAL sub-model of the UKIAM model has low computational requirements with quick models runs (~ 30 min), which make this model a perfect choice to compare various climate and air pollution policies.
- The UKIAM model outputs annual air pollutant concentrations as background and population-weighted mean concentrations (PWMC) required for the health impact assessment.
- The UKIAM model accounts for long-range, multi-scale pollutants transport, which is of crucial to estimating the contribution of pollution and health exposure. It is particularly important for particulate matter pollution which can travel large distances (e.g. a third of PM_{2.5} in the UK is from non-UK sources) and also because the detrimental health impacts have already been studied (see section 2.4.1).
- Moreover, the UKIAM-BRUTAL model was available to use at Imperial College London.

Please note that a detailed description (including inter-comparison with other models against measurements) of the UKIAM model and its BRUTAL sub-model model is presented in chapter 3, section 3.3.

2.7 Critical assessment of previous studies and existing research: climate, air quality and health

This section presents principal findings of previous studies and existing research linking climate change and air quality and health. First, studies in which spatial scale is global, regional and national are discussed. Then, previous studies and existing research at the city level are described.

2.7.1 Global, regional, and national level

Consistently, previous studies assessing climate change and air quality have shown that actions that mitigate GHG emissions have significant global benefits for air pollution control and therefore for health (Rafaj *et al.*, 2013; Riahi *et al.*, 2012; Field *et al.*, 2014; West *et al.*, 2013; McCollum *et al.*, 2013; Bollen, Hers & van der Zwaan, 2010). The target for ensuring global temperatures stay within 2 °C has been widely studied and estimated. Furthermore, the health benefits of reducing air pollution in accordance with this target have been demonstrated at global and regional scales. (Rafaj *et al.*, 2013; Riahi *et al.*, 2012; Field *et al.*, 2014; West *et al.*, 2013; McCollum *et al.*, 2013; Bollen, Hers & van der Zwaan, 2010).

At the global level, the health benefits (due to air pollution reduction) of meeting the 2 °C target through implementing stringent climate policies have been estimated to be significant, potentially avoiding millions (1×10^6) of deaths globally. With a 2 °C mitigation scenario, avoidable premature deaths are estimated to be as large as 1.2 million by 2030 by Riahi *et al.*, 2012. Similar studies have estimated 0.5 ± 0.2 , 1.3 ± 0.5 and 2.2 ± 0.8 million premature deaths will be avoided in 2030, 2050 and 2100, respectively, in a 2 °C mitigation scenario by West *et al.*, 2013.

At the regional and national level, previous studies have also estimated substantial improvements to air pollution reduction and health as a result of climate action (Amann *et al.*, 2011; van Vuuren *et al.*, 2006; Markandya *et al.*, 2009; Haines *et al.*, 2009; Smith *et al.*, 2016; Clarke *et al.*, 2014; ApSimon *et al.*, 2009). The health benefits for meeting the 2 °C target have also been estimated to be significant. Rafaj *et al.*, 2013, estimated that meeting the 2 °C target will benefit health (due to the reduction of PM_{2.5} pollution) by

increasing life expectancy in different regions of the world by 2050 as follows: 1.2 months in Europe, 19 months in China and nearly 30 months in India. This increase in average life expectancy is equivalent to a decrease in loss of life expectancy by 35% in Europe, 46% in China, and 63% in India (Rafaj *et al.*, 2013). Moreover, Rafaj *et al.*, 2013, estimated that 80 thousand cases of premature mortality are avoided yearly in these three regions due to the reduction of ground-level ozone in the 2 °C mitigation scenario.

The vast majority of global and regional scale studies have evaluated the effect of GHG mitigation scenarios on air pollutants and health for all energy sectors, without differentiating between the effects on specific energy sectors. Fewer studies at these scales (global, regional and national scales) (Takeshita, 2012) have shown the benefits of GHG mitigation strategies on air pollutant emissions, specifically for the road transport sector, which is the sector of study in this dissertation. Takeshita (2012) estimates that a climate change mitigation with CO₂ concentrations stabilised at 400 parts per million volume (ppmv) would benefit the road transport sector by reducing the rate of cumulative global emissions of SO₂, NO_x, and PM from road vehicles during the period 2020 – 2100 by 22.1%, 10.8%, and 14.4%, respectively.

2.7.2 City level

Previous studies at the city level have investigated sector-specific effects of climate change, air pollution and health. This section focuses on the existing research studying the road transport sector. First, in the section ‘Climate change and air pollution’ existing research, which does not quantify health effects but does study the links between climate change and air pollution emissions, will be reviewed. Then, the section ‘Climate change, air pollution and health’ reviews existing research which simultaneously assesses climate change mitigation, air pollution and health. In this section, studies in the two case study cities (Mexico City and London) are highlighted.

2.7.2.1 Climate change and air pollution

Previous studies, although not accounting for health effects have consistently shown that transport policies at the city level can reduce both GHG and air pollutants simultaneously (Chavez-Baeza & Sheinbaum-Pardo, 2014; Liu *et al.*, 2013; West *et al.*, 2004; Dhakal, 2003). Liu *et al.*, 2013, using the GAINS model at the city level (discussed in section 2.6), it is estimated that promoting low-carbon technologies, increasing fuel efficiency, and introducing vehicle emissions control technologies in Beijing, China, could result in

reductions of 5% to 22% of CO₂ emissions and reduce air quality emissions as follows: 38% to 42% of NO_x emissions, 37% to 55% of PM_{2.5} emissions and, 39% to 48% of SO₂, compared with a baseline scenario with no interventions.

Moreover, it has been shown that transport policies such as promoting public transportation and endorsing electric vehicles could reduce energy demand and therefore reduce air pollution and CO₂ emissions (Dhakal, 2003). Dhakal (2003), using an Energy Alternatives Planning System framework, showed that a mix of all the policies mentioned above has the potential to cut down emissions to just over 60% of CO₂ emissions and reduce air quality emissions as follows: 52% of NO_x emissions, 60% of particulate matter emissions, 47% of SO₂ emissions, 71% of CO emissions and, 72% of hydrocarbons (HC) emissions by 2020 in Kathmandu Valley, Nepal.

The most recent study revising impacts of road transport policies in Mexico City for GHG emissions and air quality estimated that policies such as the improvement of fuel efficiency, implementing new technologies, and a modal shift to bus rapid transit (BRT) transport systems could reduce CO₂eq (carbon dioxide equivalent) emissions by 1.5% in and the following reduction in air pollutants: 15.4% in NO_x emissions, 7% in PM₁₀ emissions, 2.4% in CO emissions, and 3.9% in NMVOC emissions by 2028 (Chavez-Baeza & Sheinbaum-Pardo, 2014).

Earlier studies in Mexico City evaluated the impacts of the Program to Improve the Air Quality in Mexico City (Proaire), which also accounted for CO₂eq emissions. West *et al.*, 2004, estimated the impacts of adding mitigation strategies such as improvement of fuel efficiency and implementing new technologies in the transport sector in Mexico City could reduce CO₂ emissions by 8.7% and estimated the following reductions in air pollutant emissions: 1.4% of NO_x emissions, 1.3% in PM₁₀ emissions, and 3.2% in HC emissions. The application of the Proaire program and the mitigation measures would require a total investment of £2.5 billion GBP (West *et al.*, 2004).

As reviewed in this section, the studies have consistently shown that road transport policies bring benefits for GHG emission reduction and air pollution control. The different range of reductions in GHG and air pollutant emissions may be attributable to distinctive modelling approaches, different assumptions, variable scenario design and baseline scenario definition.

2.7.2.2 Climate change, air pollution, and health

Existing studies at the city level additional to GHG emissions (generally CO₂ emissions) and air pollution estimates have calculated health impacts of transport policies. Some of these studies (which include CO₂ emissions assessment) have studied the health impacts of transport policies which promote active travel (walking, cycling and public transport travel) usually including health impacts related to three variables: physical activity, air pollution exposure, and road traffic injuries (Rojas-Rueda *et al.*, 2011, 2013, 2016, 2012; Zapata-Diomedes *et al.*, 2017; Woodcock *et al.*, 2009; Maizlish *et al.*, 2013; Mueller *et al.*, 2017; Xia *et al.*, 2015; Rabl & de Nazelle, 2012). The three variables related to transport policies which are affecting health (physical activity, air pollution exposure, and road traffic injuries), will be discussed below.

2.7.2.2.1 Physical activity

The vast majority of the existing research estimates substantial net health benefits derived from increasing physical activity; some studies assessed physical activity through a mode shift to active transportation. It has been calculated that gains in physical activity from active travel constituted at least half of the total health benefits (Mueller *et al.*, 2015). Estimated health benefits due to increases in physical activity levels, greatly outweighed associated detrimental effects of air pollution exposure and traffic accidents, as will be discussed below (Mueller *et al.*, 2015).

For example, in an interesting study, Mueller *et al.*, 2017, assessed health gains from reaching recommended levels of exposures and behaviours through pathways that can be addressed through urban design policies. Mueller *et al.*, 2017, estimated the health impacts of complying with international exposure recommendations for physical activity (WHO recommendation of 150 min of moderate-intensity or 75 min vigorous-intensity physical activity weekly), air pollution (WHO recommendation of annual mean PM_{2.5} concentrations of 10 µg/m³), noise, heat, and access to green spaces in Barcelona, Spain.

In this study, Mueller *et al.*, 2017, compared current levels in Barcelona: physical activity (74% of the population considered ‘insufficiently active’) and air pollution (annual mean concentration in Barcelona of 17.77 µg/m³), with a scenario where the recommended limits were met: physical activity (100% of the population sufficiently active) and air pollution (reduction of 7.77 µg/m³ to meet a concentration of 10 µg/m³).

Mueller *et al.*, 2017 estimations showed that the greatest portion of preventable deaths could be attributed to increases in physical activity (resulting in 1,154 deaths prevented; 95% CI: 858 – 1,577) and reductions in exposure to air pollution (resulting in 659 deaths prevented; 95% CI: 386 – 834) followed by the noise, heat, and access to green spaces health impacts. Mueller *et al.*, 2017, estimations showed that, from the five exposures that they analysed (physical activity, air pollution exposure, noise, heat, and access to green spaces), the greatest portion of preventable deaths were attributable to increases in physical activity, followed by reductions of exposure to air pollution, which are the two variables highlighted in this research.

Relevant for this dissertation, a study by Woodcock *et al.*, 2009, estimated the health impacts of low-carbon mobility measures in two urban contexts, a developed and a developing city: London, UK and Delhi, India. The two low-carbon mobility measures assessed in the study were: lower carbon emission motor vehicles and active travel. The authors estimated effects on physical activity, outdoor air pollution, and risk of road traffic injury using Comparative Risk Assessment. Woodcock *et al.*, 2009, showed that a combination of active travel and lower-emission motor vehicles would give the largest health benefits. This study only considered the benefits of ambient air pollution reductions and not the potential added risk of increased air pollution.

In the same way as Mueller *et al.*, 2017, Woodcock *et al.*, 2009, found the largest health benefits came from an increase in physical activity (accounting for more than half of the perceived health benefits), followed by air pollution and road traffic crashes. Interestingly, the authors conclude that the road transport policies which increase the acceptability, appeal, and safety of active travel, and dissuade travel in private motorised vehicles would deliver larger health benefits than policies which only promote highly efficient and lower-emission motor vehicles (Woodcock *et al.*, 2009).

As discussed by the literature, climate change mitigation in transport should benefit public health substantially, although some uncertainties remain. Some of the factors which impact the uncertainty of physical activity benefit estimates are the shape of the applied dose-response function, which significantly impacts the magnitude of the physical activity benefits. It has been shown that a more suitable approach is the application of a non-linear dose-response function which means that health benefits vary in magnitude for different physical activity levels, with the greatest benefits occurring when inactive people become moderately active (Woodcock *et al.*, 2011).

However, to apply non-linear dose-response function information to the baseline, physical activity levels are needed. Nevertheless, on most occasions, data on baseline physical activity is not available. Therefore a linear dose-response function is used. Nevertheless, a linear dose-response function assumes equal

changes in health benefits for active and non-active people; this assumption can lead to under-estimations of health benefits of physical activity for non-active people and to over-estimations of already active people (Mueller *et al.*, 2015).

2.7.2.2.2 Air pollution exposure

Existing research has shown that the health impacts of air pollution exposure are small relative to the health benefits of physical activity in active travel. However, existing literature shows that after physical activity, air pollution exposure can be the second or third (after traffic accidents) most important variable affecting the health of travellers (Mueller *et al.*, 2015). Health impacts of air pollution exposure can be estimated for changes in ambient air pollution concentrations (Woodcock *et al.*, 2009; Mueller *et al.*, 2017), and also can be estimated for the inhalation of air pollution of travellers while travelling in different modes of transport (Rojas-Rueda *et al.*, 2011, 2013).

In order to calculate these air pollution-related health impacts, information on air pollution concentrations is needed. Air pollution concentration information can be modelled, or air pollution concentration data can be obtained from a combination of monitoring station data for background air pollution and measurement studies for air pollution in travel modes (Rojas-Rueda *et al.*, 2011), from published information on air quality concentrations and source apportionment from local authorities to then model changes in concentrations from changes in travel patterns (de Sá *et al.*, 2017), and from previous modelling exercises (Cifuentes *et al.*, 2001b), among others. However, there is a clear advantage of modelling air pollution concentrations in order to account for the air pollution effect of the transport policies evaluated and their corresponding health effects.

Few studies evaluating transport policies in cities have included (in addition to CO₂ emission assessments) estimations of the health impacts when accounting for the air pollution control potential of the transport policies evaluated using air quality modelling techniques (Woodcock *et al.*, 2009; Xia *et al.*, 2015; Rojas-Rueda *et al.*, 2012; Grabow *et al.*, 2012; Maizlish *et al.*, 2013). From these studies, some (Grabow *et al.*, 2012; Rojas-Rueda *et al.*, 2012; Xia *et al.*, 2015) have only evaluated behavioural change transport strategies which shift motorised travel (for example, travel by car) to active travel modes (walking, cycling and public transport).

To the best of my knowledge only (Woodcock *et al.*, 2009; Maizlish *et al.*, 2013) have, interestingly, evaluated technological change transport strategies (e.g. introduction of low-carbon vehicles) together with

behavioural change strategies. These studies assessed CO₂ emissions and air quality modelling, to estimate the air pollution control potential of the theoretical transport policies evaluated and their corresponding health impacts. However, further analysis from (Woodcock *et al.*, 2009; Maizlish *et al.*, 2013) of technological change scenarios from real transport policies proposed by the city authorities is necessary in order to provide a complete picture of how different specific policies fair out in terms of health.

In conclusion, using air pollution data instead of modelling air pollution concentration changes due to the applied transport policies, involves uncertainty since air pollution concentrations are dependent on specific sources and their location. In many cities like Mexico City, transport sources are the main drivers of air pollution concentrations. Moreover, the vast majority of the research on air pollution exposure has focused on studying particulate matter pollution without considering the effects of other harmful air pollutants such as NO₂ and O₃ (COMEAP, 2018).

2.7.2.2.3 Traffic injuries

Existing research has shown that health risks by traffic accidents during active travel are smaller compared with the health benefits gained by increased physical activity in active modes (Mueller *et al.*, 2015). However, some studies have shown that health risks due to traffic accidents can be significant and in general, larger than the health effects of air pollution (Mueller *et al.*, 2015). For this, shifting to active modes may increase incident risk as these are considered high-risk modes. A difficulty of accounting for traffic injuries can be the lack of or missing information about traffic accident data stated in police reports. A limitation of this research is that the health effects of traffic injuries are not accounted for. Future research should include the assessment of traffic injuries to enrich this investigation.

2.7.3 Discussion

This section has highlighted findings from existing research which have consistently found benefits of climate change mitigation and air pollution control policies for both GHG emission reduction, air pollution control and health. The estimations of the effect of transport policies for climate change mitigation and air pollution emissions reduction is dependent on the location of study, the modelling approach used, the definition of different assumptions, and importantly the scenario design and baseline scenario definition. Although different studies in different locations and with different methodological approaches have been reviewed in these sections, all the studies have found benefits of holistic action for climate change and air pollution in transport policies.

Existing research assessing the effect on GHG emissions, air pollution and health have found that active transport policies bring the largest health benefits due to the increase of physical activity during active transportation. Air pollution exposure has been shown to not be as important a health variable as physical activity. However, few studies have done detailed comparative analysis modelling air pollution impacts of a variety of air pollution policies, including behavioural and technological approaches.

The literature review presented in this section aims to discuss principal findings of existing research made over the years to link climate change, air pollution and health. Additionally, this section aims to highlight the importance of this dissertation which will help improve understanding of technological and behavioural change strategies which relate to actual transport policies proposed by city governments. Moreover, this dissertation will help increase knowledge on the evaluation of transport policies in a most holistic way, including its effects on CO₂ emissions reduction, its impacts on air pollution control and the quantifying of its health co-benefits. The final objective is to help decision-makers to promote the transport policies which will bring the largest benefits to the environment and the health of the increasing population of cities around the world.

Chapter 3

Methods

3.1 Overview

The sections of this chapter address the research objectives (section 1.4) presented in the introductory chapter. The following section, section 3.2, presents the criteria for selecting the real (implemented or proposed) transport policies of study and shows the definition of the transport policy scenarios developed for London and Mexico City.

The subsequent section, section 3.3, describes the modelling framework used in this dissertation to assess the impact on CO₂ emissions and air pollution of the defined transport policy scenarios in London and Mexico City. This section includes a thorough description of the model used for the London analysis, the UKIAM model. Also, this section contains a revision of the UKIAM model uncertainty, the UKIAM model validations and projections comparison with other models. Additionally, this section includes a description of the more straightforward modelling approach used for Mexico City. Finally, the methods used to account for the CO₂ emission from electricity are described, including a discussion on the limitation of not accounting for air pollution indirect emissions from electricity generation.

The following section, section 3.4, presents the translation of transport policy scenarios as inputs for the modelling framework, for London and Mexico City. The translation of the transport policy scenarios as inputs for the modelling includes a definition of all the transport policy scenarios in terms of kilometres travelled by vehicle type and by mode of transport. Moreover, the description of the travel patterns (number of trips and time travelled by transport mode) of each transport policy scenario for London and Mexico City is included. The current and projected mortality rates used for London and Mexico City are also presented. Importantly, in this section, the baseline for London and Mexico is defined; the impacts of the transport policy scenarios were compared relative to the baseline.

Finally, section 3.5 presents the health impacts assessment modelling framework used in this dissertation. Here the estimated health impacts are described: health impacts from changes in air pollutant concentrations, health impacts for the inhalation of air pollutants and health impacts for the increase in physical activity during the use of active travel modes (walking, cycling and public transport). Moreover, this section presents the methods used for the sensitivity analysis and all the input values used for the sensitivity analysis are presented.

3.2 Transport policies and transport policy scenarios

In this section, the first and second research objectives of this dissertation (review and identify transport policies and develop transport policy scenarios) (section 1.4) are addressed. This section presents the criteria for the selection of implemented or proposed real transport policies and the development of transport policy scenarios for London and Mexico City. Each transport policy is described, and the transport policy scenario, which was developed from each real transport policy is defined. Then, a detailed description of the transport policy scenarios (Figure 3.2 and Figure 3.3) is presented by category differentiating the technological and behavioural change transport policy scenarios.

The selection of implemented or proposed real transport policies in London and Mexico City followed the eligibility criteria described below:

- Road transport policies which are city-specific. For the two case study cities, London and Mexico City.
- Road transport policies which have the main objective of reducing GHG (or CO₂) emissions, control air pollution or improve public health.
- Policies that have been implemented or proposed by the governmental authorities.
- Road transport policies from which it was feasible to calculate their impacts on CO₂ emissions and air pollution.

A primary source of information for the identification, collection and analysis of road transport policies were documentary policy materials and grey literature, such as strategies, plans and project reports, published by governmental authorities from each case study city.

In the following sections, the selected transport policies which inspired the scenarios are described together with the transport policy scenarios built from the transport policies, for London and Mexico City. The transport policy scenarios were divided into two categories, technological and behavioural change, according to their policy intervention approach. These categories have been used in previous studies to investigate transport strategies (Allwood *et al.*, 2014; Woodcock *et al.*, 2009; Kollamthodi & Watkiss, 2005). Technological change policy scenarios included technical measures often including physical

changes to the vehicle (e.g. vehicle retrofitting or switch to electric vehicles). Behavioural change policy scenarios included non-technical measures (e.g. mode shift from motorised vehicles to walking, cycling, and public transport).

It is important to notice that all the transport policy scenarios were modelled in the London-wide (32 boroughs) and Mexico City-wide area (16 boroughs). Also, please note that scenario definitions (in terms of kilometres travelled by vehicle type and vehicles technologies) for the road transport policy scenarios for London and Mexico City are presented in section 3.4 of this chapter.

3.2.1 London

The road transport policies for London were mostly derived from the Mayor's Transport Strategy (GLA, 2018c) and the London Environment Strategy (GLA, 2018b). These two documents were chosen because these are the two documents which present the latest revisions of road transport policies under the current mayoral administration of Mr Sadiq Khan.

Following the eligibility criteria (described in section 3.2), the road transport policies chosen in London were the policies referred to in the Mayor's Transport Strategy (GLA, 2018c) as policies for 'Healthy streets and healthy people' and also included in the London Environment Strategy (GLA, 2018b). These road transport policies have the objective of complying with air pollution legal limits, reducing CO₂ emissions and improving health.

Additionally, a transport policy at the national level was included. This national transport policy aims to ban the sale of new conventional petrol and diesel cars by 2040 (DfT, 2018c). Inspired by this national transport policy, the study of vehicle fuel choice trends (diesel or petrol) was included in the analysis. The description of each transport policy and the corresponding transport policy scenarios (Figure 3.2) is presented below.

3.2.1.1 Low Emissions Zone

3.2.1.1.1 Policy: Ultra Low Emission Zone

The Low Emissions Zone called Ultra Low Emission Zone (ULEZ), is a policy which was recently (April 2019) implemented in London to improve air quality. The Low Emissions Zone is a technological change transport policy which restricts vehicles that do not meet Euro exhaust emissions standards from entering a defined zone. The Euro Standards were defined in the previous chapter, section 2.2.1.2, table 2.2.

The specific emissions standards for the London ULEZ are Euro 3 for motorcycles; Euro 4 (NO_x) for petrol cars; Euro 6 (NO_x and PM) for diesel cars; Euro VI (NO_x and PM) for HGV, buses and coaches. If Euro standards are not met, a fee is charged (£12.50 for cars, motorcycles and LGV; and £100 for buses, coaches and HGV) (GLA, 2018c, 2018b). The ULEZ was implemented in central (downtown) London in 2019. The government, however, aims to expand this low emission zone over London (London-wide), requiring tighter exhaust emissions standards (GLA, 2018c, 2018b).

3.2.1.1.2 Technological change scenario: Low Emissions Zone

Assumptions

The assumptions used to develop this technological change scenario are:

- Low Emissions Zone scenario: all vehicles in the London-wide zone meet the indicated Euro Standards for exhaust emissions: all diesel vehicles meet the Euro 6/VI standard and all petrol vehicles meet Euro 4 standard.

The ULEZ policy allows vehicles which do not meet the required Euro Standard to enter the zone, charging them a fee. However, the Low Emissions Zone scenario in this dissertation assumes that all vehicles in London meet the required euro Standards. This means that the scenario modelled in this dissertation is underestimating exhaust emissions by not accounting those vehicles which do not meet the emissions standard but enter the zone by paying the fee. Additionally, some trips will be foregone altogether too, which would lower emissions.

3.2.1.2 Zero Emission Zone: Electric Vehicles

3.2.1.2.1 Policy: Zero Emission Zones

The Zero Emission Zone is a proposed policy planned to be implemented in London's central area by 2025. The objective of this policy is to achieve zero emissions London-wide by 2050 as promised by the authorities (GLA, 2018c, 2018b). A Zero Emission Zone is a technological change policy which requires vehicles that drive within a specific area to be capable of operating with zero exhaust emissions.

This road transport policy requires the inclusion of zero emissions technologies. Plug-in hybrid electric vehicles are zero exhaust emissions capable, and all-electric vehicles are zero exhaust emissions vehicles (reviewed in section 2.3.2). A zero emissions zone in London is likely to require vehicles that are not zero emissions capable of paying a road user charge (similar to those in ULEZ) (GLA, 2018b, 2018c).

The Mayor's Transport Strategy presents a zero emissions road transport timeline in which between 2025 and 2050 all vehicles in London (cars, taxis, buses, LGV and HGV) will be zero exhaust emissions vehicles (GLA, 2018b, 2018c).

3.2.1.2.2 Technological change scenario: Electric Car, Electric Taxi, Electric Bus, Electric Vehicle Fleet

Inspired by the Zero Emissions Zone policy, different technological change scenarios were constructed by electrifying a different vehicle type (cars, taxis, buses). Also, a scenario in which electrifying the entire vehicle fleet in London was electric was developed to assess the effect of the Zero Emissions Zone in the London-wide area.

Assumptions

The following scenarios were developed under the following assumptions:

- Electric Car scenario: all the cars in the London-wide area emit zero exhaust emissions.
- Electric Taxi scenario: all the taxis in the London-wide area emit zero exhaust emissions.
- Electric Bus scenario: all the buses in the London-wide area emit zero exhaust emissions.

- Electric Vehicle Fleet scenario: all the cars, taxis, buses, LGV and motorcycles in the London-wide area emit zero exhaust emissions.

3.2.1.3 Active Travel: Cycle Lanes

3.2.1.3.1 Policy: London-Wide Cycle Network

The construction of cycle lanes (or Cycle Superhighways (CS) as called in London) is an initiative implemented as part of the policy to develop a London-wide cycle network. This policy is part of the Healthy Streets program, which aims to help Londoners use cars less and walk cycle and use public transport more (GLA, 2018c). The construction of cycle lanes in London started in 2016. The constructed cycle lanes today are shown in Figure 3.1.

3.2.1.3.2 Behavioural change scenario: Cycle Lane 10 and Cycle Lane 20

The behavioural change scenario constructed from the London-wide cycle network policy evaluated the impacts of the six cycle lanes initially constructed in London from 2016 to 2017. The cycle lanes (or Cycle Superhighways (CS)) assessed in this scenario are highlighted in blue in Figure 3.1. The cycle lanes evaluated in these scenarios are the following (Figure 3.1): CS1 that goes from Tottenham to The City (length of 9 km); CS2 from Stratford to Aldgate East (length of 6 km); CS3 from Barking to Hyde Park (length of 12 km); CS5 from Oval to Pimlico (length of 1 km); CS7 from Tooting to Southwark Bridge (length of 12 km); and CS8 from Wandsworth to Lambeth Bridge (length of 7 km). The total distance covered by the cycle lanes assessed in this scenario is 47 km.

Assumptions

The behavioural change scenarios assessing this cycle lanes were built under the following assumptions:

- Cycle Lane 10 scenario: a reduction of 10% in traffic flow was assumed on the 47 km of road along which the cycle lanes pass (Figure 3.1).

- Cycle Lane 20 scenario: a reduction of 20% in traffic flow was assumed on the 47 km of road along which the cycle lanes pass (Figure 3.1).

The selected percentage of traffic flow reduction (reductions of 10% and 20%) along the road where cycle lanes are constructed, was derived from the observed reduction in traffic flow after the construction of cycle lanes in New York City, USA (NYC Department of Transportation, 2014).

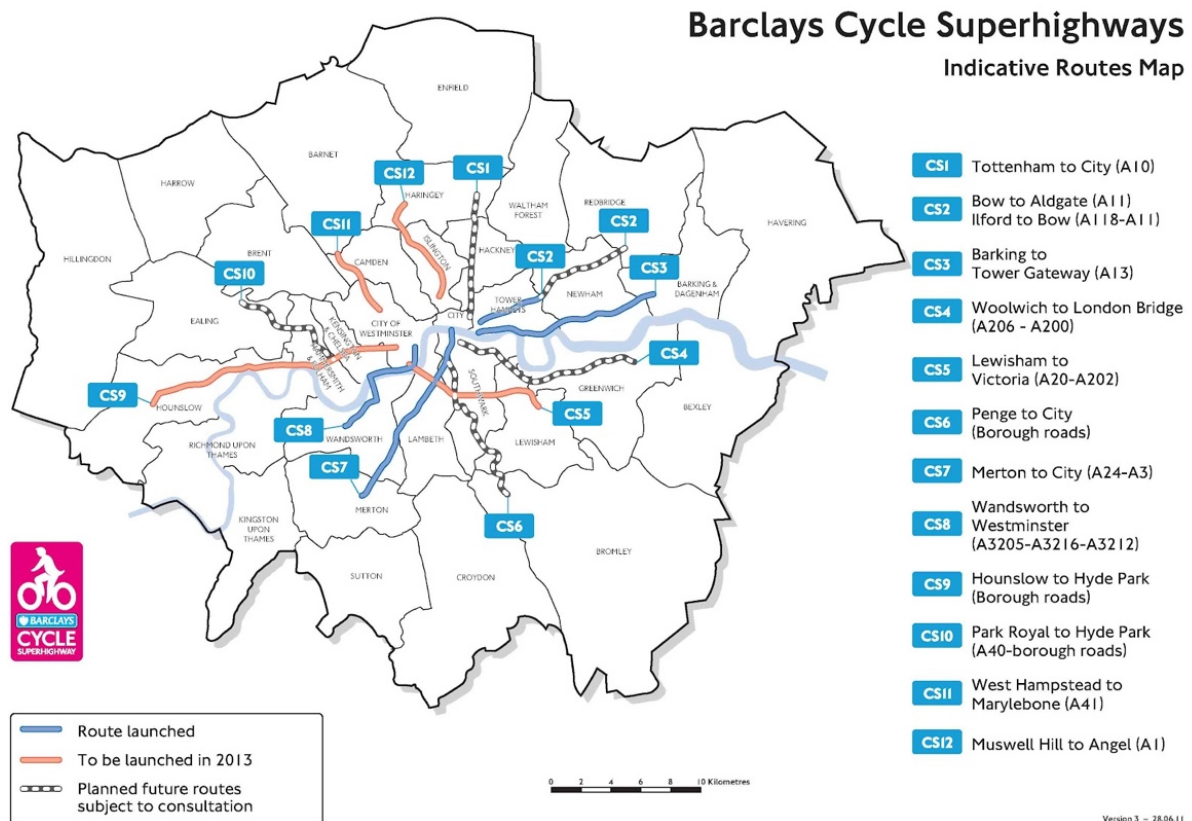


Figure 3.1 London cycle lanes (or cycle superhighways (CS) as called in London). The cycle lanes assessed in the Cycle Lane 10 and Cycle Lane 20 scenario are highlighted in blue: CS1, CS2, CS3, CS7, and CS8 (TfL, 2019).

3.2.1.4 Active travel: Reduction of Car Use

3.2.1.4.1 Policy: Active Travel Policies to Use Cars Less

Behavioural change policies aiming to reduce Londoners' dependency on cars in favour of active travel modes (walking, cycling and public transport) include: improving local walking routes; delivering a London-wide cycle network; improving the walk London network; and supporting the cycle hire scheme (GLA, 2018c).

3.2.1.4.2 Behavioural change scenario: Car Redu 10 and Car Redu 50

Reduction of car dependency by reducing travel by car and increase a shift to active modes of transport (walking, cycling and public transport) was included in the following scenarios.

Assumptions

The scenarios were built under the following assumptions:

- Car Redu 10 scenario: reduction of 10% of kilometres travelled by cars. The reduced kilometres travelled by car was shifted to active travel modes (walking, cycling and public transport).
- Car Redu 50 scenario: reduction of 50% of kilometres travelled by cars. The reduced kilometres travelled by car was shifted to active travel modes (walking, cycling and public transport).
- Also, it was assumed that no increase in public transport capacity is needed.

3.2.1.5 Fuel Choice Trends: Diesel to Petrol Cars

3.2.1.5.1 Policy: Ban the Sale of New Petrol and Diesel Cars and Vans

Additional to the transport policies present in the London Mayor's Transport and Environment Strategies was another transport policy measure included at the national level. This national transport policy is part of the UK's plan to ban the sale of new conventional petrol and diesel cars and vans by 2040 (DfT, 2018c). Driven by the need to control air pollution from road transport, several countries and cities such as Mexico City, Madrid, Athens and Paris, have announced bans on diesel cars to improve air quality (C40, 2016; Harvey, 2016). An analysis of fuel choice trends (petrol vs diesel) in the UK (DfT, 2017) was conducted to develop a fuel choice transport policy scenario.

In the UK, the proportions of newly registered petrol versus diesel cars have changed significantly during the last decades. In 2001, for every new diesel car bought, there were around five new petrol cars bought. Diesel cars represented only 18% of the total new cars. Moreover, petrol cars accounted for the majority of cars (82%). Nevertheless, due to an effective policy incentive to favour diesel cars, one decade later, in 2011 diesel cars grew to represent 50% of total new registered cars (in contrast with 48% of petrol cars). Today, due to the tax rise on new diesel vehicles and negative public perception of diesel cars as polluting vehicles, the trend has swapped again. In 2017 in the UK, only 42% of newly registered cars were diesel, vs 53% petrol (DfT, 2018b).

3.2.1.5.2 Technological change scenario: Diesel to Petrol Car

This technological change scenario assumes that all diesel cars are now petrol cars. This means that there are no diesel cars in London. This scenario evaluates the environmental effect of recent trends that show an increase in new petrol cars versus diesel cars in the UK (DfT, 2018b).

Assumption

This scenario was built under the following assumptions:

- Diesel to Petrol Car scenario: All diesel cars are switched to petrol in London.

3.2.1.6 Implementation cost

The overall implementation costs of the transport policies reviews above are reported in the Mayor's Transport Strategy. However, neither the Mayor's Transport Strategy nor the London Environment Strategy or any other official communication from the London authorities reports additional information to help us understand how the cost was calculated and what the costs include (e.g. infrastructure, vehicles costs, operating expenditure, capital expenditure, among others). This is important data and reliability constraint.

Due to this data limitation, in this dissertation, the policy implementation costs are used as a purely indicative monetary range to describe and compare the policies in a very general way. Each scenario was associated with the approximate cost of implementation, as stated in similar policies from the Mayor's Transport Strategy (GLA, 2018c).

Table 3.1 Indicative implementations costs (as presented in the Mayor's Transport Strategy (GLA, 2018c)) of transport policies used for the development of the scenarios.

Note: It is important to note that all costs are an approximation and illustrative and should not be taken as precise values.

Transport policy scenario	Associated policy from the Mayor's Transport Strategy (GLA 2018c).	Implementation cost from the Mayor's Transport Strategy (GLA 2018c) *.
Low Emissions Zone	Introduce ULEZ in inner and central London and tighten low emission zone standards.	Medium (£100m - £1bn)
Electric Car and Electric Vehicle Fleet	Ensure the electric charging infrastructure is in place to support the transition to electric vehicles. Lobby for increased low-carbon energy generation.	Medium (£100m - £1bn)
Cycle Lane 20 and Car Redu 10	Improve wayfinding for walking and cycling. Improve local walking routes, including routes to schools. Protect, improve and promote the Walk London Network.	Low (< £100m)
Car Redu 50	Deliver a London-wide strategic cycle network	Medium (£100m - £1bn)

*It is important to notice than the transport policy scenarios developed in this dissertation were informed from policies presented in the Mayor's Transport Strategy (GLA 2018c) as explained in section 3.2.1.1 to 3.2.14. Theses policies implementation costs are presented in the table above. If the scenario covered more than one policy with different investments cost, the highest cost was assigned to the scenario. For example, if one policy was low cost but another medium cost, then the medium cost was assigned to the scenario.

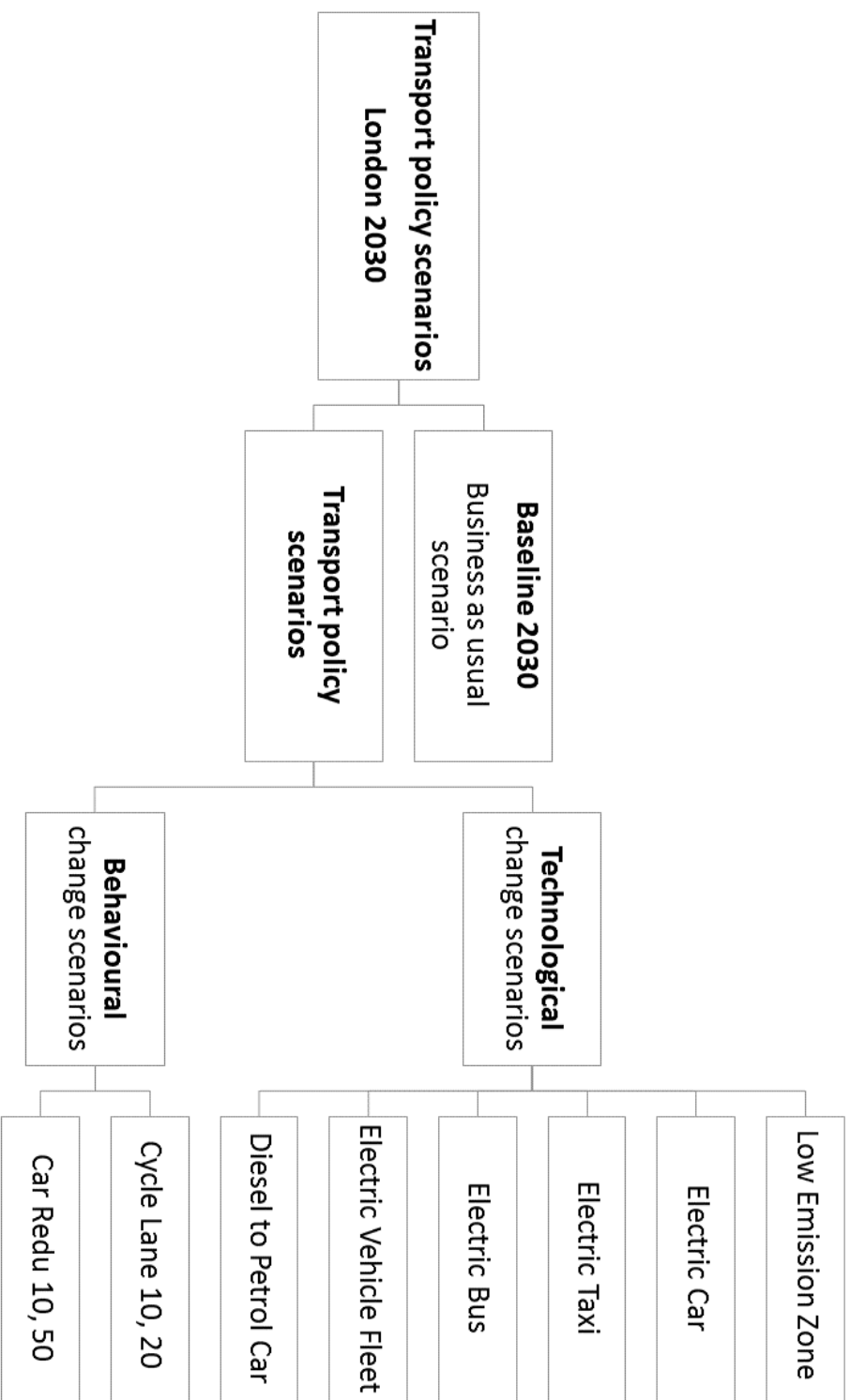


Figure 3.2 Transport policy scenarios evaluated for London, projected to 2030.

3.2.2 Mexico City

Road transport policies from Mexico City were identified and reviewed from the following policy documents: The revised version of the Program to improve air quality in Mexico City (ProAire) 2011-2020 (SEDEMA, 2018b). The Climate Action Program 2014 – 2020 (SEDEMA & CMM, 2014b) published by the Environmental Ministry of Mexico City (Secretaria de Medio Ambiente, SEDEMA). And, the recently published 2018 – 2030 Electromobility Strategy for Mexico City (C40, 2018).

In particular, the ProAire 2011 – 2020 and the Climate Action Program 2014 – 2020 are the policy documents containing the environmental policies approved under the current administration with Dr Claudia Sheinbaum serving as Mayor of Mexico City. Following the eligibility criteria defined in section 3.2, the road transport policies analysed have the objective of tackling climate change and improving air quality and health in Mexico City.

From the revision of transport policies, behavioural and technological change scenarios were defined for Mexico City (Figure 3.3). However, even if the definitions of some of the transport policy scenarios were based on the transports policies from Mexico, the long-term ambition of the scenarios was upgraded to the ambition of some of the policies in London. This because the vast majority of transport policies in Mexico do not include a long-term goal.

3.2.2.1 Introduction of High Energy Efficient Vehicles: Electric Vehicles

3.2.2.1.1 Policy: Promote High Energy Efficient Vehicles and Electric Vehicles for all Modes of Transport

Numerous policies in Mexico City (C40, 2018; SEDEMA & CMM, 2014a; SEMARNAT, 2011) have aimed to promote the introduction of high energy efficient vehicles such as electric and hybrid vehicles. Specific policies include: to promote the transition to electric taxis, to develop a route of electric buses, and to promote the insertion of electric motorcycles.

In particular, the 2018 – 2030 Electromobility Strategy (C40, 2018) highlights the following policy measures to promote electric vehicles: Privilege the provision of electrical energy infrastructure, mainly for public transport; Implement a public policy that stimulates the electric vehicle market, as well as intelligent technologies for mobility that allow the intermodality of various electric transport systems; Ensure that the supply of electricity comes from renewable and clean sources; Regulate the reuse, recycling and final disposal of batteries and their components; Promote the development of national capacities for vehicle technology research and development of electric mobility; And meet the corresponding climate change goals and have an air quality that reaches the levels recommended by the World Health Organization through the integration of electric vehicles for both public and private transport.

3.2.2.1.2 Scenario: Electric Car, Electric Taxi, Electric Bus, Electric Vehicle Fleet

Inspired by the policies presented above and upgrading the ambition to that of zero emission zone policies, such as the one in London, several technological change transport policy scenarios were developed. These technological change scenarios consisted of electrifying different vehicle types (cars, taxis, buses) and also a scenario where the entire vehicle fleet was electric.

Assumptions

The transport policy scenarios were built under the following assumptions:

- Electric Car scenario: all the cars in Mexico City emit zero exhaust emissions.
- Electric Taxi scenario: all the taxis in Mexico City emit zero exhaust emissions.
- Electric Bus scenario: all the buses in Mexico City emit zero exhaust emissions. The bus category includes minibuses, buses and bus rapid transport (BRT) buses.
- Electric Vehicle Fleet scenario: all the cars, taxis, buses, LGV and motorcycles in Mexico City emit zero exhaust emissions.

3.2.2.2 Modernisation of the Vehicle Fleet (Reduction of Old Vehicles) and Increased Active Travel

3.2.2.2.1 Policy: Renewal of the Vehicle Fleet

Several road transport policies proposed in the ProAire 2011-2020 (SEDEMA, 2018b) and the Climate Action Program 2014 – 2020 (SEDEMA & CMM, 2014b) aim to remove the highly polluting old vehicle fleet which is on average more than 18 years old.

Specific road transport policies proposed; Promoting the modernisation of the vehicle fleet by providing incentives for increasing the renewal rate of older trucks, taxis, buses and private cars through an increase in the annual property tax for older vehicles; Tightening the requirements of the currently implemented No-Driving Day program for vehicles older than ten years, to increase restrictions on the number of days that old vehicles can drive on the road; Updating regulations on permissible emission limits for diesel vehicles, especially HGV, to accelerate the introduction of new vehicles with better emission control technologies such as EURO 6, EURO VI; And tightening the requirements of the currently implemented No-Driving Day program to include not only the age of the fleet and the emissions of pollutants from vehicles but also the possible differences in the uses of the different modes of transport (e.g. kilometres travelled, distribution of trips).

3.2.2.2.2 Policy: Promote Active Travel

Road transport policies proposed in the ProAire 2011-2020 (SEDEMA, 2018b) and in the Climate Action Program 2014 – 2020 (SEDEMA & CMM, 2014b) address the expansion of non-motorised transport, favouring active travel (walking, cycling and public transport).

Specific policy measures which promote active travel are the following: Promote and significantly expand infrastructure for non-motorised transport (cycling and walking); Improve public transport safety, reliability, connectivity and comfort; Promote active travel by extending coverage of paid street parking (avoiding free street parking) and by raising the rates of street parking; Implement a congestion charge in the central area of the city like the one in London; Impulse for intermodal mobility including active modes of transport, And expand the public cycle hire scheme called EcoBici.

3.2.2.2.3 Scenarios: Old Car Redu, Old Taxi Redu, Old Bus Redu, Car Redu 10

The two policies described above (the renewal of the vehicle fleet and the promotion of active travel policies) were used to develop the transport policy scenarios described below (Figure 3.3). The transport policy scenarios were constructed assuming a reduction of kilometres travelled by old vehicles (vehicles older than ten years). This assumption of reducing kilometres travelled by the oldest vehicles was used in previous studies for the development of transport scenarios in Delhi, India by Woodcock *et al.*, 2009. The reduced kilometres travelled by car were shifted to active modes (walking, cycling and public transport) to construct the scenarios.

Assumptions

The assumptions considered when building the scenarios were the following:

- Old Car Redu scenario: kilometres driven by cars older than ten years are shifted to active travel modes (walking, cycling and public transport).
- Old Taxi Redu scenario: kilometres driven by taxis older than ten years are shifted to active travel modes (walking, cycling and public transport).

- Old Bus Redu scenario: kilometres driven by buses older than ten years are shifted to active travel modes (walking, cycling and public transport).
- Car Redu 10 scenario: kilometres driven by the 10% of older cars are shifted to active travel modes (walking, cycling and public transport).

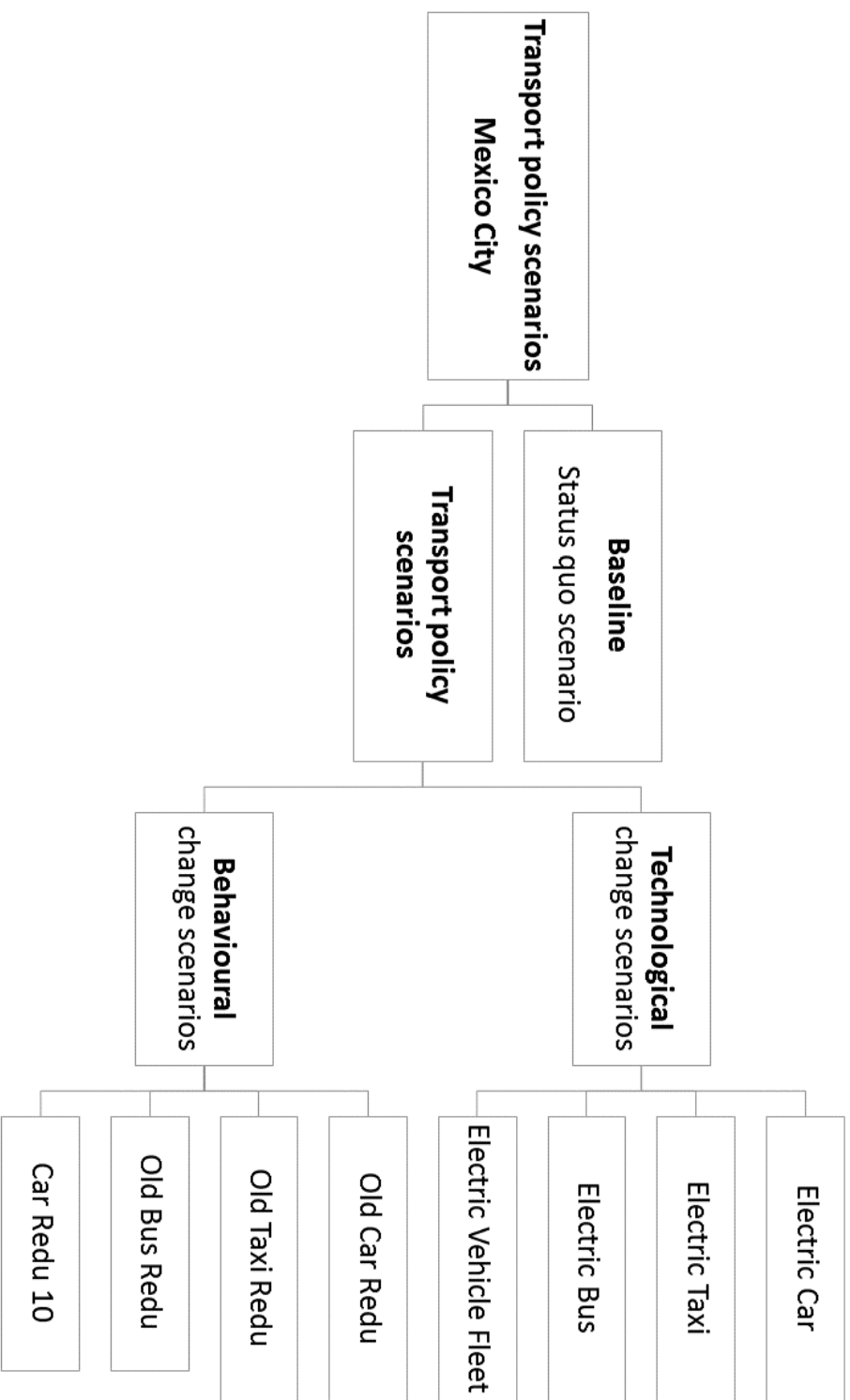


Figure 3.3 Transport policy scenarios assessed for Mexico City.

3.3 CO₂ emissions and air pollutants modelling framework

Addressing the third research objectives of this dissertation (see section 1.4), a modelling framework was developed to assess CO₂ emissions, and air pollutants emissions and concentrations from the road transport policy scenarios defined in section 3.2. After reviewing different modelling approaches used in previous studies (as discussed in section 2.6), the UKIAM model was chosen to model the impacts of the road transport policy scenarios in London. A detailed rationale for choosing the UKIAM model was presented in section 2.6.6.

In this section, the modelling approach for London using the UKIAM model is presented. This section includes a review of the UKIAM model. Also, a critique of the model is included, discussing on the UKIAM model uncertainties, the UKIAM model validation with measurements, the UKIAM model inter-comparison with other similar models, and a comparison between the UKIAM model future projections and future projections from other similar models.

This section also presents the simple modelling approach used for Mexico City, highlighting its rationale and limitations.

3.3.1 London: UK Integrated Assessment Model (UKIAM)

The UK Integrated Assessment Model (UKIAM) (Oxley *et al.*, 2003, 2013) (Figure 3.4) was developed to evaluate environmental and health impacts of air quality and climate policy scenarios in the UK. The UKIAM model evaluates the impacts of behavioural as well as technological abatement measures. The advantages of the UKIAM as an Integrated Assessment Model (IAM) is that it produces rapid and realistic assessments of environmental impacts, avoiding the use of complex atmospheric dispersion models with time-consuming runs.

The UKIAM modelling runs are faster than with dispersion models because the UKIAM uses pre-calculated source-receptor relationships from dispersion models to model the effect that changes in emissions from different sources have on the concentration and deposition of pollutants. Dispersion models calculate the source-receptor relationship each time they run, which considerably increases the time to run the models.

Moreover, the UKIAM has the flexibility to combine source relationships from different dispersion models. It is nested within the Abatement Strategies Assessment Model (ASAM) (ApSimon, Warren & Wilson, 1994; Oxley & ApSimon, 2007) (Figure 3.4), which models European imported contributions, to account for international shipping and other European emissions, in addition to UK's domestic industrial and natural sources.

The pollutants modelled by the UKIAM (Figure 3.4) are sulphur dioxide (SO₂), nitrogen dioxide (NO_x), ammonia (NH₃), and particulate matter of 10 µm of diameter (PM₁₀) and 2.5 µm in diameter (PM_{2.5}). The outputs of UKIAM include total emissions, 5 × 5 km resolution deposition, and concentration maps from the modelled pollutants. For PM₁₀, PM_{2.5}, NO_x and NO₂, which are the pollutants of interest for this study, the UKIAM outputs 1 × 1 km resolution concentration and populated-weighted annual mean concentrations maps as well as source apportionment.

3.3.1.1 BRUTAL sub-model

The Background, Road and Urban Transport modelling of Air quality Limit values (BRUTAL) transport model (Figure 3.4) is a high-resolution module of the UK Integrated Assessment Model (UKIAM) (Oxley *et al.*, 2012, 2003, 2009). The BRUTAL model uses a bottom-up approach on individual roads to model traffic (cars, taxis, LGVs, HGVs (rigid and articulated), buses and motorcycles) (Oxley *et al.*, 2012, 2009) and captures the urban transport dynamics at the city level scale.

All roads on the UK national network (major, minor, and motorways) are mapped onto a 1 km × 1 km grid-square cell. Each grid cell is merged with information of traffic flows, the composition of the traffic and the average speed on each road using Department for Transport (DfT) and London Atmospheric Emissions Inventory (LAEI) data. Traffic growth factors for London are provided by Transport for London (TfL).

The BRUTAL model uses the integrated Model Of Vehicle Emissions (iMOVE) (Figure 3.4) (Valiantis, Oxley & ApSimon, 2007) to calculate aggregated emissions factors. i. The vehicle fleet split by vehicle category; ii. The vehicle fleet split by vehicle technology (Euro standards); and iii. The assumed road speed, derived from speed-dependent emission factors.

The speed-dependent emission factors in BRUTAL are calculated using the Computer Program to calculate Emissions from Road Transport (COPERT) as recommended by the European Environment Agency. The BRUTAL model uses the latest version of emissions factors called COPERT 5. It has been shown that the latest versions of COPERT speed-dependant emission factors correlate better with real driving emissions than older software versions (O'Driscoll *et al.*, 2016).

For each road in each grid-square, the BRUTAL model calculates carbon dioxide (CO₂) emissions from the local traffic, together with air pollutant emissions of nitrogen oxides (NO_x), nitrogen dioxide (NO₂), exhaust and non-exhaust particulate matter of 2.5 µm diameter or less (PM_{2.5}), and 10 µm diameter or less (PM₁₀). BRUTAL calculates non-exhaust particulate matter emissions from tyre and brake wear.

Roadside concentrations are also calculated for the road in each grid square with the highest emissions per unit length using enhancement factors to allow for street canyons. The calculations of exposure in this research are based only on background grid average concentrations.

Transport policy scenarios reflecting different emissions abatement strategies were implemented by making suitable modifications to the traffic or technology mix and are shown in the next section 3.4. The transport policy scenarios were modelled for urban transportation projected for 2030 in London.

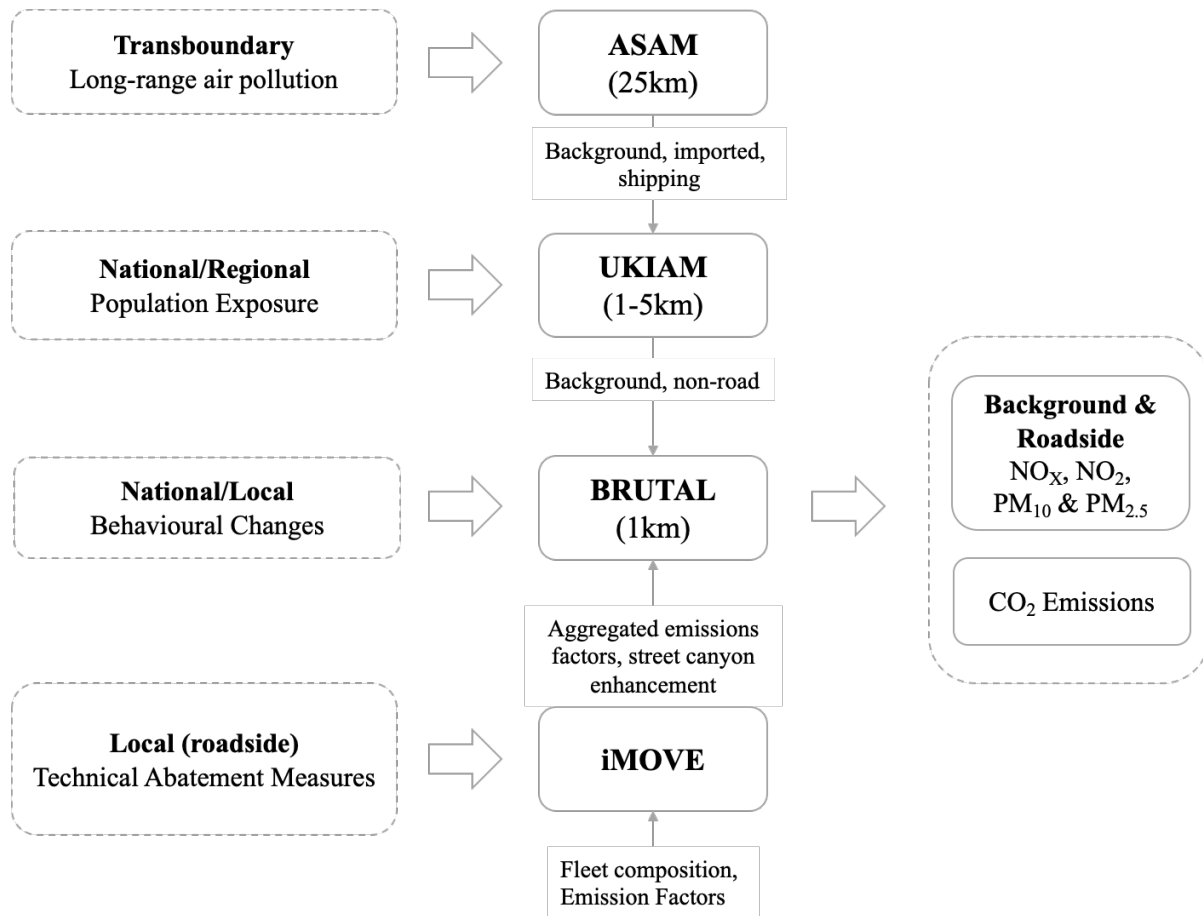


Figure 3.4 Description of the different modules included in the UKIAM model and used in the BRUTAL sub-model. Source: developed by the author from Oxley *et al.*, (2013).

3.3.1.1.1 BRUTAL sub-model assumptions and data requirements

- Traffic information:
Each grid cell is merged with information of traffic flows, the composition of the traffic and the average speed on each road using Department for Transport (DfT) and London Atmospheric Emissions Inventory (LAEI) data.
- Traffic growth:
Traffic growth factors for London are provided by Transport for London (TfL).
- Emission factors:
The BRUTAL model uses the latest version of emissions factors called COPERT 5.
- Non-exhaust emissions and concentrations:
The BRUTAL model calculates only non-exhaust emissions and concentrations from tyre and brake wear using a tier 1 (not speed dependant) approach.
- Concentration outputs:
The model predicts annual mean concentrations. The model does not predict hourly concentrations.

3.3.1.2 Exposure to air pollution

To calculate exposure to air pollution in the transport policy scenarios in London, the UKIAM model was used to calculate: background PM_{2.5} and NO₂ concentrations, and population-weighted mean concentrations (PWMC) for PM_{2.5} and NO₂.

London-wide background concentrations were calculated by weighting the background PM_{2.5} and NO₂ concentrations in each ward by the area of each ward (in London, there are a total of 625 wards). PM_{2.5} and NO₂ background concentrations were calculated for each transport policy scenario at the London-wide level.

Additionally, PM_{2.5} and NO₂ population-weighted mean concentrations (PWMC) are calculated by the UKIAM model by using the modelled spatial variability of PM_{2.5} and NO₂ concentrations at the 1 km × 1 km grid level and populations densities (Equation 3.3.1 and Equation 3.3.2) (Oxley, ApSimon & de Nazelle, 2015). The calculation of exposures can be extended for the analysis of spatially defined region (wards, boroughs, London) to derive the PWMC (Equation 3.3.2) (Oxley, ApSimon & de Nazelle, 2015).

For this research, we used PWMC at the ward and the London-wide level. Exposures at the ward level are calculated by intersecting PM_{2.5} annual mean concentrations with the ward level population density profiles of the London area (a total of 625 wards), with the information provided in the London Datastore by the Greater London Authority. PM_{2.5} and NO₂ population-weighted mean concentrations were calculated for each transport policy scenario at the London-wide level.

Equation 3.3.1

$$Exposure_{x,y} = Concentration_{x,y} \times Population_{x,y}$$

Where, x, y is the individual $1 \text{ km} \times 1 \text{ km}$ resolution grid cell.

Equation 3.3.2

$$PWMC_A = \frac{\sum_A (Concentrations_{x,y} \times Population_{x,y})}{\sum_A Population_{x,y}}$$

Where A refers to a specific, defined area/region. A could be wards or boroughs of London or the entire London-wide region.

3.3.1.3 Critical assessment of the model: Emissions factors and real-driving emissions

As mentioned before, the most updated versions of the BRUTAL model, which uses COPERT 5 emission factors were used for this research. The advantage of using COPERT factors is that they are speed-dependent emissions factors and have shown a better correlation with real-world emissions, therefore, reducing uncertainty (Kousoulidou *et al.*, 2013; O'Driscoll *et al.*, 2016). COPERT emissions factors have been validated using Portable Emissions Measurement System (PEMS), which is a valuable source of real-world operation data (Kousoulidou *et al.*, 2013; O'Driscoll *et al.*, 2016).

It has been shown that emissions of CO₂, HC and CO measure with PEMS correlated well with COPERT emission factors (Kousoulidou *et al.*, 2013). However, NO_x emission levels were shown to be consistently higher than the COPERT emission factors (Kousoulidou *et al.*, 2013; O'Driscoll *et al.*, 2016). O'Driscoll *et al.*, 2016 showed that PEMS measurements were on average 1.6 times higher than COPERT emission factors estimates for NO_x and 2.5 times for NO₂. Although 1.6 times higher sounds high, it has been shown that real-world emissions of NO_x often greatly exceed those achieved in the laboratory-based type approval process, sometimes up to 22 times (O'Driscoll *et al.*, 2016). Moreover, emissions are enhanced in congested conditions which are not represented in COPERT.

Therefore, COPERT emissions factors have shown to be representative of real-world emissions, although some uncertainty remains. For this reason, COPERT emissions factors are used by 22 of the 28 EU member states, including the UK, for road transport inventories, emissions projections, and road transport emissions modelling (Kousoulidou *et al.*, 2013).

3.3.1.4 Critical assessment of the model: Model validation

The BRUTAL-UKIAM model has been validated against measurements from London and national monitoring stations. Various locations and numerous studies showed good agreement between NO_x , NO_2 and PM_{10} concentrations modelled by UKIAM-BRUTAL and measurements from monitoring stations (Oxley *et al.*, 2013; ApSimon & Oxley, 2010; Carslaw, 2011). The latest validations of the UKIAM model with measurements has been recently published by Defra (2019). The results of this latest validation with measurements is presented below for $\text{PM}_{2.5}$ and NO_2 (Figure 3.5 and Figure 3.6), which are the main air pollutants studied in this dissertation.

Please note that performing a data collection in order to perform a model validation was outside the scope of my PhD. Therefore, all the data presented in this section was provided by my supervisor Prof. Helen ApSimon and different publications by the UKIAM modelling team.

3.3.1.4.1 Particulate matter

A comparison between UKIAM modelled $\text{PM}_{2.5}$ background concentrations and measurements of $\text{PM}_{2.5}$ concentrations from monitoring stations for the year 2016 is presented in Figure 3.5. As shown in the plot, the slope of the line is $m = 0.8477$, meaning that the UKIAM model tends to underestimate $\text{PM}_{2.5}$ background concentrations by approximately 15%.

The underestimation can be attributed to some stationary sources not included in the national inventory such as cooking; and also to uncertainties in non-exhaust emissions. Also, this slight underestimation can be the result of comparing grid-average concentrations (modelled in the UKIAM) with monitoring station highest measured values, which may be affected by local sources. Also, the inter-annual variability in the measurements due to meteorology needs to be considered as a factor to differ from modelling data.

Overall, the modelled $\text{PM}_{2.5}$ background concentration values from the UKIAM agree with the background concentration measurements of $\text{PM}_{2.5}$ concentrations from the monitoring network. The vast majority of $\text{PM}_{2.5}$ concentrations values fall within the two-factor boundary, the boundary which is used by modellers as an acceptable range. Recent UKIAM work has been focused on improving emissions and exploring uncertainties.

Note:

The validation exercise presented in this section was used to determine uncertainty ranges for the results modelled with UKIAM in this dissertation. Therefore, a 15% uncertainty range (error) (corresponding to the UKIAM underestimation showed in validation exercise) was considered in all the PM_{2.5} and PM₁₀ emissions and concentrations results modelled with UKIAM, which are presented in Chapter 4.

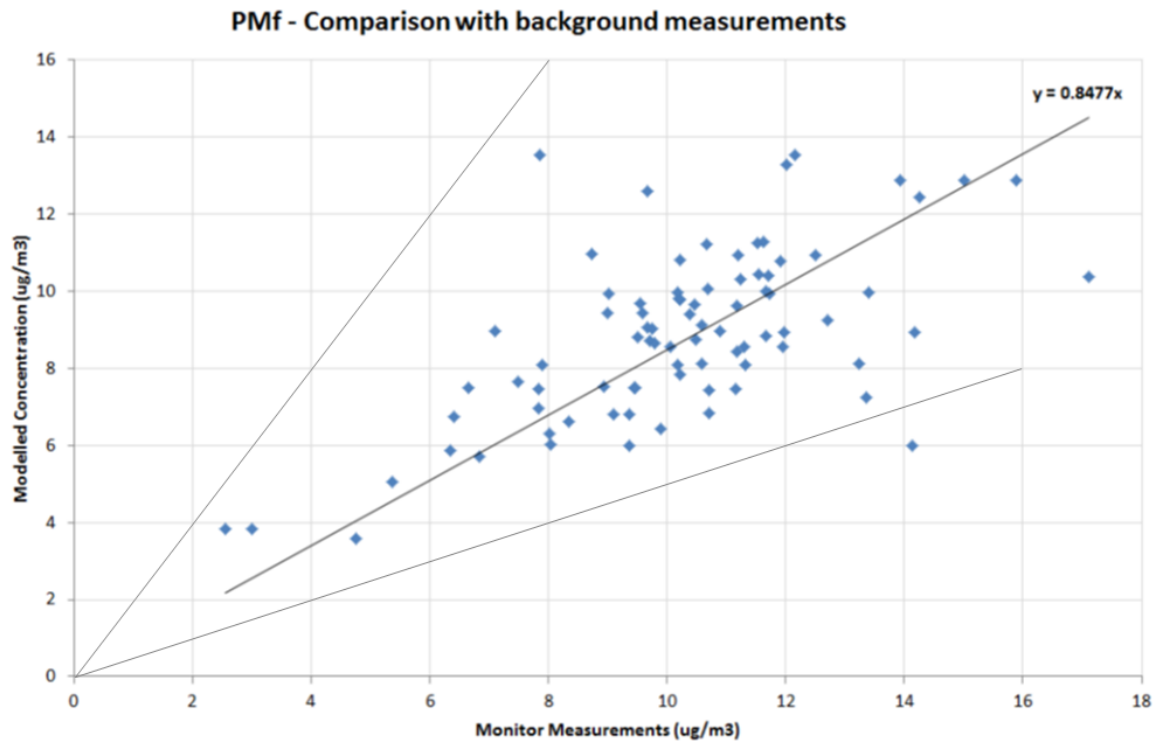


Figure 3.5 PM_{2.5} background concentrations comparison between modelled PM_{2.5} background concentrations by the UKIAM model (y-axis) and measurements of PM_{2.5} background concentrations from monitoring stations (x-axis). Source: Defra, 2019c.

3.3.1.4.2 Nitrogen Oxides

A comparison between UKIAM modelled NO₂ background concentrations taken from calculated values over a 1 × 1 km grid, and NO₂ concentration measurements from monitoring stations undertaken for the year 2015 is shown in

Figure 3.6. Similarly, to PM_{2.5} concentrations (Figure 3.5), the UKIAM underpredicts NO₂ background concentrations. However, the underprediction is larger for NO₂ than for PM_{2.5}. The slope of the line plotted, $m = 0.7263$, shows an underprediction of NO₂ background concentrations by around 28%. This underprediction is attributed to nitrogen oxide underestimation of COPERT emissions factors, as discussed in section 3.3.1.3. Future improvement of COPERT emission factors can reduce this uncertainty. Note that the scatter is less at the lower concentrations typical of background stations, but greater at the higher concentrations which include roadside monitoring stations.

Note:

The validation exercise presented in this section was used to determine uncertainty ranges for the results modelled with UKIAM in this dissertation. Therefore, a 28% uncertainty range (error) (corresponding to the UKIAM underestimation showed in validation exercise) was considered in all the NO_x and NO₂ emissions and concentrations results modelled with UKIAM, which are presented in Chapter 4.

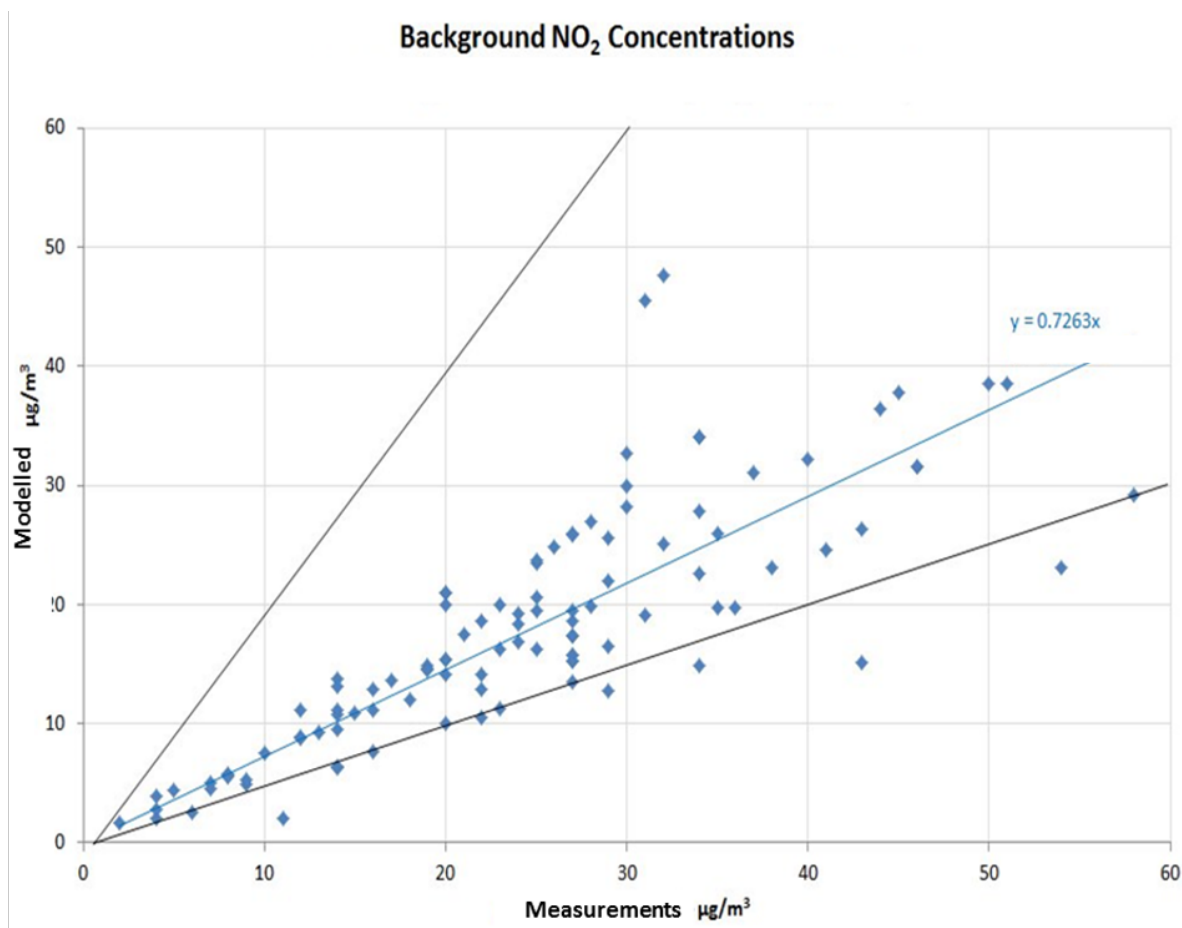


Figure 3.6 NO₂ background concentrations comparison between modelled NO₂ background concentrations by the UKIAM model (y-axis) and measurements of NO₂ background concentrations (x-axis) from monitoring stations. Source: Plot provided by supervisor Prof. Helen ApSimon.

3.3.1.4.3 Other model validation exercises

Other, older published validation exercises (Figure 3.7) of the UKIAM model and its BRUTAL sub-model (Oxley *et al.*, 2013) have also shown to be consistent with more recent measurements in the way that all data falls within the two-factor boundary. Oxley *et al.*, 2013, studied kerbside, roadside, suburban, and air quality concentrations. However, only urban background air quality concentrations are relevant for this dissertation since those were the values used for the analysis. Urban background concentrations of NO₂ and PM₁₀ were consistent with measurements in this 2010 exercise, resulting in a correlation coefficient, r , of $r = 0.72$ for PM₁₀ and $r = 0.56$ for NO₂ concentrations.

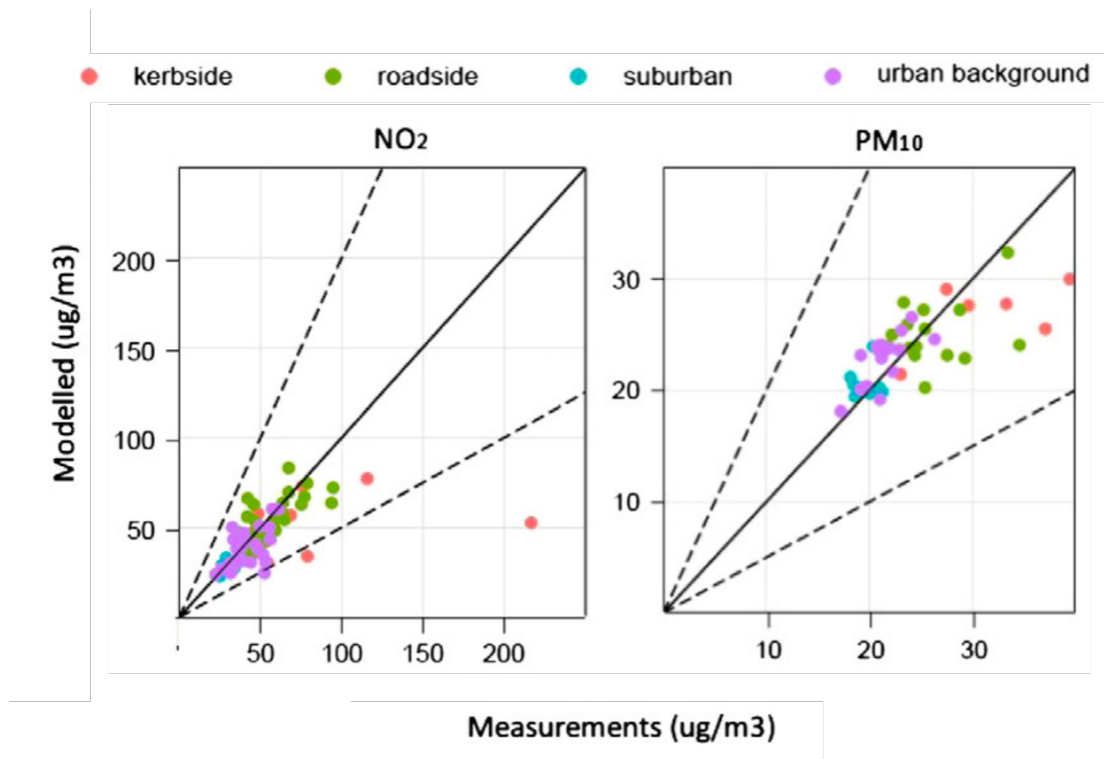


Figure 3.7 Comparison of NO₂ and PM₁₀ concentrations modelled by UKIAM/BRUTAL against measurements from the London Air Quality Network (LAQN) for 2010. Source: Oxley *et al.*, 2013.

3.3.1.5 Critical assessment of the model: Model inter-comparison, urban model evaluation

A comparison between urban air quality models in London which were capable of predicting air quality concentrations at the urban scale was made by Defra (2013). In this report (Defra, 2013) the following urban models were evaluated: ADMS-Urban from Cambridge Environmental Research Consultants (CERC); BRUTAL (Background, Roads and Urban Transport modelling of Air quality and Limit values) from Imperial College London; ERG-Toolkit; and the PCM (Pollution Climate Mapping) from Ricardo-AEA. Please refer to section 2.6 for a description of these urban models.

This urban model evaluation done by Defra (2013) helps us to understand the main differences between the BRUTAL model, used in this dissertation, and the rest of the most widely used urban models in London.

3.3.1.5.1 Particulate matter

A transverse section at a constant latitude which passes through central London, for PM_{10} and $PM_{2.5}$ concentrations by the four urban models are shown in Figure 3.8, developed by Defra (2013). The BRUTAL model tends to estimate the highest PM_{10} concentrations (left panel in Figure 3.8). The PCM tends to estimate lower PM_{10} concentrations, especially in the west part of central London (around easting = 525000). All the models agree in the location of the highest PM_{10} concentrations, around easting = 530000.

However, the most important disparity among the models is shown for $PM_{2.5}$ concentrations (right panel in Figure 3.8). BRUTAL and PCM $PM_{2.5}$ concentrations are considerably higher than ADMS-Urban and ERG-Toolkit $PM_{2.5}$ concentrations. ADMS-Urban shows a considerably lower $PM_{2.5}$ concentration profile than the other models. Also, the highest $PM_{2.5}$ concentrations are found in different locations. BRUTAL and PCM highest $PM_{2.5}$ concentrations are located at around easting = 53000 while ADMS-Urban and ERG-Toolkit highest $PM_{2.5}$ concentrations are located at around easting = 525000.

It is shown in Defra (2013) that the most significant disparity among the models with regard to particulate matter concentration relates to estimations of non-exhaust particulate matter emissions. Not all the models estimate non-exhaust emissions from the same component. For example, some models such as BRUTAL only include estimates from tyre and brake wear non-exhaust particulate matter emissions. Other models in addition to non-exhaust tyre and brake wear account for particle resuspension (PCM).

As explained in Defra (2013), the dissimilarities among the models (in particular for PM_{10} and $PM_{2.5}$ estimates) are explained by the different level of background PM_{10} and $PM_{2.5}$ used in the models. Also, the differences are caused by the use of different inventories as input for each model. The ADMS-Urban and ERG-Toolkit used the London Atmospheric Emissions Inventory (LAEI) to model most of its scenarios. BRUTAL and PCM used the National Atmospheric Emissions Inventory (NAEI) to model its scenarios. Overall, the models using the LAEI (ADMS-Urban and ERG-Toolkit) tend to give lower $PM_{2.5}$ concentrations than models using the NAEI (BRUTAL and PCM).

The assumptions used in these two inventories, LAEI and NAEI are different, particularly for the contribution from non-exhaust vehicle emissions and concentrations. The different assumptions of the input data may account for the largest differences between the models rather than inherent dissimilarities in modelling approach per se (Defra, 2013). Therefore, there is considerable scope for minimising the differences between the models by using a consistent set of input data (such as emissions inventories).

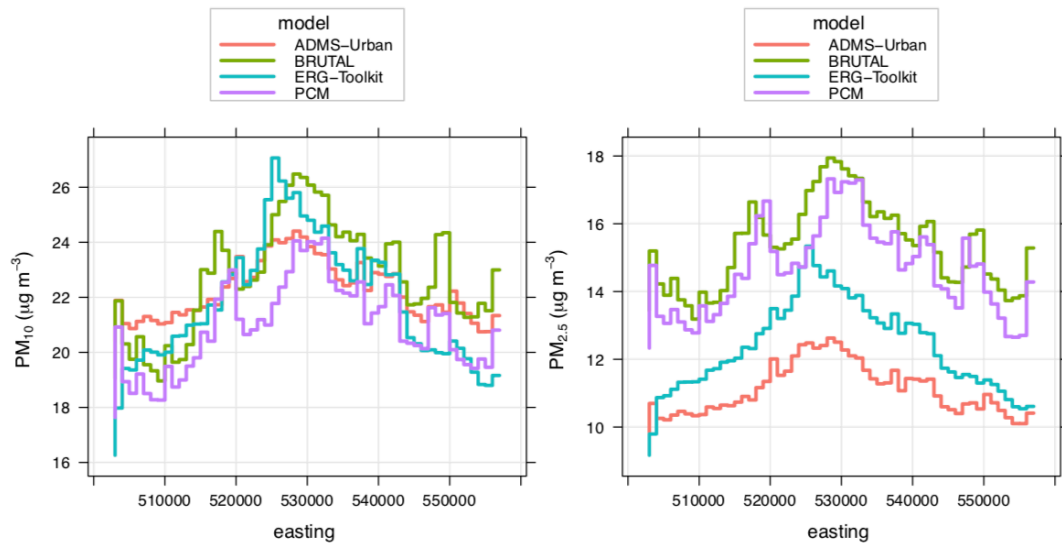


Figure 3.8 Transverse section for PM_{10} and $PM_{2.5}$ concentrations (μm^{-3}) aggregated to $1 km^2$ by four urban models in London. Source: Defra, 2013.

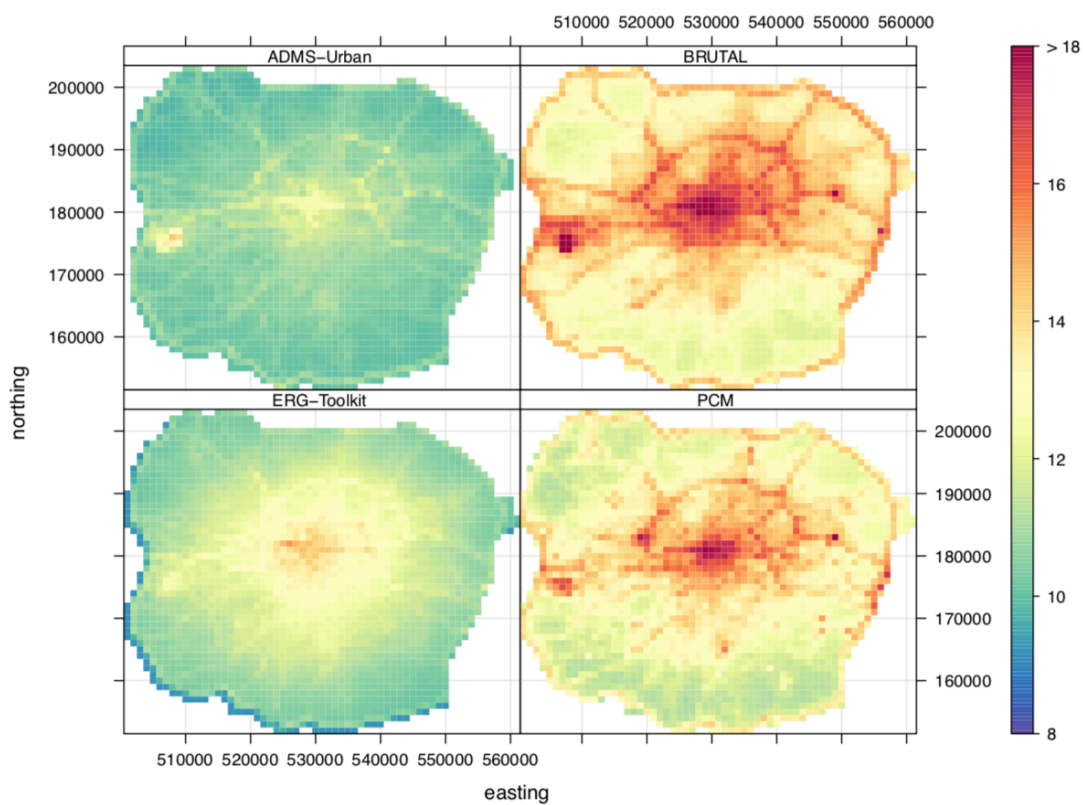


Figure 3.9 Surface distribution of annual mean PM_{2.5} concentration (μm^{-3}) by four urban models in London.
Source: Defra, 2013.

3.3.1.5.2 Nitrogen oxides

To facilitate the study of differences between the models, a transverse section at constant latitude across central London developed by Defra (2013), is presented in Figure 3.10. As can be seen in the left panel in Figure 3.10, very similar and high, NO_x concentrations are given by the ADMS-Urban and ERG-Toolkit models. BRUTAL and PCM show lower and very similar NO_x concentrations. The BRUTAL and PCM models show similar NO_x concentrations to the ADMS-Urban model in the west part of central London (around easting = 515000). The largest differences in NO_x concentrations between BRUTAL and PCM compared with ADMS-Urban and ERG-Toolkit are observed for the west part of central/inner London around easting = 525000.

Similar behaviour between the four models is observed for NO₂ concentrations (right panel in Figure 3.10). BRUTAL and PCM modelled the lowest NO₂ concentrations compared to higher NO₂ concentrations modelled by ADMS-Urban and ERG-Toolkit. The largest differences in NO₂ concentrations between BRUTAL and PCM compared with ADMS-Urban and ERG-Toolkit are also observed for the west part of central/inner London around easting = 525000.

In Figure 3.11, the distribution of NO₂ concentrations on a 1 km² basis developed by Defra (2013) are shown. In the four models, the highest NO₂ concentration (concentrations of NO₂ exceed 40 µgm⁻³) are shown across central London and Heathrow Airport. In the four models, the significance of the road sources for NO₂ concentrations can be appreciated. As was shown in the transverse section at constant latitude across central London, there are more similarities between ADMS-Urban and ERG-Toolkit and between BRUTAL and PCM. Also, as one would expect, the road sources of ADMS-Urban are more prominent than either the BRUTAL or PCM.

The differences between the NO_x and NO₂ concentrations modelled by the four urban models evaluated are likely related to the different inventories used in each model. In this urban model evaluation (Defra, 2013), most scenarios modelled with BRUTAL and PCM were based on the National Atmospheric Emissions Inventory (NAEI). For this reason, BRUTAL and PCM give similar NO_x and NO₂ concentrations. In contrast, the ADMS-Urban and ERG-Toolkit used the London Atmospheric Emissions Inventory (LAEI) to model most of its scenarios. Overall, the models using the LAEI (ADMS-Urban and ERG-Toolkit) tend to show higher NO_x and NO₂ concentration than those using the NAEI (BRUTAL and PCM).

It is important to notice that for this dissertation, an updated version (from the version used in Defra (2013)) of the BRUTAL model was used. The updated version of the BRUTAL model used in this dissertation did model most of the scenarios using the LAEI.

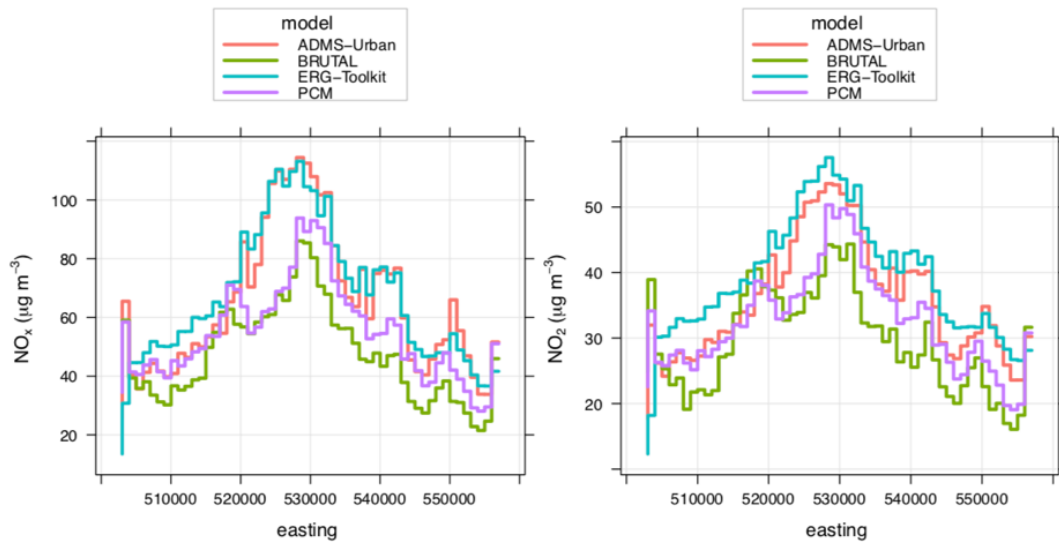


Figure 3.10 Transverse section at constant latitude (at 180000 northing) which passes through central London, for NO_x and NO_2 concentrations (μm^{-3}) aggregated to 1 km^2 by four urban models in London. Source: Defra, 2013.

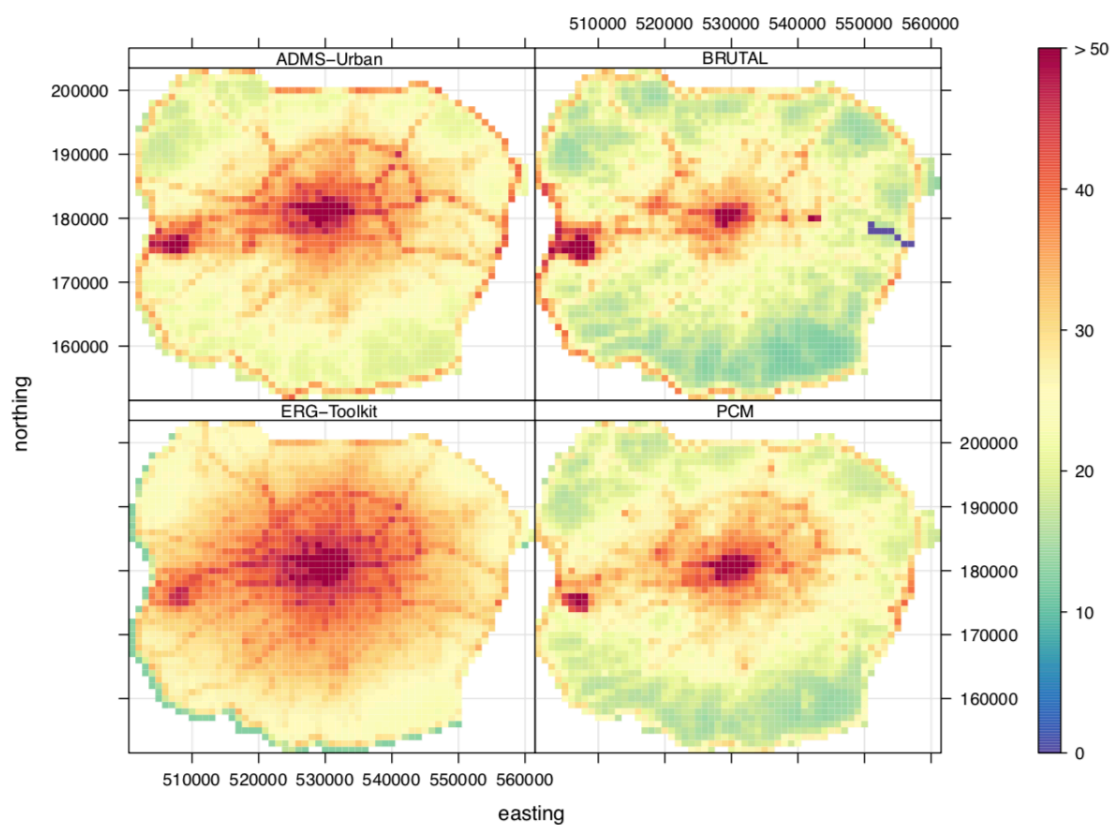


Figure 3.11 Surface distribution of annual mean NO₂ concentration (μm⁻³) by four urban models in London.
Source: Defra, 2013.

3.3.1.6 Critical assessment of the model: UKIAM-BRUTAL and LAEI 2030 emissions projections comparison

In order to evaluate and critique the BRUTAL model, I made a comparison between the 2030 BRUTAL model emissions projections and the 2030 projections reported by the London Atmospheric Emissions Inventory (LAEI) (GLA, 2017a). The LAEI 2030 projections were modelled using the King's College London CMAQ-Urban model (KCL, 2019). Please refer to section 2.6 for a detailed description of these two models.

Road transport carbon dioxide (CO₂), nitrogen oxide (NO_x), and particulate matter (PM) exhaust and non-exhaust emissions projected to 2030 by BRUTAL baseline and the LAEI are compared and discussed below. BRUTAL 2030 baseline vehicle mix and assumptions are described in detail in section 3.4.1, table 3.10.

3.3.1.6.1 Carbon dioxide (CO₂) emissions

Total road transport carbon dioxide (CO₂) emissions projected to 2030 (Figure 3.12) by the BRUTAL are overall 13% higher than total CO₂ emissions reported in the LAEI. The BRUTAL model projects 0.89 M tonnes of CO₂ more in 2030 than the LAEI.

The largest difference in 2030 CO₂ emissions projected to 2030 is for taxis. BRUTAL projects 60% more CO₂ emissions in 2030 than the LAEI. This significant difference of the CO₂ emissions from taxis could be explained by the LAEI assuming a larger amount of electric taxis by 2030 than those assumed in the BRUTAL model. Unfortunately, the LAEI 2030 does not report the exact assumptions used for its emissions calculations. Therefore, we cannot make a comparison with the assumptions made in the construction of BRUTAL 2030 baseline (described in section 3.4 and table 3.10).

Also, for buses, the CO₂ emissions projected by 2030 by the two models are in disagreement by 35%. In contrast to an overestimation of CO₂ emissions for taxis by BRUTAL, this time the BRUTAL model assumes 35% lower CO₂ emissions by buses in 2030 than LAEI. This may be likely explained by the fact that BRUTAL 2030 baseline does include electric buses. LGV CO₂ emissions projected to 2030 are the most similar, with only a 2% difference between BRUTAL and LAEI.

Note:

The comparison exercise presented in this section was used to determine uncertainty ranges for the results modelled with UKIAM in this dissertation. Therefore, a 13% uncertainty range (error) (corresponding to the difference resulted with LAEI) was considered in all the CO₂ emissions results modelled with UKIAM, which are presented in Chapter 4.

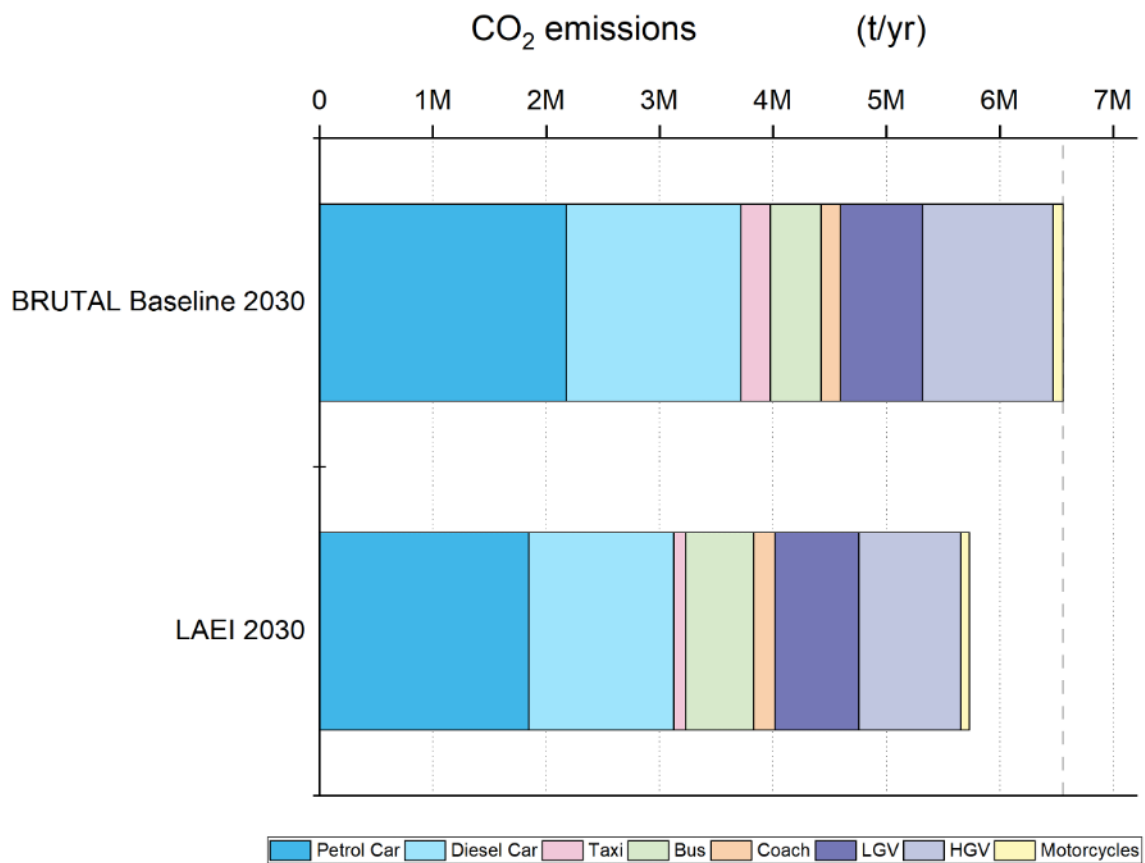


Figure 3.12 Road transport carbon dioxide (CO₂) emissions projected to 2030 by the BRUTAL sub-model and reported in the London Atmospheric Emissions Inventory (LAEI). The emissions per vehicle type are indicated.

3.3.1.6.2 Nitrogen oxide (NO_x) emissions

Total road transport nitrogen oxide (NO_x) emissions projected to 2030 (Figure 3.13) are 24% higher in BRUTAL than in LAEI. The largest difference in the NO_x projections is from taxi emissions (similar to that of CO₂ emissions). BRUTAL projects 79% higher NO_x emissions from taxis than LAEI in 2030. As discussed for CO₂ emissions, this difference could be explained by the LAEI, including more electric taxis in its vehicle fleet projections in 2030. Including electric taxis in the vehicle fleet will considerably reduce NO_x (and CO₂) emissions, more NO_x emission would be reduced if diesel taxis are replaced.

Again similar to CO₂ emissions, the second largest difference between emission projections in 2030 is for buses. BRUTAL projects 53% fewer NO_x emissions than LAEI in 2030. As mentioned before, a possible explanation for this disparity is that BRUTAL includes electric buses in its baseline 2030. The introduction of electric buses would reduce NO_x emissions significantly since buses run with diesel fuel-producing high NO_x emissions.

The vehicle type with the most similar NO_x emissions projected to 2030 by BRUTAL and LAEI are HGVs and LGVs. BRUTAL estimates 1% fewer emissions than LAEI for HGVs and 6% more NO_x emissions than LAEI for LGVs. This behaviour could mean that BRUTAL and LAEI project similar kilometres driven by HGVs and LGVs in 2030.

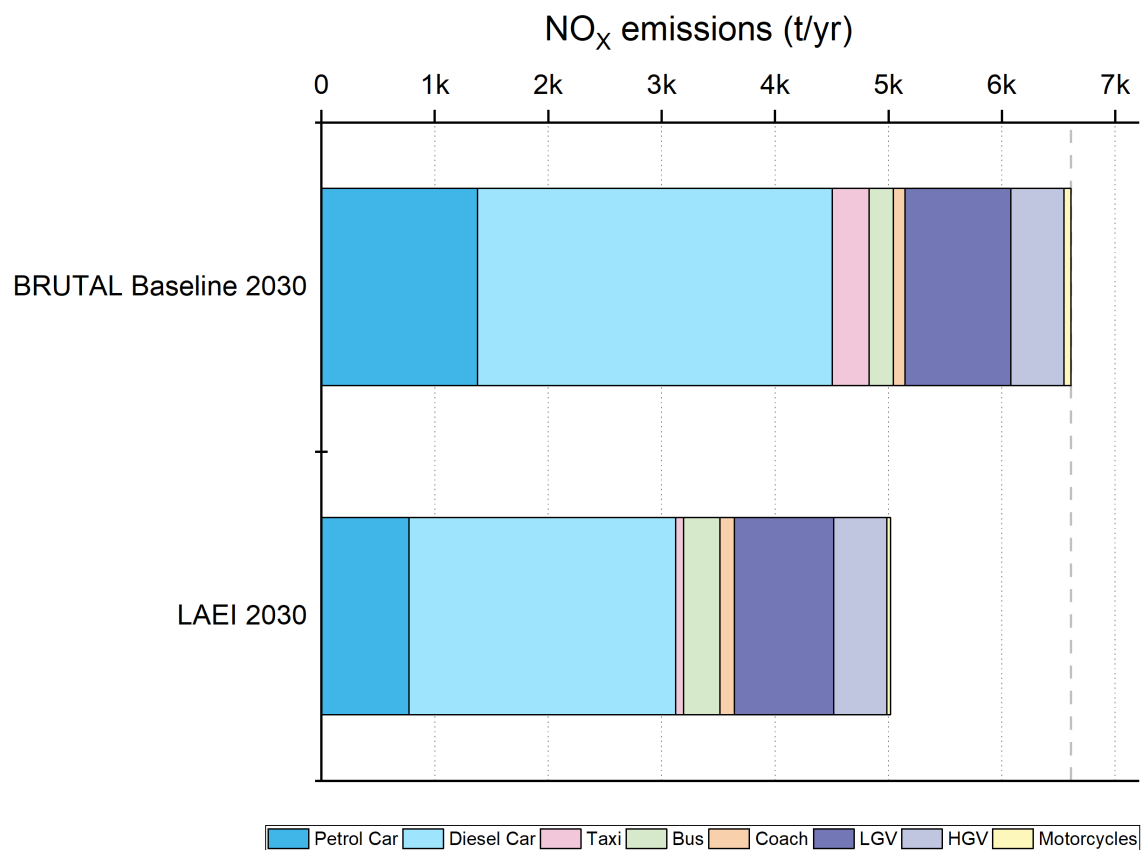


Figure 3.13 Road transport nitrogen oxide (NO_x) emissions projected to 2030 by the BRUTAL sub-model and reported in the London Atmospheric Emissions Inventory (LAEI). The emissions per vehicle type are indicated.

3.3.1.6.3 Particulate matter (PM) emissions

Exhaust particulate matter emissions

Road transport exhaust particulate matter (PM₁₀) emissions projected to 2030 (Figure 3.14) are 34% lower in BRUTAL than in LAEI. In contrast to a higher prediction of CO₂ and NO_x emissions, for exhaust particulate matter the UKIAM projects lower emissions in 2030.

The vehicle type with the largest difference in PM₁₀ exhaust emissions projections between the models are buses; LAEI projects 2.6 times higher PM₁₀ exhaust emissions than BRUTAL. In the same way, for HGV the LAEI projects two times higher PM₁₀ exhaust emissions than BRUTAL. Also, for petrol cars, BRUTAL projects 70% lower PM₁₀ exhaust emissions than LAEI. This larger difference in PM₁₀ exhaust emissions may be related to the use of different PM₁₀ exhaust emission factors in urban areas plus different projections of kilometres driven by vehicle types in 2030.

For taxis, BRUTAL does estimate higher emissions than LAEI. This is consistent with the behaviour observed for CO₂ and NO_x emissions from taxis, where BRUTAL always projected higher emissions than LAEI. As mentioned before, this may be explained by the LAEI, including a higher rate of electric taxis in its vehicle fleet distribution.

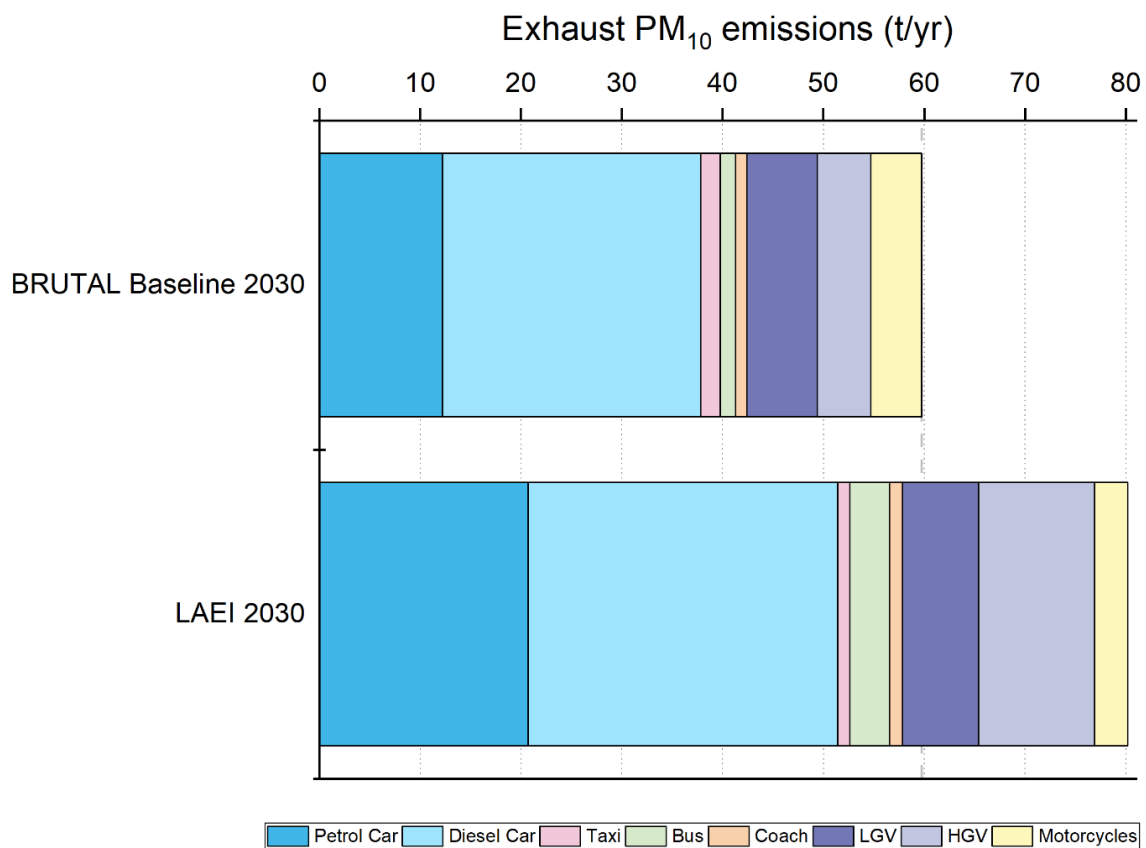


Figure 3.14 Road transport particulate matter (PM₁₀) exhaust emissions projected to 2030 by the BRUTAL sub-model and reported in the London Atmospheric Emissions Inventory (LAEI). The emissions per vehicle type are indicated.

Non-exhaust particulate matter emissions

The most critical difference between 2030 emissions projections by BRUTAL and LAEI is for non-exhaust particulate matter emissions (Figure 3.15). As mentioned in the sections above (3.3.1.1), BRUTAL calculates non-exhaust particulate matter emissions from tyre and brake wear. LAEI 2030 projections were also published for non-exhaust particulate matter emissions from tyre and brake wear. However, it is important to mention that LAEI 2016 current inventory (GLA, 2019) additionally to non-exhaust particulate matter emissions from tyre and brake wear, also includes non-exhaust particulate matter emissions from resuspension (GLA, 2017a).

The significant disparity of non-exhaust particulate matter 2030 estimates by BRUTAL and LAEI are driven by how brake wear non-exhaust particulate matter emissions are estimated (Figure 3.15). LAEI projects 5.6 times higher 2030 brake wear non-exhaust PM_{10} emissions than BRUTAL. In contrast, tyre wear non-exhaust PM_{10} emissions estimates are in agreement. BRUTAL 2030 tyre wear non-exhaust PM_{10} emissions are only 22% lower than LAEI 2030 tyre wear non-exhaust PM_{10} emissions estimates.

The different brake wear non-exhaust PM_{10} emissions estimates are explained because the LAEI uses speed dependant brake wear non-exhaust PM_{10} emission factors, and BRUTAL does not. For this reason, brake wear non-exhaust PM_{10} emissions are significantly higher in LAEI since in London traffic congestion considerably augments brake wear non-exhaust particulate matter emissions. Urban areas are dominated by brake wear emissions. Brake wear emission factors are nine to ten times higher at low speeds, 0 to 40 km/h, (common vehicle speeds in the urban area) (AQEG, 2019).

This is clearly a source of uncertainty for the particulate matter projections done with BRUTAL. My analysis helped to give the evidence on how using non-speed dependant non-exhaust emissions factors could involve a high underestimation of particulate matter emissions. Thanks to my analysis, the Imperial College London modelling group is currently modifying BRUTAL to use speed dependant non-exhaust emissions factors.

Correct estimation of non-exhaust particulate matter emissions in London is critical because in 2030, for example, non-exhaust emissions are projected to account for 96% of total PM_{10} emission according to LAEI and 90% of total PM_{10} emissions according to BRUTAL. The same behaviour occurs for $PM_{2.5}$ emissions.

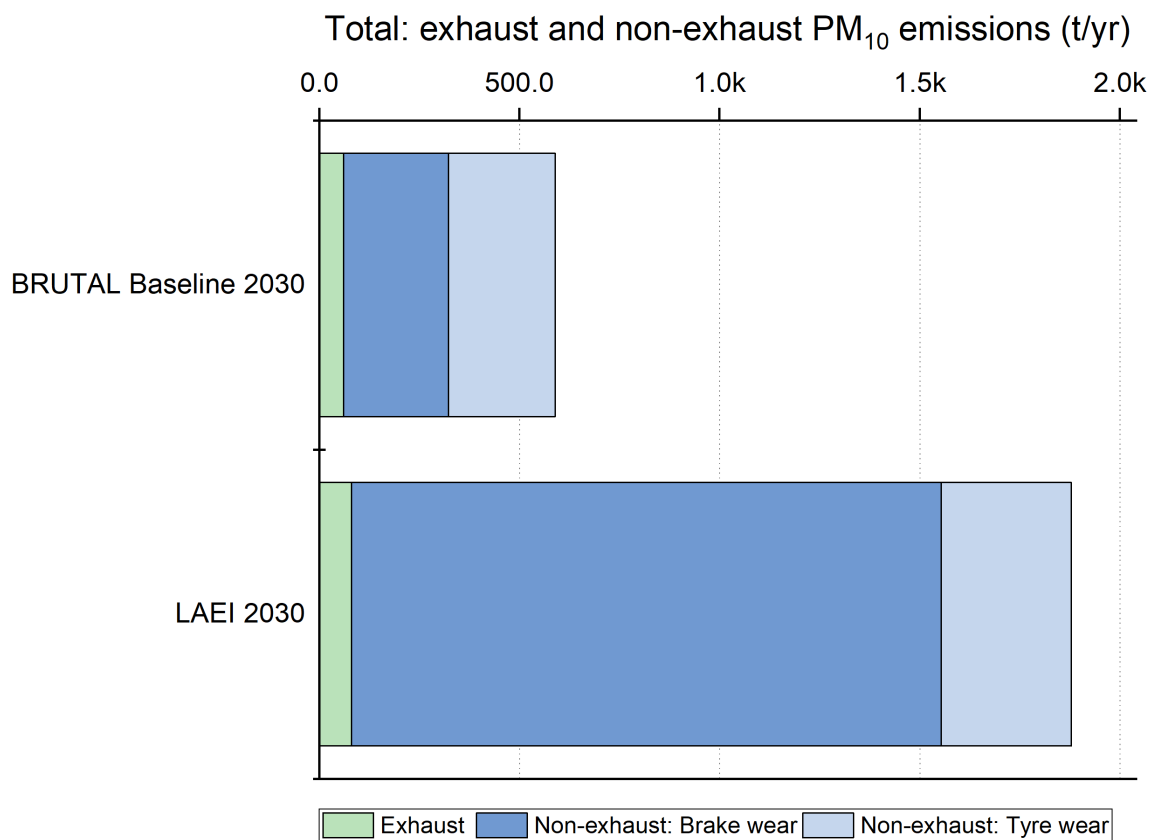


Figure 3.15 Road transport total particulate matter (PM₁₀) exhaust and non-exhaust emissions projected to 2030 by the BRUTAL sub-model and reported in the London Atmospheric Emissions Inventory (LAEI). Non-exhaust emissions from brake and tyre wear are displayed, and the emissions per vehicle type are indicated.

3.3.1.6.4 Discussion

The 2030 emissions projection is consistent with results from the LAEI and the BRUTAL studies for CO₂ and NO_x. BRUTAL projects higher CO₂ emissions by 22% and higher NO_x emission by 24% than LAEI. The differences in estimating CO₂ and NO_x 2030 emissions could be explained by the different vehicle mix distribution used in BRUTAL and LAEI. Unfortunately, LAEI did not make public the vehicle mix used in its estimations neither the assumptions of electric vehicle fleet penetration. The detailed description of BRUTAL 2030 baseline (used in this comparison) is described in section 3.4.1, table 3.10.

For example, consistently higher estimations of taxi emissions (CO₂, NO_x, and PM₁₀ exhaust) were observed by the BRUTAL model. This is likely to be justified by the number of electric taxis projected to 2030 in the vehicle fleet of the two models. LAEI could have assumed a larger amount of electric taxis in the 2030 fleet. Electric taxis would reduce CO₂, PM₁₀ exhaust emissions and especially NO_x emissions because diesel taxis with high NO_x emission factors would be converted to electric.

The most significant difference between BRUTAL and LAEI 2030 emissions projection is for particulate matter emissions, in particular, non-exhaust particulate matter emissions. LAEI 2030 projects three times higher total PM₁₀ emissions than BRUTAL. This important difference is driven by how brake wear non-exhaust PM emissions are calculated in LAEI and BRUTAL. LAEI, different to BRUTAL, uses speed dependant emissions factors for non-exhaust PM emissions to reflect the higher brake wear emissions in urban areas due to traffic congestion. My analysis highlighted this flaw of the BRUTAL model, and thanks to this, the modelling team at Imperial College is currently correcting the BRUTAL model to include speed-dependant non-exhaust particulate matter emission factors.

3.3.2 Mexico City

The analysis for Mexico City was limited by lack of data and modelling resources. However, a simpler modelling approach was taken. This analysis was included in the dissertation because even if the analysis is simple, no similar analytic approach has been published in the literature specifically for Mexico City.

3.3.2.1 Emissions inventory

The analysis of transport policy scenarios in Mexico City was restricted by lack of input data and lack of modelling capability which prevented air pollution modelling. The analysis of CO₂ emissions and air pollutants was restricted and simplified to the use of the latest Emissions Inventory 2016 (SEDEMA, 2017b). The analysis was still completed, albeit with a non-sophisticated modelling approach, because there is a need to increase knowledge and understanding of the impacts of transport policies such as electric vehicles and active travel modes on Mexico City.

The modelling tool used by the Ministry of Environment for Mexico City (SEDEMA) to develop the emissions inventory is an adaptation of Environmental Protection Agency's (USA) MOtor Vehicle Emission Simulator (MOVES) (EPA, 2016) developed specifically for Mexico (called MOVES-Mexico), which allows estimating emissions from mobile sources for air pollutants, greenhouse gases, and air toxics.

The analysis of emissions of the transport policy scenarios for Mexico City was done using the reported emissions in the inventory which are desegregated by vehicle type and vehicle model year for the following pollutants: CO₂, NO_x, PM_{2.5} and PM₁₀. NO₂ emissions were not reported in the inventory and could not be considered. The technological and behavioural change transport policy scenarios were constructed by changing the kilometres travelled by different vehicle types.

The average emissions factors (Table 3.2) of CO₂, NO_x, PM_{2.5}, PM₁₀ reported in the emissions inventory of Mexico City, desegregated by vehicle type and vehicle fuel, were used to estimate emissions for the different vehicle types in each transport policy scenario (SEDEMA, 2017a). The emissions estimated for

the scenarios were constructed by subtracting emissions reported in the inventory which are disaggregated by vehicle type.

The estimation of emissions for each transport policy scenario was done using a spreadsheet model based on information from the Emissions Inventory in Mexico City (SEDEMA, 2017b). Emissions of CO₂, NO_x, PM_{2.5} and PM₁₀ were estimated for every transport policy scenario relative to the baseline scenario that captured the current road transport composition in Mexico City.

All the information provided in the emissions inventory was used to build this spreadsheet model that allows us to calculate changes in emissions due to variations in the vehicle fleet composition (kilometre travelled or some vehicles). With the information in the emissions inventory we can quickly know, for example, that in 2016 in Mexico City there were 1,168 cars of the model year 1988 (approximately 30 years old) that travelled 5.2 M km per year (so each car model 1988 travelled approx. 12 km/day). Moreover, the information provided in this model tells us that these old cars emitted a total of 13.19 t NO_x, 2.4 kt of CO₂. Using the model, we can also know what would happen to the emissions in Mexico City if we could get scrappage or replace all of those 30 year-old cars.

Table 3.2 Average emissions factors reported in the Emissions Inventory 2016 of Mexico City for CO₂, NO_x, PM_{2.5} and PM₁₀ desegregated by vehicle type and vehicle fuel (petrol or diesel) (SEDEMA, 2017b).

Vehicle type	CO ₂		NO _x		PM _{2.5}		PM ₁₀	
	(g/km)		(g/km)		(g/km)		(g/km)	
	Petrol	Diesel	Petrol	Diesel	Petrol	Diesel	Petrol	Diesel
Car	308.59	335.59	0.77	0.35	0.021	0.010	0.071	0.059
Taxi	277.80	357.07	0.64	0.67	0.015	0.044	0.066	0.097
SUV	437.06	633.55	1.24	2.09	0.021	0.213	0.075	0.276
Pick up van	437.13	613.56	1.16	1.79	0.026	0.195	0.081	0.265
Van	440.18	634.18	0.87	2.03	0.025	0.210	0.082	0.284
Bus	1,039.57	1,644.70	5.31	14.89	0.145	1.630	0.263	2.150
BRT	-	916.17	-	5.10	-	0.534	-	0.883
LGV	434.39	585.31	0.82	1.62	0.016	0.160	0.072	0.229
HGV	964.85	1,179.25	3.89	10.31	0.094	1.115	0.310	1.507
Tractor	-	1,748.11	-	14.76	-	1.715	-	2.347
Motorcycles	236.61	-	0.41	-	0.014	-	0.028	-

3.3.2.1.1 Uncertainties

The Emissions Inventory of Mexico City 2016 (SEDEMA, 2017b) only reports uncertainties for greenhouse gases emissions following IPCC methodology to calculate uncertainties. This methodology weights the uncertainty of the emissions from each vehicle type by its percentage contribution to the total emissions. The uncertainties percentage reported in the Emissions Inventory for CO₂ (Table 3.3) were used to calculate uncertainties of CO₂ emission in the transport policy scenarios, due to lack of information about uncertainties of other gases, the average weighted uncertainty for greenhouse gases ($\pm 7.8\%$) was used as the uncertainty of air pollutants (NO_x, PM_{2.5} and PM₁₀).

Table 3.3 Percentage contribution to CO₂ emission by vehicle type, and corresponding uncertainty by vehicle type, total weighted uncertainties for CO₂ and greenhouse gases (SEDEMA, 2017b).

Vehicle type	Contribution to CO ₂ emissions	Uncertainty
	Percentage (%)	Percentage (%)
Car	24.3	5.7
Taxi	11.8	2.8
SUV/Van	7.9	1.8
Pick up van/LGV	2.8	0.7
Bus/BRT	9.5	0.9
HGV	4.2	0.4
Tractor	7.8	0.8
Motorcycles	7.4	1.7
Total weighted uncertainty for CO ₂		6.65
Weighted uncertainty for greenhouse gases		7.8

Note: *Uncertainty percentage used for air pollutant due to lack of information.

3.3.2.2 Particulate matter non-exhaust emissions from electric vehicles

Technological change policy scenarios for Mexico City (described in Section 3.2.2) included the introduction of electric vehicles in the vehicle fleet. Emissions factors from non-exhaust emissions (Table 3.4), necessary to calculate particulate matter emissions from electric vehicles, are not reported in the Emissions Inventory of Mexico City.

Thus, the particulate matter non-exhaust emissions factors from the UKIAM model were used to estimate particulate matter non-exhaust emissions factors for Mexico City. A factor of two was applied to the particulate matter non-exhaust emissions factors from London (UKIAM model) as an approximation to the particulate matter non-exhaust emissions factors for Mexico City. Factor two came from the analysis of PM_{2.5} and PM₁₀ emissions in Mexico City and London. Even if the two cities have a similar number of cars (2.3 and 2.7 million cars, respectively), Mexico City's PM_{2.5} and PM₁₀ emissions are 2.2 to 2.5 times higher than PM_{2.5} and PM₁₀ emissions in London. Not having particulate matter non-exhaust emissions factors for Mexico City is a limitation of the study.

Table 3.4 Particulate matter (PM) non-exhaust (tyre and brake wear) emissions factors for Mexico City derived as a factor of two from London's PM non-emissions emissions factors (from the UKIAM model).

Vehicle type	PM non-exhaust emissions factors for electric vehicles (g / km)			
	London		Mexico City	
	(UKIAM model)		(factor of two from London emission factors)*	
	PM _{2.5} (g/km)	PM ₁₀ (g/km)	PM _{2.5} (g/km)	PM ₁₀ (g/km)
Electric Car, Electric Taxi	0.0058	0.0105	0.0116	0.0210
SUV, Pick Up Van, Van	0.0093	0.0166	0.0186	0.0332
Electric Bus, BRT	0.0289	0.0565	0.0578	0.1130
LGV	0.0093	0.0166	0.0186	0.0332
Electric Motorcycles	0.0028	0.0051	0.0056	0.0102

Note *A factor of two is taken to calculate emissions factors in Mexico City from the proportion of PM emissions from London and Mexico City.

3.3.2.3 Air pollutants annual mean concentrations

As explained earlier, air pollution modelling for Mexico City was not possible to perform due to the lack of modelling resources. Thus, information on current PM_{2.5} and NO₂ air pollutants average annual mean concentrations (Table 3.5) from monitoring stations were used, from Mexico City's analysis (SEDEMA, 2018a). These PM_{2.5} and NO₂ average annual mean concentration values were used as input values for the Health Impact Assessment (HIA) modelling. For the HIA modelling exercise, the annual mean concentration values in the metropolitan area were used. For the uncertainty analysis of health impacts in Mexico City, an upper limit (highest concentration recorded in the Metropolitan area) and the lowest limit (WHO limit) were used (SEDEMA, 2018a) (Table 3.5).

Table 3.5 PM_{2.5} and NO₂ average annual mean concentration values from monitoring stations in Mexico City used as input values for the Health Impact Assessment modelling, for the calculation of the mean value.

Note: For the sensitivity analysis, the highest value of annual mean concentration recorded from monitoring stations was used as the upper limit and the recommended WHO annual mean concentration values were used as the lower/WHO limit.

Pollutant	PM _{2.5} (µg/m ³)	NO ₂ (µg/m ³)	Notes	Source
Mean value	23.1	29.5	Average annual mean concentration value from monitoring stations in Mexico City	(SEDEMA, 2018a)
Upper limit	52	52		
WHO limit	10	40	Discussed in section 2.4.1.1, Table 2.4	(WHO, 2006)

3.3.3 Emissions from electricity generation to power electric vehicles

3.3.3.1 CO₂ emissions from electricity generation

In order to calculate CO₂ emissions factors from electricity generated to power electric vehicles (Table 3.6) for London and Mexico City transport policy scenarios, the UK Government Conversion Factors for greenhouse gas (GHG) for electric vehicles (BEIS, 2018) were used as a reference.

The electricity conversion factors (Table 3.6) represent the average CO₂ emission from the UK national grid per kWh of electricity generated at UK power stations and from auto generators, plus those from the proportion of imported electricity. In addition to the CO₂ emissions resulting directly from the generation of electricity, there are also indirect CO₂ emissions resulting from transport (transmission) and distribution (5% loss) of electricity to power electric vehicles (BEIS, 2018). The CO₂ emission conversion factors calculation accounts for real-world performance such as charging losses, although the charging loss percentage is not reported.

For Mexico City, a factor of two from London's CO₂ emission conversion factors was taken because the electricity carbon intensity in Mexico (600 g/kWh) is approximately twice as high as the electricity carbon intensity in the UK (300 g/kWh). However, the emissions from electricity generation are reducing fast in the UK as the capacity for renewable energy increases; the use of coal is reducing fast, and by 2030 and by 2030 the use of fossil fuels for electricity generation will be small. Exact values are difficult to predict and will depend on how renewable energy increases.

Table 3.6 London and Mexico City CO₂ emission conversion factors from electricity generation, transmissions and distribution for electric vehicles (BEIS, 2018).

Battery electric vehicle type	Vehicle category as reported by BEIS (BEIS, 2018)	UK electricity generation (BEIS, 2018)	Transmissions and distribution (BEIS, 2018)	Electricity CO ₂ emission conversion factors	
				London [*]	Mexico City [†]
Grams of CO ₂ per kilometres driven (g CO ₂ /km)					
Electric Car, Electric Taxi	Average electric car	59.47	5.07	64.54	129.1
Van, SUV, Pickup van	Average electric van	63.32	5.40	68.72	137.4
Electric Bus, BRT	Electric van (1.3 to 1.7 tonnes)	63.17	5.38	68.55	137.1
LGV	Electric van (1.7 to 3.5 tonnes)	92.96	7.92	100.88	201.8
Electric Motorcycle	Supermini electric car	47.78	4.07	51.85	103.7

Note: *London electricity CO₂ emission factors are calculated by adding the CO₂ emissions factors UK electricity generation plus transmissions and distribution.

†For Mexico City, a factor of two from London's emission factors was taken because the electricity carbon intensity in Mexico is approximate twice as high as the electricity carbon intensity in the UK. The carbon intensity in the UK is approximate ~ 300 g/kWh. The carbon intensity in Mexico is approximate ~ 600 g/kWh.

3.3.3.2 Air pollutant emissions from electricity generation

The scope of this dissertation is the analysis of emissions at the city level. For this reason, air pollutant emissions not emitted within the city area were not accounted for. However, this is acknowledged as a

limitation of the study. Air pollutants have a local negative impact. For this reason, air pollutants emitted at the power stations where electricity is generated to power electric vehicles driven in the city affect the local air quality and local population health and not necessarily the air quality of the city where the electricity is used.

In contrast to air pollutants, GHG such as CO₂, have a global effect, and it does not matter where CO₂ is emitted, it will warm the planet. Due to its global effect, CO₂ emissions from the electricity generation, to power electric vehicles, were accounted for. Future research should include an analysis of the air pollution caused by the electricity generation to power electric vehicles driven in the city. However, this is out of the scope of this dissertation.

3.3.3.2.1 Life cycle emissions of electric and conventional vehicles

Although electric vehicles do not emit tailpipe emissions, electric vehicles generate a substantial amount of emissions in their energy supply (electricity production and distribution) and vehicle manufacturing stages. Therefore, the environmental benefits of using electric vehicles instead of conventional vehicles (internal combustion, petrol and diesel vehicles) have to be quantified in a systematic way.

Life cycle assessment (LCA) is a standardised method to assess the environmental performance and resource consumption of products or systems, throughout its whole life cycle. While the development of a comprehensive emissions assessment of the whole life cycle of electric and conventional vehicles was out of the scope of this research, LCA studies were reviewed.

Several vehicle LCA studies have shown that battery-electric vehicles power with low carbon energy sources reduces GHG and air pollutant emissions compared to conventional vehicles (Figure 3.16) (Rangaraju *et al.*, 2015; Hawkins *et al.*, 2012; Faria *et al.*, 2013). Rangaraju *et al.*, 2015, compared the life cycle CO₂eq, SO₂, NO_x and PM emissions of battery-electric and conventional internal combustion (petrol and diesel) vehicles in a Belgian case study (Figure 3.16).

Unlike many LCA studies, Rangaraju *et al.*, 2015, used real-world energy consumption data, for battery electric vehicles, real-world energy performance and yearly average emissions of the Belgian electricity

mix. Rangaraju *et al.*, 2015, showed that in the LCA, the battery electric vehicle had the lowest emissions, for CO₂eq and the other air pollutants studied (CO₂eq, SO₂, NO_x and PM).

Battery electric vehicles have the lowest CO₂eq, SO₂, and NO_x life cycle emissions, because they do not emit tailpipe emissions. Therefore, electric vehicles have zero CO₂eq, SO₂, NO_x tank-to-wheel (TTW) emissions (Figure 3.16) (Rangaraju *et al.*, 2015). However, as discussed before, electric vehicles do emit non-exhaust PM emissions; therefore, emitting only TTW PM emissions (Figure 3.16).

Battery electric cars emit more in the vehicle manufacturing stage (vehicle cycle in Figure 3.16), compared to petrol and diesel vehicles. These emissions are generated during the production of the lithium battery and the power electronic components. However, the vehicle production stage is a one-time process, and the emissions are unavoidable. These emissions should be minimised by, for instance, employing advanced technologies and cleaner production methodologies (Rangaraju *et al.*, 2015).

The petrol vehicle has the highest CO₂eq emissions (Figure 3.16) (Rangaraju *et al.*, 2015). The combustion of fossil fuels in conventional vehicles generates CO₂eq emissions in the tank-to-wheel TTW phase of the LCA. The petrol vehicle also emits the highest SO₂ emissions but (unlike CO₂eq) SO₂ is emitted during the WWT stage. Tailpipe SO₂ emissions are insignificant for conventional vehicles.

The diesel vehicle has the highest NO_x emissions, by a significant difference with the petrol vehicle (almost doubling the amount of g/km emitted) and almost four times larger g/km than the battery electric vehicle. The diesel vehicle also shows the highest TTW PM emissions in comparison with the battery-electric and the petrol vehicle (Figure 3.16).

Overall, this relevant study shows that battery electric vehicles have the lowest life cycle GHG and air pollutant emissions (Rangaraju *et al.*, 2015). This was an important conclusion to consider because as part of this dissertation, air pollutant emission from the electricity generation and other LCA components were not accounted for.

However, the assessment of the overall effects of electric vehicles is not a straightforward topic. Hawkins *et al.*, 2012, highlight how considering vehicle production is very important when comparing conventional vehicles and electric vehicles. Hawkins *et al.*, 2012, found that electric vehicles powered by the present European electricity mix could decrease the global warming potential in 10% to 24% relative to conventional diesel or gasoline vehicles, assuming lifetimes of 150,000 km.

However, Hawkins *et al.*, 2012, show how electric vehicles have the potential for significant rises in human toxicity, freshwater ecotoxicity, freshwater eutrophication, and metal depletion impacts, largely emanating from the vehicle supply chain. Hawkins *et al.*, 2012, show that production impacts are more significant for electric vehicles than conventional vehicles. Improving the environmental profile of electric vehicles is essential and needs a reduction of vehicle production supply chain effects and endorsing clean electricity sources (Hawkins *et al.*, 2012).

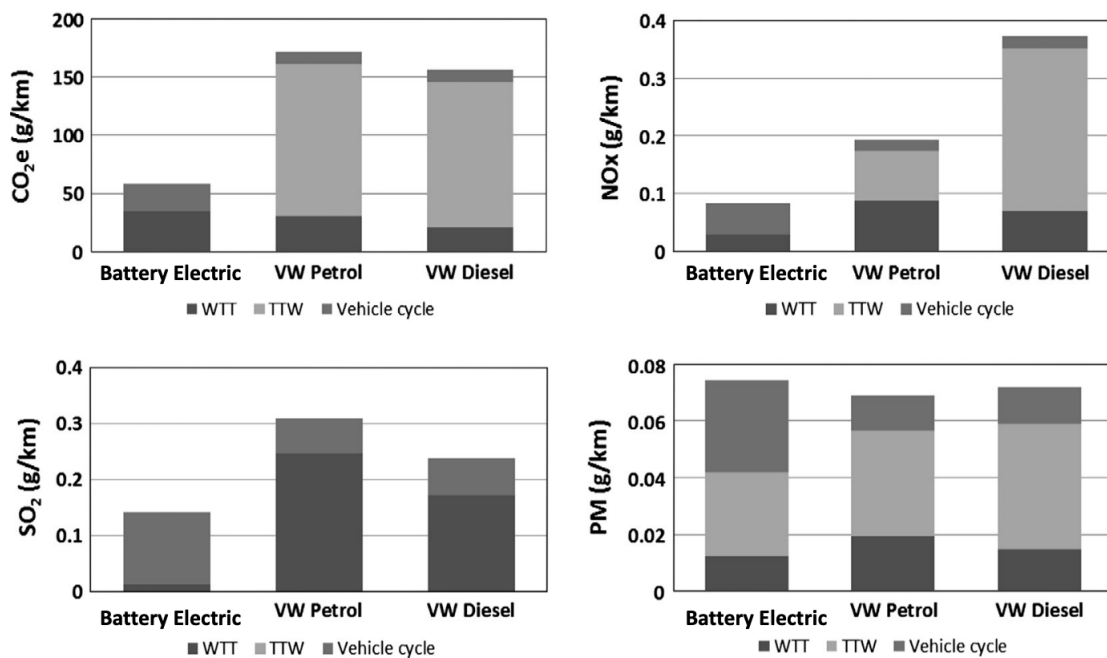


Figure 3.16 Comparison of life cycle emissions of battery electric (Peugeot iOn) and conventional vehicles (VW Petrol and VW Diesel) for a Belgian case study. WTT: well-to-tank emissions. TTW: tank-to-wheel emissions. Source: Rangaraju *et al.*, 2015.

3.3.4 Cost assessment

The cost assessment included in this dissertation accounted for the reduction in air pollutants concentration in London, using the Damage cost methodology and the most recent calculations of Carbon offset pricing in London. Due to the lack of information for Mexico City, the cost assessment analysis was restricted to the London case study.

3.3.4.1 Damage costs per unit of air pollutant exposure

The damaging effects of air pollution on public health and the environment have corresponding economic and social costs (known as external costs or externalities) that are not accounted for in the market value of the goods or services consumed that produce air pollution. Ricardo (2019) defines damage costs as “a set of impact values defined per tonne of emission. These values estimate the external costs associated with a marginal change in pollutant emissions.” Ricardo (2019) have developed a tool for quantifying the damage costs of air pollutants generated in the UK. This tool has been used to generate the unit damage costs (expressed as £/tonne emission) recommended for use in the evaluation of UK government policy by Defra (Defra, 2019b).

The general methodology used to derive the damage costs is the impact pathway approach (IPA) developed originally in the ExternE Project of the European Commission in the early 1990s (ExternE, 2005). This approach describes a logical, sequential pathway from emission, through pollutant dispersion and chemistry to exposure of the population and other sensitive receptors (buildings, ecosystems, etc.) to impact assessment and monetary valuation. Defra adopted this approach for damage assessment in the late 1990s. Whilst the overall approach has not changed since that time, details of the method (dispersion models, response functions and valuation data) have been updated to reflect developments in the scientific literature.

Monetised health impacts of exposure to air pollutants, in particular PM_{2.5}, have also been estimated by Mike Holland of Ecometrics Research and Consulting, for all EU countries, and used in cost-benefit analysis in conjunction with the GAINS model in developing the Gothenburg protocols and NECD. For use in UKIAM in work for the UK government Mike Holland has revised these monetised values in accordance with recommendations from the UK's Committee on Medical Effects of Air Pollution,

COMEAP, and extended to include NO₂ as well as PM_{2.5}. These values are documented in a report for government, and Mike Holland has kindly made them available for use in this thesis (See Table 3.7).

Mike Holland developed low, central and high ranges for damage cost estimates related to the change in population-weighted mean air pollutant concentrations (PWMC) (Table 3.7). Mike Holland's estimates are expressed in low, central and high ranges for damage cost estimates related to the change in population-weighted mean air pollutant concentrations (PWMC). Prices are correct for the year 2017. The calculations are expressed per person and assuming that there is not significant demographic change, quantification of underlying impacts on health, among others, should be reliable for the foreseeable future. The damage costs values followed the most recent guidance from COMEAP (COMEAP, 2018; Holland, Pye & Jones, 2013).

The low, central and high ranges are composed of the following impacts. Low: Chronic mortality, Respiratory hospital admissions, Cardiovascular hospital admission, Productivity, Building soiling, and Ecosystems. Central, as low, but including also: Coronary Heart Disease, Stroke, Asthma in children, and Lung cancer morbidity. High, as central, but including also: Respiratory hospital admissions, Productivity, Chronic Bronchitis, Asthma in adults, Diabetes, and Lung cancer morbidity. The analysis is based on the recommendations of (COMEAP, 2018). Mortality is valued using a value of life year (VOLY) of £42,780.

Table 3.7 Value costs of health impacts linked to direct exposure of PM_{2.5} and NO₂ pollutants per one µg/m³ change in population-weighted mean concentrations (PWMC).

Pollutant	Value of direct impacts - £(2017) per population-weighted mean 1 µg/m ³ change per person.		
	Low	Central	High
PM _{2.5}	13.8	50.1	119.7
NO ₂	0.6	6.3	19.1
Source:	Estimates by Mike Holland using: (COMEAP, 2009; Holland, Pye & Jones, 2013)		

3.3.4.2 Carbon offset pricing

A recent Greater London Authority (GLA) study, (AECOM, 2017), designed to recommend suitable carbon prices for offsetting in London, was used to calculate the monetary value of reducing CO₂ by 1 tonne (Table 3.8).

To arrive at a recommended carbon price, the study (AECOM, 2017) considered and developed approaches considering the following four assumptions. First, the study (AECOM, 2017) assumed a target offset ratio of one to one in which Councils would manage their offset funds with the aim of achieving “carbon equivalence”, where the quantity of carbon saved through offsetting projects equals the residual emissions from development.

Second, the study (AECOM, 2017) assumed that offset funds would adopt a carbon accounting approach referred to as ‘proportional shares by subsidy’. This means that the carbon savings from an offsetting project are shared among all public or regulatory obligated co-funders.

Third, the study (AECOM, 2017) approach was to continue to base carbon prices for offsetting in London on a nationally recognised carbon pricing mechanism rather than on the cost of carbon savings derived from potential offsetting projects.

Fourth, rather than identifying a single carbon price, the study (AECOM, 2017) identifies a set of carbon prices consisting of a low, a central, and a high price that could support the setting of carbon prices in three different zones in London.

Table 3.8 CO₂ offset pricing per tonne mitigated in London.

Pollutant	Value/cost (£/tonne)			Metric	Source
	Low	Central	High		
CO ₂	32	64	95	Per tonne of CO ₂ mitigated	(AECOM, 2017)

3.4 Translation of transport policy scenarios as inputs for the modelling framework

Addressing the fourth and five research objective of this dissertation (section 1.4), this section presents how the transport policy scenarios (described in section 3.2) for London and Mexico City were translated as inputs for the CO₂ and air quality modelling framework (described in section 3.3). The transport policy scenarios were translated in terms of vehicle fleet composition and transport mode distribution to be used as inputs for the CO₂ and air quality modelling framework.

Moreover, the transport policy scenarios translated in terms of its transport mode distribution (km travelled by transport mode) for the CO₂ and air quality modelling framework determined the travel patterns in each scenario. Subsequently, travel patterns in each scenario were used as inputs for the Health Impact Assessment (HIA) modelling. Travel patterns were translated from km travelled by transport mode to travel trips distribution to be used as inputs for the HIA modelling, and are presented here.

3.4.1 Vehicle fleet composition

3.4.1.1 London

The transport policy scenarios were evaluated relative to the reference baseline 2030 scenario. Two categories of transport policy scenarios were evaluated: technological and behavioural change scenarios.

3.4.1.1.1 Baseline 2030 scenario

The baseline 2030 is the reference scenario projected for 2030 (Table 3.9). It captures the effect of current legislation and forecasts traffic growth in London, but does not include more recent measures like the ULEZ

(GLA, 2017a). Differences between the current 2016 fleet composition and the 2030 baseline (Table 3.9) include the following:

- 85.90% of vehicles meet the highest Euro 6 standard in their corresponding vehicle category, in contrast to the negligible ≈ 0 proportion in 2016; and
- Electric vehicles account for 3.5% of the vehicle composition, compared to 0.06% in 2016, including 2% of electric cars, 0.5% of electric buses and 1% of electric LGV.

Table 3.9 London vehicle fleet composition per kilometre travelled by vehicle type and by vehicle technology in the baseline 2030 scenario. Total kilometres travelled by the vehicle fleet are indicated.

Kilometres travelled by vehicle in billion kilometres 10^9 km and (proportion of each vehicle type in the vehicle fleet mix (%))			Percentage of vehicles meeting the strictest Euro standard	
Car	Diesel	11.6 (35.9%)	Euro 6	97.43%
	Petrol	13.4 (41.3%)	Euro 6	97.90%
	Electric	0.6 (2.0%)	-	-
Taxi	Diesel	0.8 (2.6%)	Euro 6	88.45%
Bus	Diesel	0.3 (1.0%)	Euro 6	100.00%
	Electric	0.2 (0.5%)	-	-
Coach	Diesel	0.1 (0.4%)	Euro 6	97.49%
LGV	Diesel	3.0 (9.3%)	Euro 6	98.89%
	Petrol	0.04 (0.1%)	Euro 6	85.90%
	Electric	0.3 (1.0%)	-	-
HGV	Diesel Rigid	1.0 (3.1%)	Euro VI	100.00%
	Diesel Artic	0.3 (0.8%)	Euro VI	100.00%
Motorcycle	Diesel	0.7 (2.0%)	Euro 5	100.00%
<i>Total km travelled (2030) = 32.34×10^9 km (100.0%)</i>				

3.4.1.1.2 Transport policy scenarios

The transport policy scenarios (described in section 3.2) were transformed as inputs for the CO₂ and air quality modelling in terms of the kilometres travelled by vehicle type (Table 3.10). Total kilometres travelled in all the transport policy scenarios remain constant (32.3 billion km travelled per year) throughout the scenarios. Table 3.10 describes in detail all the 2030 transport policy scenarios modelled, presenting the kilometres travelled per transport mode in the technological and behavioural change scenarios.

Technological change scenarios

Low Emission Zone

The Low Emissions Zone technological change scenario (Table 3.10) (discussed in section 3.2.1.1) aims to change the vehicle technology by implementing stricter Euro Standards. However, the kilometres travelled by vehicle type do not change. This means, for example, that although diesel cars will drive the same 11.6 billion km per year in both the Baseline 2030 scenario and in the Low Emissions Zone scenario, in the Low Emissions Zone scenario all diesel cars will be at least Euro 6.

In the same way, petrol cars will be driven the same 13.4 billion km per year in both the Baseline 2030 scenario and in the Low Emissions Zone scenario. However, in the Emissions Zone scenario, only petrol cars meeting the Euro 4 standard or more, will be driven in London. For this reason, the kilometres travelled by vehicle type in the Baseline 2030 scenario and in the Low Emissions Zone scenario, are the same. This assumed that the Low Emissions Zone technological change scenario changes vehicle technology, not the vehicle type.

Zero Emission Zone: Electric Vehicles

The Electric Vehicles technological change scenarios (Table 3.10) (discussed in section 3.2.1.2) aim to electrify each vehicle type. In the Electric Car scenario, all the km driven by cars (25.6 billion km per year) are driven by electric cars. In the same way in the Electric Taxi scenario, all the km driven by taxis (0.8 billion km per year) are driven by electric taxis. In other words, the kilometres driven by conventional

vehicles are progressively transformed to kilometres driven by electric vehicles. The most radical scenario in this group is the Electric Vehicle Fleet scenario in which all kilometres driven by cars, taxis, buses, LGV, and motorcycles are driven by electric vehicles.

Fuel Choice Trends: Diesel to Petrol Cars

The Diesel to Petrol Car scenario (Table 3.10) (discussed in section 3.2.1.5), inspired by recent fuel trends choice, transforms all diesel cars to petrol cars. Thus, diesel cars drive zero kilometres per year, and petrol cars drive 24.5 billion kilometres per year, in contrast to 13.4 billion kilometres driven per year in the Baseline 2030 scenario.

Behavioural change scenarios

Active Travel: Cycle Lanes

The Cycle Lane 10 and Cycle Lane 20 behavioural change scenarios (discussed in section 3.2.1.3), assumed a reduction of 10% and 20% of the traffic flow where cycle lanes are built. This assumption translates in a reduction of km driven by motorised vehicles where cycle lanes are built. In the Cycle Lane 10 scenario, 0.1 billion kilometres driven per year by motorised vehicles are reallocated to cycle. In the same way, in the Cycle Lane 20 scenario, 0.3 billion kilometres driven per year by motorised vehicles are reallocated to cycle.

Active Travel: Reduction of Car Use

The Car Redu 10 and Car Redu 50 behavioural change scenarios (Table 3.10) (discussed in section 3.2.1.4), aim to reduce kilometres driven by car by 10% and 50% of, respectively and reallocate the reduced kilometres to active travel (walk, cycle, and public transport). The Car Redu 10 scenario resulted in a reduction of 2.4 billion kilometres driven by car per year, which were reallocated to active travel modes. The Car Redu 50 more aggressive scenario resulted in a reduction of 12.2 billion kilometres driven by car per year, which were reallocated to active travel modes.

Table 3.10 Kilometres travelled per transport mode in the technological and behavioural change 2030 transport policy scenarios.

Mode	Baseline Technological change scenarios				Behavioural change scenarios						
	BAU2030	Low Emissions Zone	Diesel to Petrol Car	Electric Car	Electric Taxi	Electric Bus	Electric Vehicle Fleet	Cycle Lane 10	Cycle Lane 20	Car Redu 10	Car Redu 50
Billion kilometres travelled (1×10^9 km)											
Petrol Car	13.4	13.4	24.5	0.0	13.4	13.4	0.0	13.3	13.3	12.1	6.9
Diesel Car	11.6	11.6	0.0	0.0	11.6	11.6	0.0	11.6	11.5	10.5	6.2
Electric Car	0.6	0.6	1.2	25.6	0.6	0.6	25.6	0.6	0.6	0.6	0.3
Taxi	0.8	0.8	0.8	0.8	0.0	0.8	0.0	0.8	0.8	0.8	0.8
Electric Taxi	0.0	0.0	0.0	0.0	0.8	0.0	0.8	0.0	0.0	0.0	0.0
Bus	0.3	0.3	0.3	0.3	0.3	0.0	0.0	0.3	0.3	0.3	0.3
Electric Bus	0.2	0.2	0.2	0.2	0.2	0.5	0.5	0.2	0.2	0.2	0.2
Coach	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
LGV	3.0	3.0	3.0	3.0	3.0	3.0	0.0	3.0	3.0	3.0	3.0
Electric LGV	0.3	0.3	0.3	0.3	0.3	0.3	3.4	0.3	0.3	0.3	0.3
HGV	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
Motorcycles	0.7	0.7	0.7	0.7	0.7	0.7	0.0	0.6	0.6	0.7	0.7
Electric	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.0
Motorcycles											
Cycle	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.0	0.0
Active modes*	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.4	12.2
(walk, cycle, public transport)											
Total km travelled (2030)	32.3										

*The active modes with 0 kilometres travelled in this table do not mean that active modes do not exist. This table shows the additional kilometres travelled by active modes in the behavioural change scenarios.

3.4.1.1.3 Role of collaborators

The translation of the transport policy scenarios for London, as inputs for the UKIAM-BRUTAL model required to write a computational code. Since learning how to write computational code for a model was out of the scope of my dissertation, Dr Tim Oxley, helped me translate the transport policies of my analysis into computational code.

Therefore, after I determined which policies I wanted to model (as presented in section 3.2), Dr Tim Oxley, who has developed the UKIAM model, helped me to write the computational code to run each transport policy scenario in the UKIAM-BRUTAL model. Writing the computational code and showing me how to run the UKIAM model was the only role that Dr Tim Oxley played in my PhD research, and I am very grateful for Dr Tim Oxley help. I was responsible for defining each scenario, running the UKIAM model, and interpreting the results.

In no other part of my research and my dissertation, any other collaborator helped me or played any role in the development or analysis.

3.4.1.2 Mexico City

The vehicle fleet composition in the transport policy scenarios, used as the input for the emissions modelling, was defined using information reported in the most recent 2016 emissions inventory technical report of Mexico City (SEDEMA, 2017a). The information reported in the inventory was used to define the vehicle fleet composition in the transport policy scenarios. The transport policy scenarios were defined in terms of the following,

- Number of vehicles by vehicle type and vehicle model year (average date when the vehicle was produced).
- Annual vehicle kilometres travelled, and average kilometres travelled per day, by vehicle type and vehicle model year.

The vehicle types reported in the emissions inventory and considered as inputs for the emissions modelling of transport policy scenarios are the following, car, taxi, sport-utility vehicle (SUV), van, pick up van, bus, bus rapid transport system (BRT), light goods vehicles (LGV), heavy goods vehicle (HGV), tractor, motorcycle.

The transport policy scenarios were built by varying the number of vehicles, and vehicle kilometres travelled of different vehicle types. The model was used to calculate the corresponding effect on emissions for each scenario. The transport policy scenarios were compared to the reference baseline scenario.

3.4.1.2.1 Baseline scenario

The baseline scenario (Figure 3.17) reflects the current vehicle fleet composition in Mexico City, as reported in the emissions inventory (SEDEMA, 2017a). Interestingly, the baseline scenario in Mexico City which reflects the actual state of the road transport in the city shows how private cars, which are 58% of the total vehicles in the city, only drive 37% of the total kilometres driven in the city.

In contrast, non-private vehicles such as taxis represent only 6% of the total number of vehicles in the city but are driven intensively accounting for 20% of total kilometres driven in Mexico City. In a similar way

to taxis, buses are driven intensively in Mexico City. Buses only represent 2% of the vehicles in Mexico City but account for the driving of 4% of total kilometres driven in the city.

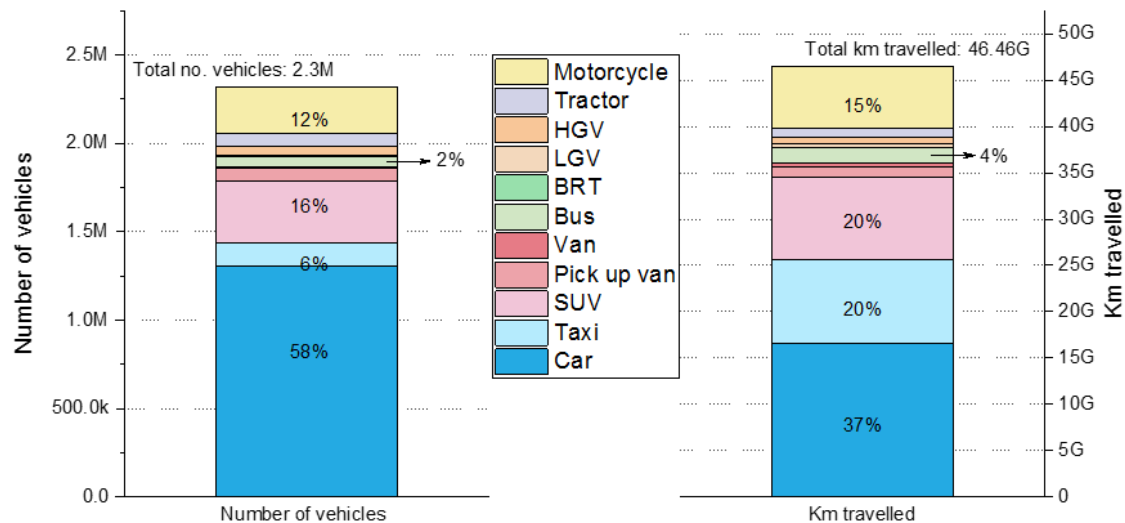


Figure 3.17 Mexico City Baseline scenario: Number of vehicles by vehicle type and kilometre travelled by vehicle type. Mexico City Baseline scenario represents the current distribution of vehicles and kilometre travelled by vehicles in Mexico City today. Source: SEDEMA, 2017a.

Another important characteristic of the vehicle fleet is how old the vehicle fleet is. The vehicle model year gives us an approximation of the number of years that the vehicle has been on the road (vehicle age). Using the model year, I did an analysis of the vehicle fleet distribution by vehicle age (Figure 3.18, Table 3.11) using information reported in SEDEMA (2017a). The oldest vehicles in the baseline scenario and currently in Mexico City are buses. This is problematic because, as it was discussed above, buses are driven intensively (Figure 3.17). Older buses usually emit significantly more emissions than newer buses.

In the baseline scenario in Mexico City, the average number of years on the road of a bus (bus age) is 15.4 years. In contrast to buses, according to official numbers, taxis in the baseline scenario are relatively new with an average age (number of years on the road) of 4.5 years, which is something positive because taxis

are also intensively driven. The average age of the vehicle fleet (Figure 3.18, Table 3.11) will be relevant for the construction of the transport policy scenarios.

Table 3.11 Mexico City Baseline scenario: Average number of years in the road (based on model year information) of cars, taxis, buses and general fleet.

Note: Mexico City Baseline scenario represents the current situation of road transport in Mexico City. The percentage of vehicles five years old and older than ten years are also indicated—source: SEDEMA, 2017a.

Vehicle type	Average number of years in the road (years)	Newest vehicles: 1-5 years in the road (%)	Oldest vehicles: 10 or more years in the road (%)
Car	6.7	47%	27%
Taxi	4.5	50%	3%
Bus	15.4	15%	71%
Vehicle fleet (all vehicles)	7.1	45%	28%

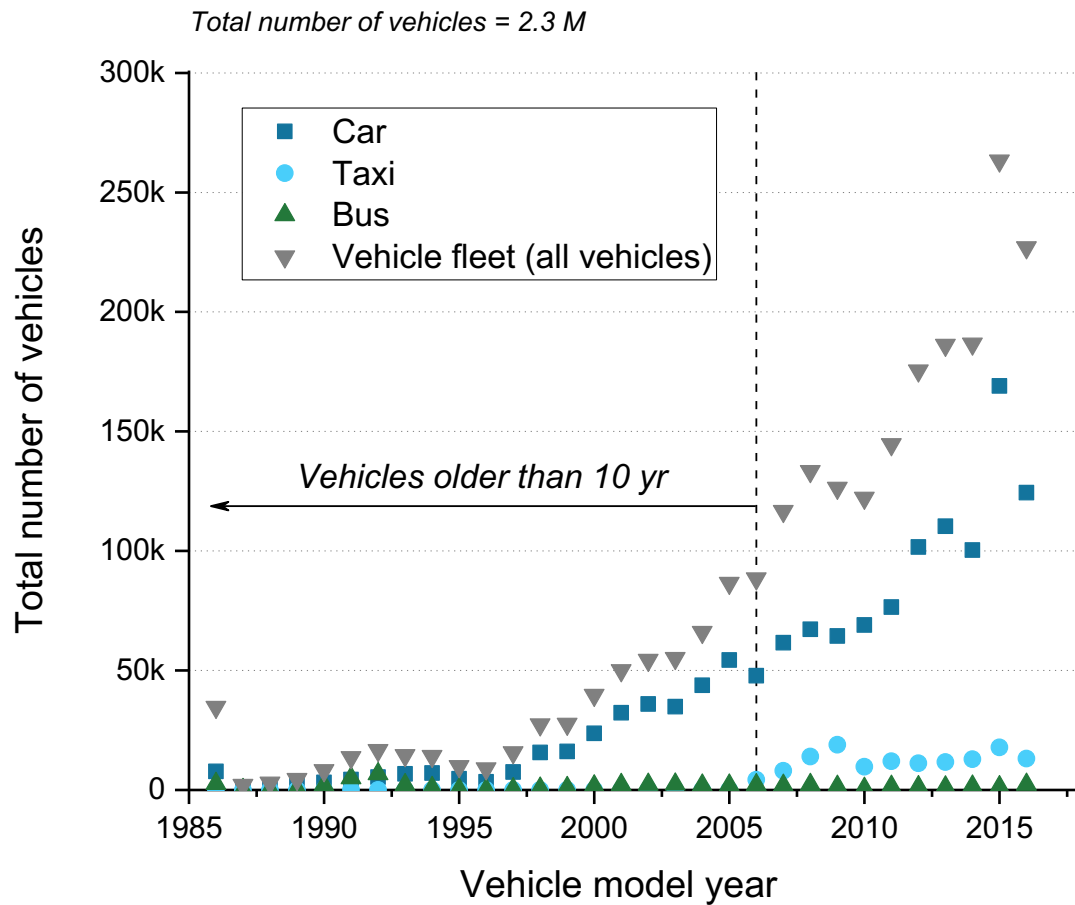


Figure 3.18 Mexico City Baseline scenario: Distribution of the total number of vehicles by vehicles model year (vehicle production date).

Note: Mexico City Baseline scenario represents the current distribution of vehicles in Mexico City. The horizontal arrow shows the vehicles older than ten years limited by the dotted line. Source: SEDEMA, 2017a.

3.4.1.2.2 Transport policy scenarios

The transport policy scenarios evaluated in Mexico City (discussed in section 3.2.2) encompass the following categories: Technological change scenarios including, vehicle electrification, the shift from internal combustion vehicles to battery electric vehicles. And behavioural change scenarios including, a shift of kilometres travelled by the oldest vehicles to active travel transport modes (walking, cycling and public transport) and a shift of a percentage of kilometres driven by car to active transport modes. The transport policy scenarios were compared to the baseline scenario, which captures the current landscape of the road transport sector in Mexico City.

Technological change scenarios

Introduction of High Energy Efficient Vehicles: Electric Vehicles

The technological changes scenarios studied for Mexico City (Table 3.12) (discussed in section 3.2.2.1) included the introduction of electric vehicles which are high energy efficient vehicles. Electric cars, taxis, buses, and the electric vehicle fleet were modelled. In each of these electrification scenarios, the kilometres driven by conventional vehicles were shifted to kilometres driven by electric vehicles. In this way, for example, if in the baseline scenario, conventional cars drove 16.63 billion kilometres per year. Then, in the Electric Car scenario, the same 16.63 billion kilometres per year will be driven by electric cars.

Behavioural change scenarios

Modernisation of the Vehicle Fleet (Reduction of Old Vehicles) and Increased Active Travel

Behavioural change scenarios for Mexico City (Table 3.12) (discussed in section 3.2.2.2) to increase active travel assumed a reduction of kilometres travelled by old vehicles (older than ten years old). The Old Car Redu, Old Taxi Redu, and Old Bus Redu scenarios, 2.80, 0.28, and 1.36 billion kilometres travelled per year, respectively, are reallocated to active travel modes (walk, cycle, and public transport with newer buses). The Car Redu 10pct scenario assumes a reduction of 10% of the kilometres travelled by the oldest car. The reduced kilometres travelled per year, 1.84 billion kilometres, are reallocated to active travel modes.

Table 3.12 Description of transport policy scenarios for Mexico City by kilometres travelled by vehicle type and mode of transport. Additional kilometres travelled by active modes are indicated for the behavioural change scenarios.

Vehicle type and mode of transport	Baseline	Technological change scenarios					Behavioural change scenarios			
		Electric Car	Electric Taxi	Electric Bus	Electric Vehicle Fleet	Old Car Redu	Old Taxi Redu	Old Bus Redu	Car Redu 10pct	
		Annual billion kilometres travelled (1×10^9 km)								
Car	16.63	-	16.63	16.63	-	13.83	8.70	0.41	14.79	
Electric Car	-	16.63	-	-	16.63	-	-	-	-	
Taxi	8.98	8.98	-	8.98	-	8.98	8.98	8.98	8.98	
Electric Taxi	-	-	8.98	-	8.98	-	-	-	-	
SUV	3.79	3.79	3.79	3.79	-	3.79	3.79	3.79	3.79	
Electric SUV	-	-	-	-	3.79	-	-	-	-	
Pick up van	0.07	0.07	0.07	0.07	-	0.07	0.07	0.07	0.07	
Electric pick up van	-	-	-	-	0.07	-	-	-	-	
Van	0.38	0.38	0.38	0.38	-	0.38	0.38	0.38	0.38	
Electric van	-	-	-	-	0.38	-	-	-	-	
Bus	1.76	1.76	1.76	-	-	1.76	1.76	1.76	1.76	
Electric Bus	-	-	-	1.76	1.76	-	-	-	-	
BRT	0.04	0.04	0.04	-	-	0.04	0.04	0.04	0.04	
Electric BRT	-	-	-	0.04	0.04	-	-	-	-	
LGV	0.30	0.30	0.30	0.30	-	0.30	0.30	0.30	0.30	
Electric LGV	-	-	-	-	0.30	-	-	-	-	
HGV	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	
Tractor	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	
Motorcycles	0.27	0.27	0.27	0.27	-	0.27	0.27	0.27	0.27	
Electric Motorcycles	-	-	-	-	0.27	-	-	-	-	
Additional km to active modes (walk, cycle, public transp.)	-	-	-	-	-	2.80	0.28	1.36	1.84	
Total annual billion km travelled 41.27										

*The active modes with 0 kilometres travelled in this table do not mean that active modes do not exist. This table shows the additional kilometres travelled by active modes in the behavioural change scenarios.

Electric vehicles

The resulting number of vehicles shifted to electric vehicles or replaced by active travel modes in each scenario are shown in Table 3.13. Under the electrification scenarios, the proportion of electric vehicles in the vehicle fleet by the number of vehicles is the following, electric cars (58%), electric taxis (6%) and electric buses (2%). Active travel modes replace 20 - 30% of cars (in the Car Redu 10 and Old Car Redu scenario, respectively). In the same way, active travel modes replace 3% of taxis in the Old Taxi Redu scenario and 71% of buses Old Bus Redu scenario.

Table 3.13 Mexico City transport policy scenarios: Number of vehicles replaced by electric vehicles or replaced by active travel modes in each transport policy scenario.

Scenario	Number of Vehicles
<i>Technological change scenarios (>)</i>	
Electric vehicles	Number of electric vehicles in thousands (10 ³)
Electric Car	1,303
Electric Taxi	134
Electric Bus	52
Electric Vehicle Fleet	2,248
<i>Behavioural change scenarios (+)</i>	
Active travel	Number of vehicles replaced by active modes in thousands (10 ³)
Old Car Redu	358
Old Taxi Redu	5
Old Bus Redu	37
Car Redu 10pct	256

3.4.2 Travel patterns

As mentioned before, the vehicle fleet composition and the kilometres travelled by transport mode were used to define the travel patterns in each transport policy scenarios. In this section, the distribution of trips per transport mode (travel patterns) in each transport policy scenarios is presented. Also, this section explains how the kilometres travelled by motorised vehicles were reallocated to active travel modes (walk, cycle, and public transport).

3.4.2.1 Reallocation of trips by motorised vehicles to active travel modes

In the behavioural change transport policy scenarios, the distance travelled (or driven) by motorised vehicles in the baseline scenario was reallocated to active travel modes (Table 3.10 and Table 3.12). For each scenario, specific kilometres driven by car were reallocated to kilometres travelled by active modes of transport: walk, cycle, and public transport. The methodology followed to reallocate trips to active travel modes in London and Mexico City is described below.

The kilometres driven by motorised vehicles shifted to active modes was calculated according to trip distance. Short trips were defined as trips shorter than 8.1 kilometres, as defined by TfL (2017b, 2017a). Short trips made by motorised private vehicles were reallocated to walking and cycling. Trips equal or longer than 8.1 kilometres made by motorised private vehicles were reallocated to public transport.

The reallocation of short trips to walking and cycling was done using the definitions of a walkable and a cyclable trip, as defined by TfL (2017b, 2017a). A walkable distance trip is defined as a trip less than 1.6 kilometres long (TfL, 2017b). A cyclable distance trip is defined as a trip shorter than 8 kilometres, as defined by (TfL, 2017a).

Thus, the criteria for the reallocation of trips (and kilometres travelled) by motorised vehicles to active travel modes was the following (TfL, 2017b, 2017a):

- Car trips between 0.0 and 1.6 km were reallocated to walking—average distance per trip of 0.8 km.
- Car trips between 1.7 and 8.0 km were reallocated to cycling—average distance per trip of 4.9 km.
- Car trips longer than 8.1 km were reassigned to public transport, with the same proportion to underground (average distance per trip of 10 km) and rail (average distance per trip of 20 km). The distribution of trips to underground and rail was based on current distance distribution of trips longer than 8.1 km as published in TfL (2018). Long trips were not relocated to buses to limit the increased use of buses and its emissions.

Travel surveys usually publish the distribution of trips by distances (TfL, 2018). Using the number of short trips travelled by motorised transport I could reallocate these trips to active travel modes. Then, the total kilometres travelled in short trips in active modes of transport was calculated by multiplying the number of trips in each interval distance by the average trip length.

A limitation of the analysis is that the distribution of trips by distance published in London's Travel Survey (TfL, 2018) was used for Mexico City, due to lack of data in Mexico City. Also, the definition of a walkable and cyclable trip was defined using information from London, for both cities.

3.4.2.2 London

Travel patterns (distribution of trips by travel mode) in the baseline 2030 scenario were defined as the current travel patterns in London reported in the London Travel Demands Survey (LTDS) 2016/17 (TfL, 2018). As described before, the transport policy scenarios were grouped into two categories, technological and behavioural change transport policy scenarios.

Travel patterns in the technological change transport policy scenarios are the same as in the baseline 2030 because these technological change scenarios follow changes in vehicles technologies without changing the modes of transport. For example, in the technological change transport policy scenarios,

a trip made by petrol or diesel car is now made by an electric car. In contrast, behavioural change transport policy scenarios do follow a change in transport modes, replacing motorised transport modes (cars) with active transport modes (walking, cycling and public transport).

Using the methodology described in section 3.4.2.1, the resulting reallocation of trips to active travel modes in London is presented in Table 3.14. After the reallocation of additional trips to active travel modes of transport, the travel patterns (number of trips per day and distribution by mode) (Table 3.15 and Figure 3.19) for each transport policy scenario were calculated.

3.4.2.2.1 Assumptions

The input data and the corresponding uncertainties used for the sensitivity analysis in the Health Impact Assessment modelling are presented in the tables below. Assumptions made to calculate the travel patterns for each transport policy scenario are discussed below.

- **Distribution of trips:**

The distribution of trips by distance, used to reallocate car trips to active travel trips, was taken from the country level (England) Travel Survey for lack of data at the city level. It is important to clarify that only the distribution (as a percentage of trips per distance) was used at the England level (DfT, 2018a). Information about the number of trips per mode was taken from the London Travel Demands Survey (LTDS) (TfL, 2018).

This approximation was made because the LTDS did not include complete information about the distribution of trips by all range distances and all modes. A TfL report (TfL, 2013), reported distributions up to 5km and for the year 2013. Nevertheless, since the modelling of trip distances had to be up to 20 kilometres, it was chosen to keep one source of information with distances up to 20 km as needed and a more recent source.

This assumption can incur in an underestimation of the number of short trips since the England level data includes rural areas where the trips are usually longer than in urban areas like London. This is acknowledged as something that has to be corrected, and the sensitivities to the distance distribution have to be studied in future research.

- **Daily trips:**
Data on the number of daily trips were used as reported by LTDS (TfL, 2018). LTDS reports travel patterns (daily trips) weighted across the week, which means that LTDS weight weekday trips and weekend trips. Therefore, the LTDS data of daily trips must be multiplied by seven days of the week. Conscious that this approach could result in an overestimation of physical activity benefits, the sensitivity analysis included the use of only weekday trips, calculating the weekly trips by multiplying the weekday trips by five.
- **Car driver trips:**
Only trips made by car by a driver, car (driver), were assessed because the modelling estimated a reduction of km travelled by cars. The modelling assumes a car is taken off the street (reduction of km travelled by car) which approximated to the reduction of a trip by a car driver. Car trips by passengers, car (passenger), do not assure us that a car is actually taken off the street. To be conservative in the physical activity benefits and to do not introduce additional layers of uncertainty and complexity, I did not study or accounted for passengers.
- **Average trip length:**
Using average trip length is an approximation of a distance interval. The analysis of individual travel data results in more precise outcome results. Unfortunately, individual-level travel data was not available. Future research should take this into consideration. Also, I assumed an average within a distance interval (Table 3.14). And I used National level data instead of London data for the distance intervals (as explained in the section above “Distribution of trips”).
- **Kilometres travelled:**
The total kilometres travelled (or driven) by vehicles is reported by the UKIAM as an annual average. For the travel pattern calculation, the annual average km travelled by vehicle (i.e. transport mode) was divided by 365 to have a daily average of km travelled. Thus, the variations on weekday and weekend travel were not accounted for and were out of the scope of the study. To translate kilometres travelled to trips, data from London (TfL, 2018) on distance per trips was used (Table 3.16).

- Public transport trips:

Public transport trips were considered as rail and underground trips. Bus trips were not considered because this will have resulted in an increase of emissions from buses (for the additional buses needed) which was not modelled with the UKIAM model. Then, it was assumed that the additional trips reallocated to train and underground have no impacts on emissions.

However, the study of the capacity for additional trips in train and underground was not assessed. Also, implications for the need for more trains, for example, to allocate the new trips in these public transport modes could increase emissions. For example, for the increase in electricity consumption of the underground, which would increase emissions if the additional electricity used is not reviewable.

- Additional walking for public transport trips:

An additional 10 min walk was added to each trip by public transport, as estimated by *Chaix et al., 2014*. The sensibility of the results to this assumption was assessed in the sensitivity analysis.

Table 3.14 Reallocation of trips to active travel modes for the behavioural change transport policy scenarios in London. The indicated travelled distance intervals were used to calculate active travel (walk, cycle and public transport) trips shifted from car trips to trips by active modes of transport.

Distance travelled interval (km) (~ average trip length) (DfT, 2018a)*	Trips per day (percentage of total trips) (TfL, 2018; DfT, 2018a)	Equivalent average distance travelled* (km/day), (annual average distance travelled, km)	Active mode of transport (TfL, 2017a, 2017b)
0 - 1.6 (~ 0.8)	256,946 (6.2 %)	206,757 **(annual 0.08×10^9)	Walkable distance
1.7 - 3.2 (~ 2.4)	692,481 (16.6 %)	1,671,659 **(annual 0.61×10^9)	Cyclable distance
3.3 - 8.0 (~ 5.6)	1,397,550 (33.6 %)	7,871,986 **(annual 2.87×10^9)	Cyclable distance
Longer than 8.1 (Underground ~ 10, Rail ~ 20) †	1,812,908 (43.6 %)	Mode dependant	Public transport distance
Total	4,159,885 (100 %)	-	-

Note: *Calculated as the multiplication of the number trips/day by the average trip length for each distance interval.

**Equivalent average annual distance travelled. Annual distances are indicated so they can be compared with annual distances defined for the transport policy scenarios in London, see Table 3.10.

†Average underground and rail trip lengths were taken from TfL (2018).

*Distribution (as the percentage) of trips per distance was taken from (DfT, 2018a) due to lack of complete data for London for all the distances studied. Number of trips was always taken from TfL (2018) data.

Table 3.15 Trips per day by mode of transport in the London Baseline 2030 and behavioural change transport policy scenarios.

	Baseline 2030	Cycle Lane 10	Cycle Lane 20	Car Redu 10	Car Redu 50
Trips per day (percentage of total trips)					
Cycle	457,926 (2.5 %)	794,275 (4.4 %)	970,902 (5.3 %)	2,013,170 (11.1 %)	2,546,189 (14.0 %)
Walk	5,941,812 (32.6 %)	<i>5,941,812</i> (32.6 %)	<i>5,941,812</i> (32.6 %)	6,199,724 (34.0 %)	6,199,724 (34.0 %)
Car driver	4,159,885 (22.8 %)	3,823,537 (21.0 %)	3,646,909 (20.0 %)	2,346,729 (12.9 %)	34,703 (0.2 %)
Car passenger	2,132,664 (11.7 %)	<i>2,132,664</i> (11.7 %)	<i>2,132,664</i> (11.7 %)	<i>2,132,664</i> (11.7 %)	<i>2,132,664</i> (11.7 %)
National Rail	1,078,265 (5.9 %)	<i>1,078,265</i> (5.9 %)	<i>1,078,265</i> (5.9 %)	<i>1,078,265</i> (5.9 %)	1,671,267 (9.2 %)
Underground	1,717,021 (9.4 %)	<i>1,717,021</i> (9.4 %)	<i>1,717,021</i> (9.4 %)	<i>1,717,021</i> (9.4 %)	2,903,025 (15.9 %)
Bus	2,379,287 (13.1 %)	<i>2,379,287</i> (13.1 %)	<i>2,379,287</i> (13.1 %)	<i>2,379,287</i> (13.1 %)	<i>2,379,287</i> (13.1 %)
Taxi	276,835 (1.5 %)	<i>276,835</i> (1.5 %)	<i>276,835</i> (1.5 %)	<i>276,835</i> (1.5 %)	<i>276,835</i> (1.5 %)
Motorcycle	66,700 (0.4 %)	<i>66,700</i> (0.4 %)	<i>66,700</i> (0.4 %)	<i>66,700</i> (0.4 %)	<i>66,700</i> (0.4 %)
All	18,210,394 (100 %)	<i>18,210,394</i> (100 %)	<i>18,210,394</i> (100 %)	<i>18,210,394</i> (100 %)	<i>18,210,394</i> (100 %)

Note: Numbers in italics indicate that the number of trips is the same as in the baseline 2030 scenario. As can be seen in this table, the number of car driver trips were reallocated to active transport modes. In this way, we could model that a car was taken out of the streets. The car passenger trips were kept constant. Then, the analysis did not include assessment of car occupancy.

As is shown in the figure below (Figure 3.19), which illustrates the data from Table 3.15, the travel patterns in the technological changes scenarios do not change from the Baseline 2030 scenario since there is not a modal change of transport, only a technological vehicle change. In contrast, in the behavioural change scenarios, there is an important change in the distribution of trips with a significant increase in trips made by active travel modes. In the more aggressive behavioural change scenario (Car Redu 50) there is an increase of cycle trips from representing the 3% in the baseline to representing the 14% of the distribution of trips in the Car Redu 50 scenario.

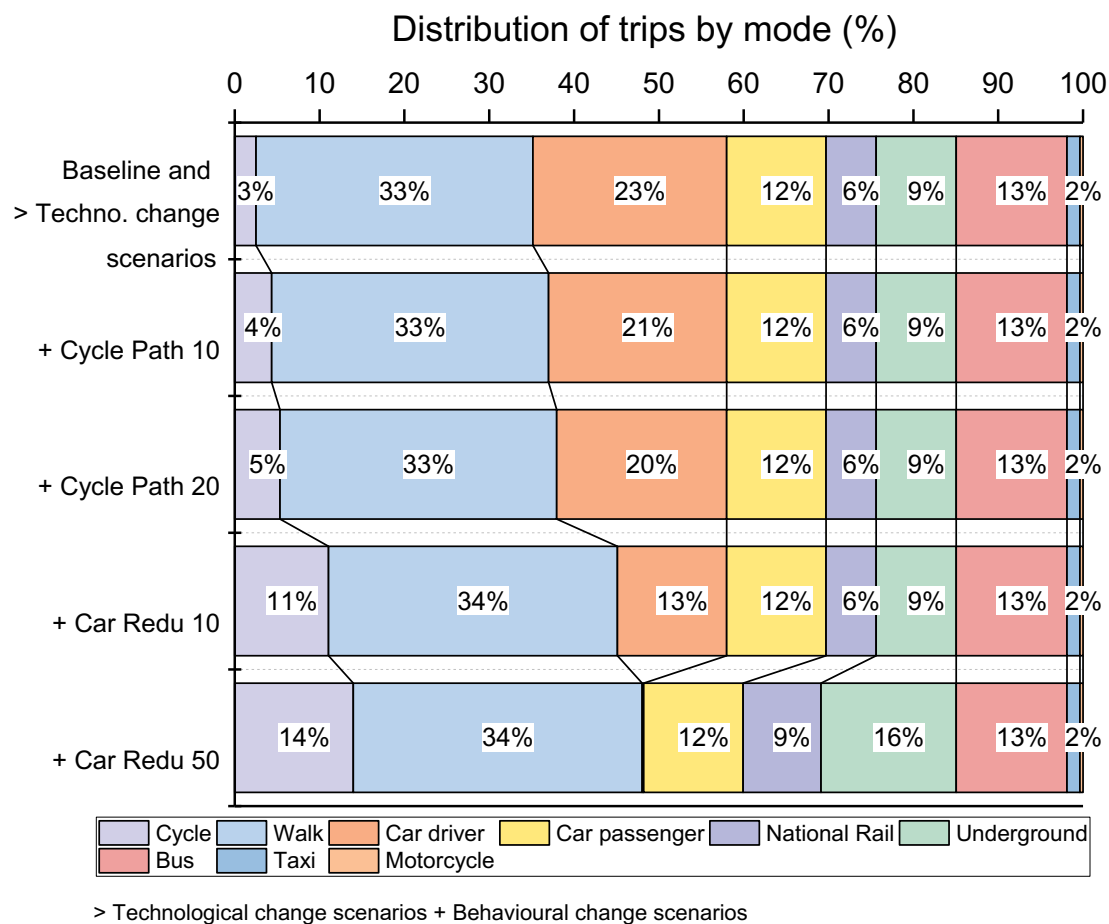


Figure 3.19 Distribution of trips by mode of transport in the baseline 2030, technological change and behavioural change transport policy scenarios in London. Input variables and uncertainties.

This section presents the travel patterns (and its uncertainties) for London's transport policy scenarios, used as input variables in the Health Impact Assessment (HIA) modelling (section 3.5). As mentioned before, the baseline 2030 scenario (Table 3.16) was defined as the current travel patterns in London, as reported in the London Travel Demands Survey (LTDS) 2016/17 (TfL, 2018).

The uncertainty ranges were calculated by the author using TfL (2018) data in the following way: For every variable (travel time, trips per day, trip time, travel speed), for each mode of transport (cycle, walk, car drive, public transport) the rate of change from one year to the next one was calculated for the period 2005 to 2017 using information from the LTDS (TfL, 2018). After calculating the rate of change from one year to the next one, the annual rate of change was averaged over the period (2005 to 2017). The resulting averaged annual rate was used to define the uncertainty range as a $\pm$ percentage from the mean value of the corresponding variable.

Table 3.16 Travel patterns in the baseline 2030 scenario in London. This table presents the travel patterns input variables and uncertainties used in the Health Impact Assessment modelling for the Baseline 2030 reference scenario in London. Source: TfL (2018).

Variable (unit)/mode of transport	Mean value. Source: TfL (2018).	Uncertainty range was calculated from TfL (2018), as the annual avg. rate of change (across the years from 2005 to 2017).
Time travelled per day per person (min/day per person)		
Cycle	1.3	1.2 – 1.3
Walk	11.7	11.6 – 11.8
Car driver	12.4	12.0 – 12.8
Rail	9.1	8.9 – 9.3
Underground	10.5	10.3 – 10.7
Trips per day per person (trips/day per person)		
Cycle	0.06	0.058 – 0.062
Walk	0.73	0.72 – 0.74
Car driver	0.51	0.49 – 0.53
Rail	0.132	0.129 – 0.134
Underground	0.210	0.205 – 0.214
Distance travelled per day per person (km/day per person)		
Cycle	0.2	0.19 – 0.22
Walk	0.7	0.7 – 0.8
Car driver	3.6	3.4 – 3.7
Rail	2.6	2.5 – 2.7
Underground	2.0	1.95 – 2.05

Data on trip time (min/trip) and travel speed (km/h) by mode in all transport policy scenarios in London (including the behavioural, technological and baseline 2030 scenarios) (Table 3.17) was taken from data reported in the London Travel Demands Survey (LTDS) 2016/17 (TfL, 2018). In the behavioural change scenarios, trips were shifted from private motorised modes to public transport, and an additional 10.2 min walk to public transport was accounted for, following the methods from Chaix *et al.*, 2014.

Table 3.17 Travel patterns in London transport policy scenarios. Trip time, travel speed, and additional walking time in public transport trips used in the transport policy scenarios in London.

Mode of transport	Mean value	Uncertainty range
Trip time (min/trip). <i>Source: TfL (2018)</i>		
Cycle	23.1	21.3 – 24.9
Walk	16.1	15.9 – 16.3
Car driver	24.3	22.7 – 26.0
Rail	69.1	66.3 – 71.9
Underground	50.0	48.0 – 52.0
Travel speed (km/h). <i>Source: TfL (2018)</i>		
Cycle	9.5	8.6 – 10.5
Walk	3.8	3.8 – 3.9
Car driver	17.3	16.2 – 18.5
Rail	17.2	16.1 – 18.2
Underground	11.4	11.0 – 11.9
Additional walking time during public transport trips (min/public transport trip). <i>Source: Chaix et al., 2014.</i>		
Walk for public transport trip	10.2	9.6 - 10.9

Note: The uncertainty range for trip time and travel speed was calculated from TfL (2018), as the annual avg. rate of change (across the years from 2005 to 2017). The uncertainty range for the Additional walking time during public transport trips was the uncertainty range reported by the source.

3.4.2.3 Mexico City

3.4.2.3.1 Baseline scenario

The travel patterns in the baseline scenario for Mexico City were defined as the current travel patterns reported in the latest Mexico City travel survey (INEGI, 2017). The number of total trips and the number of trips per person per day by mode in the baseline scenario is presented in Figure 3.20.

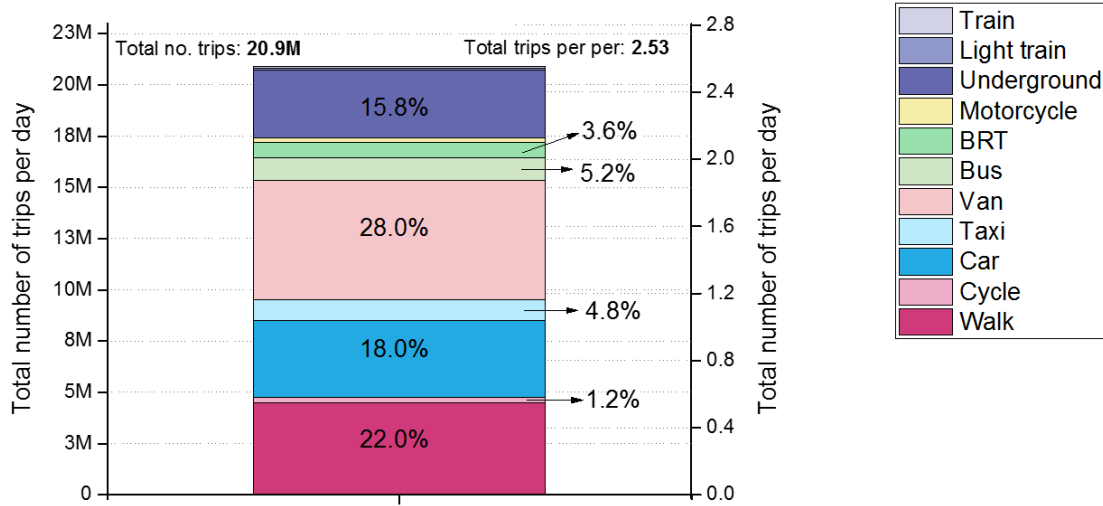


Figure 3.20 Total number of trips per day and number of trips per person per day by mode in the baseline scenario in Mexico City (INEGI, 2017).

3.4.2.3.2 Transport policy scenarios

Travel patterns in the technological change scenarios were defined as the travel patterns in the baseline because there is not a modal shift in the technological change scenarios, just a vehicle technology change. For the behavioural change scenarios, the approach described in section 3.4.2.1 to calculate the additional number of short trips shifted to active modes from motorised modes was used. The distribution of the average number of trips by trip length and the main mode was taken from the UK's National Travel Survey for the estimations in Mexico due to lack of data in Mexico (DfT, 2018a).

The reallocation of kilometres travelled by motorised vehicles to active modes resulted in the following distribution of trips per mode (Figure 3.21). To estimate the trips per person per day (Table 3.19) (used as inputs for the health impact modelling) a total population of 8.26 million people was assumed to travel, according to the Mexico City travel survey.

An assumption that could be questioned in the behavioural change scenarios is that all trips made by taxi and buses will be reallocated to active modes. Then, taxi and bus drivers will not be able to drive their old taxis and buses. Future work should review the behavioural change scenarios to make them more realistic.

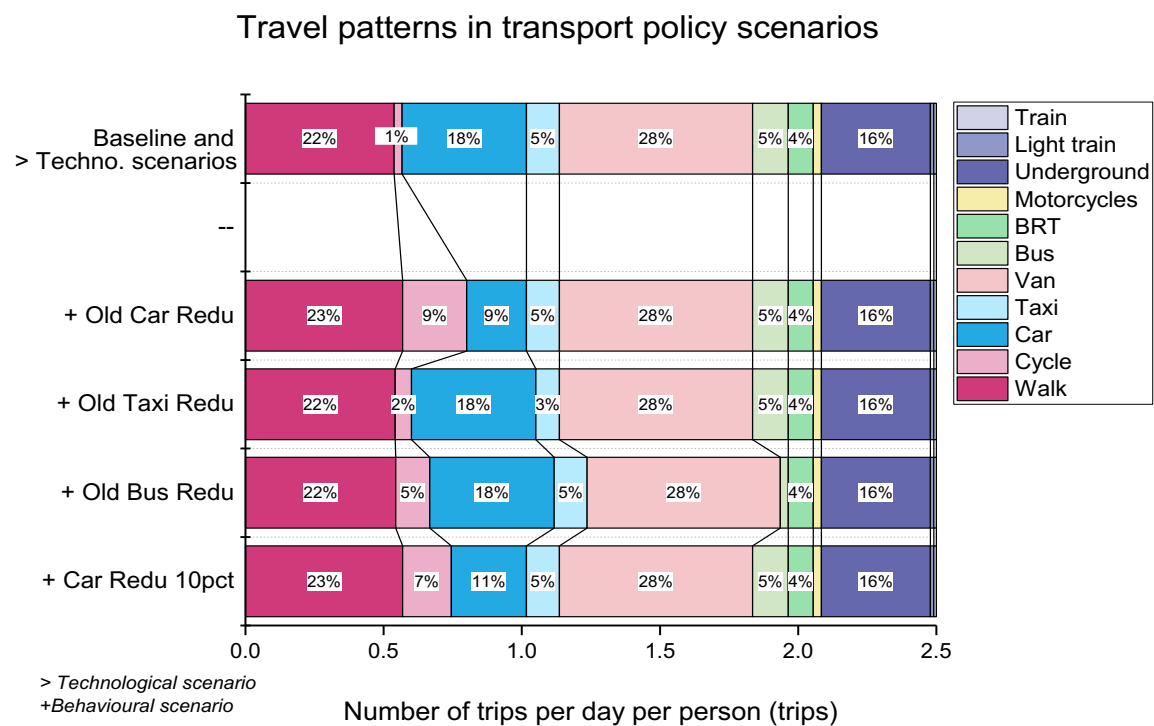


Figure 3.21 Number of trips per person per day in transport policy scenarios in Mexico City.

Table 3.19 Average trips per person per day in baseline and transport policy scenarios in Mexico City.

Mode	Baseline &	Behavioural change scenarios						
	Technological change	Old	Car	Old	Taxi	Old	Bus	Car Redu
	scenarios	Redu		Redu		Redu		
Average trips per person per day (number of trips)								
Walk	0.54	0.58		0.55		0.55		0.58
Cycle	0.03	0.24		0.06		0.12		0.18
Car	0.46	0.22		0.46		0.46		0.28
Taxi	0.12	0.12		0.09		0.12		0.12
Bus	0.13	0.13		0.13		0.03		0.13

After the trips per person per day were estimated, the time per person per day travelling per trips (min/trip) (Table 3.20) was calculated using average speeds for walking and cycling (km/h) from Kelly *et al.*, 2014, and average distance per trip (km/trip) from DfT and TfL; the same approach used in the HEAT model (Kahlmeier *et al.*, 2017). These assumptions were used because (in contrast with London), the Mexico City Travel survey did not provide information on travel times.

Table 3.20 Average speed (km/h) and average distance trip (km/trip) in transport modes (walk, bicycle, car, taxi, and bus) (Kelly *et al.*, 2014; Kahlmeier *et al.*, 2017; DfT, 2018a) used to calculate travel times.

	Walk	Bicycle	Car, taxi	Bus
Average speed (km/h)	5.3 [*]	14.0 [*]	42	6.5 [†]
Average distance trip (km/trip)	1.3	4.1	15.6	4.03 [†]
Source	[*] (Kelly <i>et al.</i> , 2014) [†] (TfL, 2018) (DfT, 2018a; Kahlmeier <i>et al.</i> , 2017)			

Average trip per person per day (Table 3.20) and the information presented in Table 3.20 were used to calculate the travel patterns for all transport policy scenarios in Mexico City after the reallocation of trips to active travel modes.

Table 3.21 Trip duration (min/day) per person in the transport policy scenarios for each mode of transport included in the health impact assessment modelling.

Mode	Baseline & Technological change scenarios	Behavioural change scenarios			
		Old Car Redu	Old Taxi Redu	Old Bus Redu	Car Redu
Travel time (min/day per person)					
Walk	7.95	8.54	8.09	8.09	8.54
Cycle	0.53	4.22	1.05	2.11	3.16
Car	10.25	4.90	10.25	10.25	6.24
Taxi	2.67	2.67	2.01	2.67	2.67
Bus	2.04	2.04	2.04	0.47	2.04

3.5 Health impact assessment modelling framework

Addressing the sixth research objective of this dissertation (described in section 1.4), a health impact assessments (HIA) modelling framework (Figure 3.22) was developed to estimate the health effects of the transport policy scenarios relative to the baseline scenario. The HIA framework follows existing methodologies such as those described by WHO, 2019, and Perez & Künzli, 2009, and Mueller *et al.*, 2017, to study health impacts at the city level.

The health effects of all-cause mortality due to two pathways, physical activity and air pollution exposure (PM_{2.5} and NO₂ air pollution exposure) were assessed (as shown in Figure 3.22). Two types of air pollution exposures were assessed: the benefits on the general population from decreases in ambient air pollution concentrations, and the impacts on travellers who shift modes towards active travel and who suffer from an increased inhalation of air pollution.

These behavioural (physical activity) and environmental (exposure to air pollution) pathways were assessed because they have been shown to have significant impacts on health and robust epidemiological studies to base health effects estimates on (de Nazelle *et al.*, 2011). Impacts of other pathways such as traffic injuries are not accounted for, but its effects were discussed in the literature review (section 2.7.2.2).

A comparative risk assessment approach has been adopted in which long-term changes in exposures to air pollution and behaviours (physical activity) in two scenarios are compared; the approach was also used in Woodcock *et al.*, 2009. In our HIA analysis, exposures and behaviours in the transport policy scenarios (Figure 3.22) were compared to exposures and behaviours in the baseline (counterfactual) scenario. The exposure/behavioural difference (Figure 3.22) was calculated as the difference of exposure/behaviour in the transport policy scenario and exposure/behaviour in the baseline scenario.

The exposure-response functions (ERFs) (Figure 3.22) used to quantify the relationship between exposure to air pollution or physical activity behaviour and mortality were taken from epidemiological literature (discussed in the following sections). The relative risk (RR) functions (Figure 3.22), the attributable fraction (AF) and the attributable mortality were calculated for the change in air pollution exposures, and

the change in physical activity for each transport policy scenario using equations described in Table 3.22 and Table 3.23. The specific input values used for the health impact assessment modelling with its corresponding uncertainties are shown in Table 3.26.

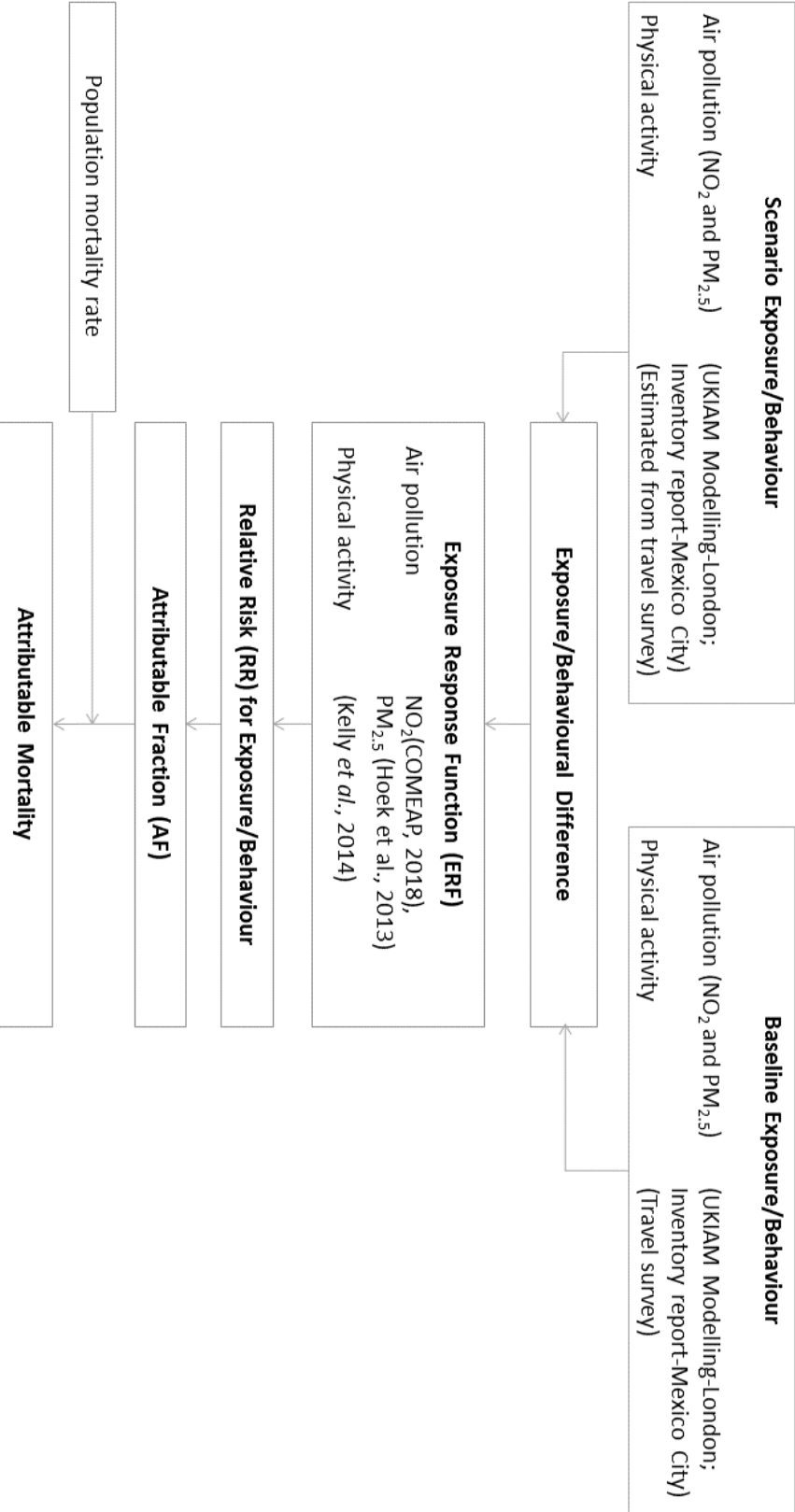


Figure 3.22 Health impact assessments (HIA) general modelling framework used to estimate the health impacts of changes in air pollution exposure and physical activity (behavioural) of the transport policy scenarios (for London and Mexico City) relative to the baseline scenario (following Mueller *et al.*, 2017, HIA framework structure).

3.5.1 Air pollution

Health impacts for the exposure to air pollution were calculated for two air pollutants, PM_{2.5} and NO₂ using the relations presented in Table 3.23 and input values presented in Table 3.26. It has been shown that there is a strong association of PM_{2.5} with all-cause mortality from studies mostly in cities (see section 2.4.1 for details) (Pope, 2007; Wichmann *et al.*, 2000; Laden *et al.*, 2000). NO₂ epidemiology studies are not as abundant as those for PM, but a number of studies have shown an important association of NO₂ with all-cause mortality and have evaluated the interaction of NO₂ and PM_{2.5} on health impacts (COMEAP, 2018; Beelen *et al.*, 2013; Jerrett *et al.*, 2013; Fischer *et al.*, 2015; Crouse *et al.*, 2015b).

Two measures of health impacts of air pollution exposure were evaluated. First, health impacts for air pollution exposure considering the inhaled dose of the population following the travel patterns from the transport policy scenarios compared with the baseline. Second, health impacts for the exposure to different air pollution concentration in the transport policy scenarios compared with the baseline. Changes in air pollution concentrations were modelled with the UKIAM model and are due to vehicle technology changes or decreases in motorised travel modes in the transport policy scenarios.

The air pollution Relative risk (RR) estimates ratio chosen in this dissertation followed the RR values used in the most recent study addressing PM_{2.5} and NO₂ pollution exposure (COMEAP, 2018). Justification of RR values used in this dissertation is presented in section 3.5.4.

3.5.1.1 Changes in air pollution concentration

Changes in air pollutants (PM_{2.5} and NO₂) concentration in each transport scenario were modelled using the UKIAM model described in the previous section. The impacts on mortality due to changes in exposure to different pollution concentrations were calculated using the ‘change in air pollutant population-weighted mean concentration (PWMC)’ relation (presented in Table 3.23) and input values from Table 3.26 to calculate the RR for each scenario relative to the baseline and then the attributable mortality.

3.5.1.2 Air pollutants inhalation

The detailed framework for air pollution exposure mortality impacts for increased inhalation rate follows methodology from Rojas-Rueda *et al.*, 2011, and it is shown in Figure 3.23 (derived from the general framework in Figure 3.22). The inhaled dose in the transport scenario and the baseline were calculated using the inhaled dose equation (Table 3.22) and input values presented in Table 3.26.

The inhaled dose was calculated as μg per day (24 h) for each of the three activities, sleep, rest, and transport, with the transport activity detailed by mode of transport (car, public transport, cycling, walking). The total duration of the three activities combined was 24 hours. The inhaled dose equation (Table 3.22) accounts for the following elements: the minute ventilation rates per activity and per transport mode; the activity duration and transport duration by mode; and the background concentration scaled by the corresponding conversion ratio per mode.

Following methodology from Rojas-Rueda *et al.*, 2011, once the inhaled dose was calculated per each activity and travel mode, the total dose (following relation in Table 3.22) was estimated for each transport scenario and the baseline. To enable the use of RR functions from the air pollution epidemiologic literature, the measure of the incremental total dose inhaled was normalised to an equivalent incremental exposure concentration: the ratio between the total dose inhaled in the transport scenario and in the baseline was scaled to the background concentration in the baseline (using the ‘Equivalent change’ equation shown in Table 3.22).

Once the equivalent change was calculated the relative risk (RR) formula for pollutant inhalation (shown in Table 3.23) was estimated. The RR for pollutant inhalation was calculated for every transport scenario, for each of the two pollutants of study ($\text{PM}_{2.5}$, NO_2) in order to calculate its corresponding attributable mortality (Figure 3.23).

3.5.2 Physical Activity

The physical activity impact associated with mortality were calculated using RR for cycling and walking equations described in Table 3.23, and input values presented in Table 3.26. The difference in time travelled

by bike and walking in the scenario, and the baseline was calculated as minutes per week. The travel times were calculated per day and scaled to weekly travel multiplying by seven days of the week.

Justification of RR values used in this dissertation is presented in section 3.5.4.

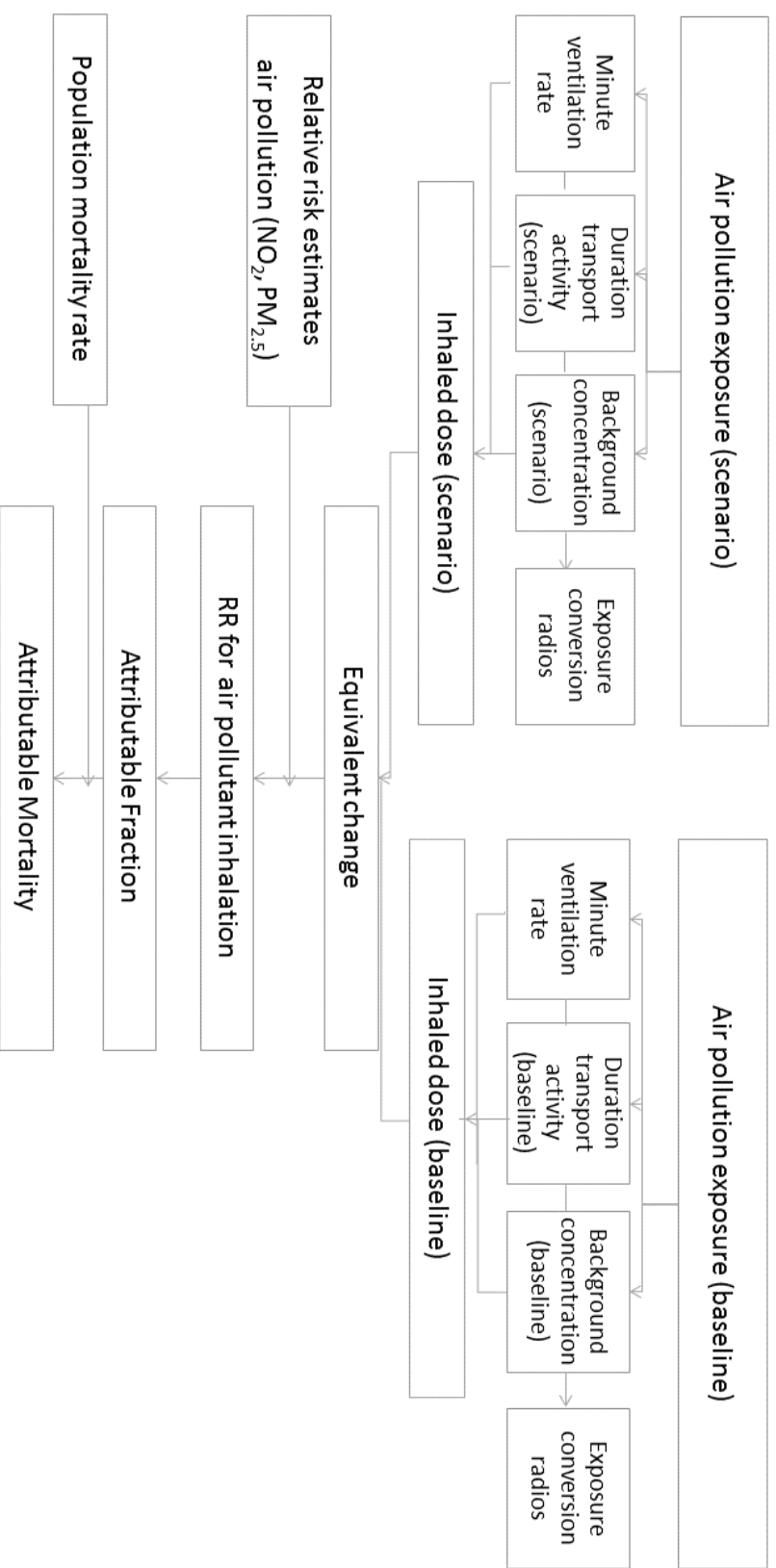


Figure 3.23 Framework used to estimate the health effects due to air pollutants inhalation for the transport policy scenarios relative to the baseline scenario.

Table 3.22 General formulas to quantify health impacts.

Measures of health impact	Formula
Attributable fraction among exposed (AF_{exp}) in terms of the Relative Risk (RR)	$AF_{exp} = \frac{RR - 1}{RR}$
Attributable mortality (exposed)	Mortality rate in population $\times AF_{exp}$
Inhaled dose ($\mu\text{g}/\text{day}$)*	Minute ventilation (m^3/h) $\times$ Duration (h/day) $\times$ Concentration ($\mu\text{g}/\text{m}^3$)
Total dose ($\mu\text{g}/\text{day}$)	Inhaled dose during Sleep + Rest + Transport
Equivalent change ($\mu\text{g}/\text{m}^3$)	Background concentration in baseline $\times \left[\frac{\text{Total dose in scenario}}{\text{Total dose in baseline}} - 1 \right]$

Note: Each formula was calculated for every transport policy scenario.

*This formula was calculated for each activity and each mode of transport (car, public transport, cycling, walking).

Table 3.23 Relative risk (RR) formulas for each variable of the study, air pollution and physical activity (walking and cycling).

Variables	Relative Risk (RR) formula
Air pollution*	
Pollutant inhalation	$\text{Exp} \left[\ln(\text{RR}_{10}) \times \left(\frac{\text{Equivalent change}}{10} \right) \right]$
Change in air pollutant population-weighted mean concentration (PVMC)	$\text{Exp} \left[\ln(\text{RR}_{10}) \times \left(\frac{\text{PVMC in baseline} - \text{PVMC in scenario}}{10} \right) \right]$
Physical activity**	
Cycling	$\text{Exp} \left[\ln(\text{RR}_{100}) \times \left(\frac{\text{Time cycling in baseline} \left(\frac{\text{min}}{\text{week}} \right) - \text{time cycling in scenario} \left(\frac{\text{min}}{\text{week}} \right)}{100 \left(\frac{\text{min}}{\text{week}} \right)} \right) \right]$
Walking	$\text{Exp} \left[\ln(\text{RR}_{168}) \times \left(\frac{\text{Time walking in baseline} \left(\frac{\text{min}}{\text{week}} \right) - \text{time walking in scenario} \left(\frac{\text{min}}{\text{week}} \right)}{168 \left(\frac{\text{min}}{\text{week}} \right)} \right) \right]$

Note: The RR values used in this dissertation are presented in Table 3.26.

*The subscript 10 in the RR_{10} indicates that the coefficient is responding to a per 10 $\mu\text{g}/\text{m}^3$ increase in exposure. The equivalent change was defined in Table 3.22.

**The RR subscript numbers are a reference to the systematic analysis by Kelly *et al.*, 2014. In Kelly *et al.*, 2014, the reference for cycling duration is 100 minutes/person per week, the reference for walking duration is 168 minutes/person per week.

3.5.3 Assumptions and sensitivity analysis

A number of assumptions were made in the modelling approach and are presented below. A sensitivity analysis (Table 3.26 and Table 3.27) was done to understand how the uncertainty in the input variables contribute to uncertainty in the output variables.

3.5.3.1 Air pollution

3.4.3.1.1 Relative Risk estimates

- The air pollution exposure-response function (ERF) used was linear. Thus, in the analysis, it was assumed that each dose of air pollution (expressed as concentrations of PM_{2.5} and NO₂) leads to the same risk reduction.
- No minimum air pollution thresholds were assumed to have to be reached for health effects. Since concentrations in the two case study cities are not greater than 25 µg/m³ PM_{2.5}, no maximum threshold for health effects was set.
- Men and women were assumed to have the same increase in relative risk.
- For the two-pollutants (PM_{2.5} and NO₂) modelling, the unadjusted RR coefficient was used for PM_{2.5}, and an adjusted RR coefficient for NO₂ was used following recommendations by (COMEAP, 2018).

Sensitivity analysis (Table 3.26)

- Assessment of results with an unadjusted RR coefficient for NO₂, as assessed in COMEAP (2018).
- Assessment of results with two pairs of adjusted RR coefficients for PM_{2.5} and NO₂ as assessed in COMEAP (2018).

3.4.3.1.2 Pollution exposure conversion ratios/Mode specific concentrations

- Mode-specific ratios for exposure contrast vs background concentrations of PM_{2.5} were taken from the literature (de Nazelle, Bode & Orjuela, 2017), as shown in (Table 3.26). The same ratios were used for NO₂ concentrations, as done in previous studies (de Nazelle, Bode & Orjuela, 2017).
- Concentrations while travelling by bike, walking, car, rail, and underground were assumed to be specific to each microenvironment, scaling background concentrations to the conversion rate exposure factor (de Nazelle, Bode & Orjuela, 2017).

Sensitivity analysis (Table 3.26)

- It was assumed that there is no contrast on exposure vs background concentration and all pollution exposure conversion ratios equal one.

3.4.3.1.3 Background concentrations

- PM_{2.5} concentrations in the underground were assumed to be constant at 88 µg/m³ based on (Smith *et al.*, 2020)
- Sleeping and resting were assumed to take place at background air pollutant concentration levels. Background concentration inputs for London were taken from UKIAM model. For Mexico City, background concentration values were taken from monitoring station background concentration values.

3.5.3.2 Physical activity

3.5.3.2.1 Relative Risk estimates

- The response function (ERF) used to estimate mortality impacts for walking and cycling had a linear distribution. A linear relationship between walking or cycling duration (assuming a constant average speed) and the mortality rate is assumed. Thus, each dose of walking or cycling leads to the same risk reduction.
- The relative risks of reduction in all-cause mortality from walking and cycling are assumed to be the same in men and women and across adult age groups.
- No thresholds of active travel duration have to be reached to achieve health benefits. There was no need to establish a maximum threshold (no more health benefits above a certain threshold) because in all the scenarios, no more than 30 min was modelled. For example, in the HEAT model, there is a maximum threshold and to up to a maximum of about 60 minutes of cycling or walking per day.

Sensitivity analysis (Table 3.27):

- Non-linear response function (ERF) (log-linear and 0.25 power) for walking and cycling were tested to evaluate the effect of the assumed linear distribution (Kelly *et al.*, 2014).

3.5.3.2.2 Population

- The assessment does not distinguish between sedentary or very active individuals. This could lead to a certain overestimation of benefits in highly active populations or a certain underestimation of benefits in less active ones.

3.5.3.2.3 Public transport tips

- All trips on public transport are assumed to include an extra ten-minute walk to account for the time that travellers walk to the public transport station based on data collection from Chaix *et al.*, 2014.

Sensitivity analysis (Table 3.27):

- Assessment of results assuming no extra walking time in public transport trips.

3.5.4 Justification of choices of input variables

3.5.4.1 Relative risk (RR) estimates

The Relative Risk (RR) estimates used in this dissertation followed recommendations by COMEAP (2018), which provide the most updated approach to analysing two-pollutant evidence (NO₂ and PM_{2.5}).

3.5.4.1.1 Air pollution

Particulate matter (PM_{2.5})

Following COMEAP, 2018, recommendations, for the two-pollutant analysis (NO₂ and PM_{2.5}) the unadjusted coefficient for PM_{2.5} of 1.06 (95% CI: 1.04 - 1.08) (Table 3.26) per 10 µg/m³ annual average PM_{2.5} (derived from a meta-analysis of single pollutant studies) was used (Hoek *et al.*, 2013). Hoek *et al.*, 2013, recommended that risk coefficient was based on a meta-analysis of all cohort studies published before January 2013 by Hoek *et al.*, 2013. Eleven different studies conducted in adult populations of North America and Europe contributed to the estimation of this coefficient.

Nitrogen dioxide (NO₂)

When assessing the mortality associated with long-term exposure to multi-pollutants (NO₂ and PM_{2.5}) COMEAP, 2018, recommends that the effects on mortality attributable to NO₂ itself lay within the range of 25 - 55% of the unadjusted coefficient (1.023 (95% CI: 1.008, 1.037)). This gives a reduced coefficient of 1.0095 (Table 3.26), within the range of 1.006 to 1.013 per 10 µg/m³ of NO₂ for estimating the effects attributable to NO₂ alone. The unadjusted RR coefficient used for single-pollutant model evidence of 1.023 (95% CI: 1.008, 1.037) per 10 µg/m³ NO₂ as an annual average, comes from eleven study estimates for mortality associated with long-term exposure to NO₂ selected for meta-analysis by COMEAP (2018). There was substantial heterogeneity between the estimates from different studies (I^2 , a measure of heterogeneity, was 97%).

3.5.4.1.2 Physical Activity

Relative Risk (RR) estimates for physical activity (walking and cycling) (Table 3.27) were used as recommended in the most comprehensive study in this regard by Kelly *et al.*, 2014. In this study, Kelly *et al.*, 2014, show 18 results from 14 studies for walking and eight results from seven studies for cycling to reduce the risk of all-cause mortality, adjusted for other physical activity. For a standardised dose of 11.25 MET per hours per week (or 675 MET. minutes per week), the reduction in risk for all-cause mortality was 11% (95% CI = 4 to 17%) for walking and 10% (95% CI = 6 to 13%) for cycling (Table 3.27). The estimates for walking were based on 280,000 participants and 2.6 million person-years, and for cycling, they were based on 187,000 individuals and 2.1 million person-years.

3.5.4.2 Population and mortality rates

3.5.4.2.1 London

Population and mortality rates projections to 2030

Information on population and mortality rates projected to 2030 in London were used from the Greater London Authority (GLA) Population and Household Projections (GLA, 2017b). The 2016-based projections were used because these are the most up-to-date complete set of GLA projections. GLA's trend projections are based purely on trends in fertility, mortality and migration. Projections are produced from the starting point of the most recent year (2016) and each subsequent year's population is generated taking the previous year's projected population as the start point.

Three different projection scenarios (central, short-term and long-term scenarios) were modelled by the GLA and used in this study (Table 3.24), primarily to reflect uncertainty in future migration patterns. Migration flows are the most variable and difficult to project component of population change, and the very large scale of flows into and out of London makes the projections especially sensitive to the assumptions used (GLA, 2017b).

The short-term scenario (Table 3.24) assumes that recent migration patterns will persist for the duration of the projection period. While projections based on this approach are suitable for use in the near-term, the GLA has argued: "that a projection based only on recent patterns, especially those which are so heavily

influenced by a single event is not a suitable basis for long-term planning. When projecting further ahead, it is generally better to base assumptions on longer historical trends, preferably spanning a full, or multiple, economic cycles”.

To this end, the GLA explains how “a variant based on a longer period of past migration data. In addition to being more conceptually sound as a basis for projection, using a longer trend has the advantage of yielding more stable projections between successive projection rounds when compared to those produced using short-term trends only, as each additional year of data has a smaller proportional impact on the overall trend”.

The trends used for the 2016-based scenarios are the following:

- The short-term scenario bases the patterns on estimates for the five-year period of mid-2012 to mid-2016.
- The central scenario bases the patterns on estimates for the 10-year period of mid-2007 to mid-2016.
- The long-term scenario bases the patterns on estimates for the 12-year period of mid-2002 to mid-2016.

Table 3.24 Scenario projections on population and mortality rate for London for the year 2030 used for the HIA modelling (GLA, 2017b).

	Central trend	Long trend	Short trend
Population London 2030	9,924,970	9,796,811	9,919,002
Mortality rates 2030	54,315	53,141	55,175

Note: *The central scenario values were used as the input values for the HIA modelling. The short-term and long-term values were used as the uncertainty range and were assessed in the sensitivity analysis.

3.5.4.2.2 Mexico City

Population and mortality rates for Mexico City (Table 3.25) were taken from the most recent (2017) official data reported by the National Institute of Statistics and Geography of Mexico, INEGI (INEGI, 2018). The analysis for Mexico City did not include future projections, like in the analysis for London.

Table 3.25 Population and mortality rate for Mexico City in 2017 used for the HIA modelling (INEGI, 2018).

Mexico City	2017 statistics (Number of persons)
Population	8,918,653
Mortality rate	75,609

Table 3.26 Input values and uncertainties for the health impact assessment modelling and sensitivity analysis of air pollution exposures.

Variable (unit)	Mean value	Uncertainty range	Description	Source
Air pollution				
Relative risk (RR) estimates (ratio)				
RR of PM _{2.5} (ratio)	1.06	1.04 - 1.08	Unadjusted coefficient per 10 µg/m ³ increase in exposure.	(Hoek <i>et al.</i> , 2013) and used in (COMEAP, 2018)
RR of NO ₂ (ratio)	1.0095	1.006 - 1.013	Adjusted coefficient for PM _{2.5} taking the mid-point of the 25 - 55% range from the unadjusted coefficient. Estimated per 10 µg/m ³ increase in exposure.	(COMEAP, 2018)
<i>Sensitivity analysis: RR estimates</i>				
Unadjusted RR for NO ₂				
RR of NO ₂ (ratio)	1.023	1.008 – 1.037	Unadjusted coefficient. Estimated per 10 µg/m ³ increase in exposure.	(Hoek <i>et al.</i> , 2013) and used in (COMEAP, 2018)
Pairs of adjusted RR				
Pair 1:				
RR of NO ₂ (ratio)	1.019	Not reported	NO ₂ (19%) adjusted for PM _{2.5} (53%) and vice versa (derived as paired NO ₂ and PM _{2.5} percentage reductions from unadjusted to adjusted coefficients from different studies). Estimated per 10 µg/m ³ increase in exposure.	Calculated by (COMEAP, 2018) using (Jerrett <i>et al.</i> , 2013)
RR of PM _{2.5} (ratio)	1.029			

Table 3.26 (Continued) Input values and uncertainties for the health impact assessment modelling and sensitivity analysis of air pollution exposures.

Variable (unit)	Mean value	Uncertainty range	Description	Source
Pair 2:				
RR of NO ₂ (ratio)	1.011	Not reported	NO ₂ (53%) adjusted for PM _{2.5} (14%) and vice versa (derived as paired NO ₂ and PM _{2.5} percentage reductions from unadjusted to adjusted coefficients from different studies). Estimated per 10 µg/m ³ increase in exposure.	Calculated by (COMEAR, 2018) using (Beelen <i>et al.</i> , 2014)
RR of PM _{2.5} (ratio)	1.053			
Minute ventilation (m³/h)				
Sleep (m ³ /h)	0.27	0.14 - 0.41	The data values did not include any uncertainty distribution, so the uncertainty was assumed to be +/- 50% around the mean.	(de Nazelle, Rodríguez & Crawford-Brown, 2009; Johnson, 2002)
Rest (m ³ /h)	0.61	0.31 - 0.92		
Cycling (m ³ /h)	2.55	1.28 - 3.83		
Walking (m ³ /h)	1.37	0.69 - 2.06		
Car (m ³ /h)	0.61	0.31 - 0.92		
Public transport* (m ³ /h)	0.61	0.31 - 0.92		
Pollution exposure conversion ratios (ratio)				
Cycling (ratio)	2	1.9 - 2.1	Values for exposure contrast vs. background concentrations of PM _{2.5} .	(de Nazelle, Bode & Orijuela, 2017)
Walking (ratio)	1.9	1.7 - 2.0		
Car (ratio)	2.5	2.4 - 2.6		
Public transport (ratio)	1.9	1.8 - 2.0		

Table 3.26 (Continued) Input values and uncertainties for the health impact assessment modelling and sensitivity analysis of air pollution exposures.

Variable (unit)	Mean value	Uncertainty range	Description	Source
<i>Sensitivity analysis: Pollution exposure conversion ratios (ratio)</i>				
Cycling (ratio)	1		Assuming there are no exposure contrasts vs background concentrations of PM _{2.5} .	
Walking (ratio)	1			
Car (ratio)	1			
Public transport (ratio)	1			
Underground background concentration				
PM _{2.5} concentration in the underground (µg/m ³)	88	44 - 132	The data values did not include any uncertainty distribution, so the uncertainty was assumed to be +/- 50% around the mean.	(Smith <i>et al.</i> , 2020)
Activity duration (h)				
Sleep (h)	8	-	The units refer to hours per person per day. Constant 24 hours in a day is assumed. The transport activity time is scenario dependent.	-
Rest (h)	16 – (transport activity)	-		

Table 3.27 Input values and uncertainties for the health impact assessment modelling and sensitivity analysis of the physical activity pathway.

Variable (unit)	Mean value	Uncertainty range	Description	Source
Physical activity				
Relative risk (RR) estimates (ratio)				
RR for Walking (ratio)	0.89	0.83 - 0.96	Reference duration 168 minutes/person per week, 11.25 MET vs. 0 MET h/week	(Kelly <i>et al.</i> , 2014)
RR for Cycling (ratio)	0.90	0.87 - 0.94	Reference duration 100 minutes/person per week, 11.25 MET vs. 0 MET h/week	
Note: Metabolic equivalent of task (MET) (1 MET = 1 kcal/kg/h).				

<i>Sensitivity analysis: RR estimates</i>				
RR for Walking (ratio)	0.90	0.85-0.95	Log-linear dose-response function distribution. Estimated per 10 µg/m ³ increase in exposure.	(Kelly <i>et al.</i> , 2014)
RR for Walking (ratio)	0.9	0.86-0.94	0.25 power dose-response functions distribution. Estimated per 10 µg/m ³ increase in exposure.	
RR for Cycling (ratio)	0.90	0.86-0.94	Log-linear dose-response function distribution. Estimated per 10 µg/m ³ increase in exposure.	
RR for Cycling (ratio)	0.84	0.79-0.90	0.25 power dose-response functions distribution. Estimated per 10 µg/m ³ increase in exposure.	

Table 3.27 (Continued) Input values and uncertainties for the health impact assessment modelling and sensitivity analysis of the physical activity pathway.

Variable (unit)	Mean value	Uncertainty range	Description	Source
Additional walk trip leg added to public transport trips (min/trip)				
Time walking (min/trip)	10.2	9.6 – 10.9		(Chaix <i>et al.</i> , 2014)
<i>Sensitivity analysis: Additional walk trip leg added to public transport trips (min/trip)</i>				
Time walking (min/trip)	0		Assuming no additional time walking in public transport trips	

Chapter 4

CO₂ emissions and air quality modelling of transport
policy scenarios in London

4.1 Overview

This chapter presents the results of the carbon dioxide (CO₂) and air quality modelling of the technological and behavioural change transport policy scenarios assessed for London. Section 4.1.1 of this chapter presents an overview of the methodology used. Please note that a detailed and complete description of the methods used for the analysis of transport policy scenarios for London was described in the previous chapter.

Section 4.2 presents the modelling results using the BRUTAL sub-model of the UKIAM model for the assessment of transport policy scenarios for London. CO₂ emissions and air quality emissions are presented first, and then, air quality concentrations are shown. The next section, Section 4.2, also presents the cost assessment for each transport policy scenario.

The final section, Section 4.3, presents the discussion of the results. This section discusses the principal findings, the uncertainties and sensitivities of the results, the strengths and limitations of the results, it compares the results to other studies and presents concluding remarks.

4.1.1 Methods overview

The methods used for the assessment of transport policy scenarios for London were described in detail in the previous chapter. This section intends to give a brief overview of the methods previously presented. The transport policies which inspired the development of transport policy scenarios for London were described in Section 3.2.1. The assumptions for the development of each transport policy scenario were also described in Section 3.2.1.

The CO₂ emissions and air quality modelling framework used for London was presented in Section 3.3. The BRUTAL sub-model of the UKIAM model (Section 3.3.1) was used to model CO₂ emissions and nitrogen oxide (NO_x) and particulate matter (PM) emissions and concentrations. As discussed in Section 3.3.3, CO₂ emissions from the electricity production process to power electric vehicles are included.

In this chapter, all the emissions from electric vehicles which have been accounted for have been indicated with a striped line texture. The results of the cost assessment regarding damage costs per unit or air pollutant exposure and carbon offset pricing are also presented in this chapter, following the methodology described in Section 3.3.4.

The translation of transport policy scenarios for London as inputs for the modelling framework, in terms of vehicle fleet composition, was presented in Section 3.4.1.1. In Section 3.4.1.1 each scenario was described in terms of kilometres travelled by vehicle fleet. The description of kilometre travelled per vehicle type per scenario were the inputs used to model each scenario with the BRUTAL sub-model of the UKIAM model. The modelling results are presented below.

4.2 Results

4.2.1 Emissions

4.2.1.1 Carbon dioxide (CO₂)

All of the technological change scenarios (Figure 4.1) which included the shift to electric vehicles (*Electric Car, Electric Taxi, Electric Bus, and Electric Vehicle Fleet scenario*) or improved the Euro Standard of the vehicle fleet (*Low Emission Zone scenario*) resulted in a reduction of carbon dioxide (CO₂) emissions relative to 2030 baseline levels. The technological change scenario, which resulted in the most considerable CO₂ emission reductions was the *Electric Vehicle Fleet scenario* in which 3.1 ± 0.4 Mt (- 46.3%) CO₂ emissions were reduced, relative to 2030 baseline levels.

It is important to note that, as mentioned and explained before (Section 3.3.3), the CO₂ emissions presented here include CO₂ emissions generated during the electricity generation process needed to power the electric vehicle fleet in each transport policy scenario (striped line texture in Figure 4.1). There are significant net savings of CO₂ emissions in the electric vehicle fleet scenarios. CO₂ emissions from electricity generation accounted for the following percentage from total transport-related emissions in each scenario: 40.5% in the *Electric Car scenario*, 2.3% in the *Electric Taxi scenario*, 1.7% in the *Electric Bus scenario* and 62.9% in the *Electric Vehicle Fleet scenario*. All-electric vehicle scenarios yield reductions in CO₂ emissions.

The only technological change scenario, which resulted in an increase in CO₂ emissions relative to 2030 baseline levels, was the *Diesel to Petrol Car scenario*. In this scenario, *Diesel to Petrol Car scenario*, all diesel cars were converted to petrol cars and therefore, resulted in an increase of 0.3 ± 0.04 Mt (+ 4.5%) relative to 2030 baseline levels.

Overall, in the technological change scenarios for carbon dioxide (CO₂) emissions relative to 2030 baseline levels varied from an increase of 0.3 ± 0.04 Mt (+ 4.5%) in the *Diesel to Petrol Car scenario* to a reduction of 3.1 ± 0.4 Mt (- 46.3%) in the *Electric Vehicle Fleet scenario*.

All of the behavioural change scenarios (Figure 4.1) resulted in reductions of CO₂ emissions relative to 2030 baseline levels. The behavioural change scenario, which resulted in the largest reductions of CO₂

emissions, relative to 2030 baseline levels, was the *Car Redu 50 scenario*. The behavioural change scenario, which resulted in the smallest reductions of CO₂ emissions, relative to 2030 baseline levels, was the *Cycle Lane 10 scenario*. The reductions in CO₂ emissions (Figure 4.1) relative to 2030 baseline levels ranged from 0.04 ± 0.005 Mt (- 0.7%) in the *Cycle Lane 10 scenario* to 1.8 ± 0.3 Mt (- 27.3%) in the *Car Redu 50 scenario*.

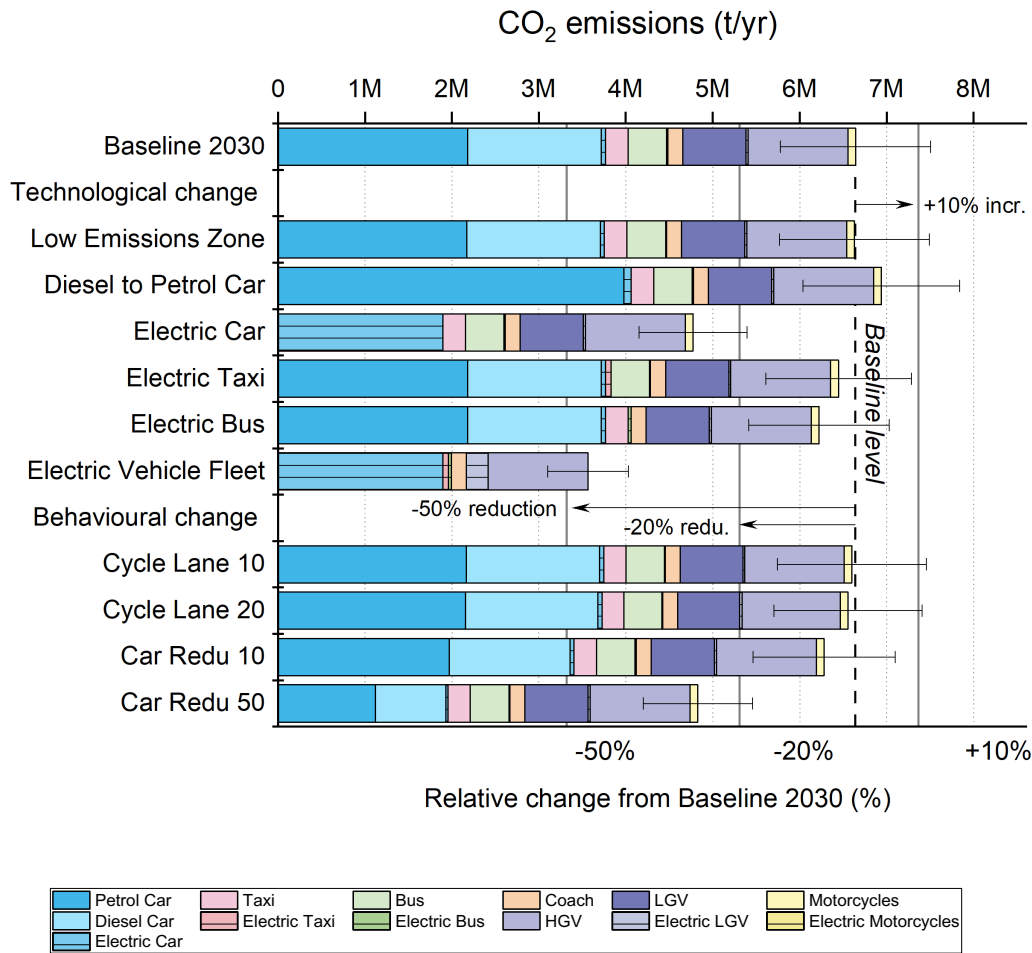


Figure 4.1 Carbon dioxide (CO₂) emissions (ton/year) projected to 2030 (upper x-axis) in the technological and behavioural change transport policy scenarios modelled. Percentage change relative to the baseline 2030 scenario (bottom x-axis) is also shown.

4.2.1.2 Nitrogen oxides (NO_x)

All of the technological and behavioural change scenarios resulted in reductions of NO_x emissions (Figure 4.2) relative to 2030 baseline levels. The technological change scenarios showed significantly larger NO_x emissions (reduction up to 91.5%) than the behavioural change scenarios (reductions up to 32.6%).

The technological change scenario which showed the smallest reduction of NO_x emissions (Figure 4.2) was the *Electric Buses scenario* with a reduction of 0.2 ± 0.06 kt relative to the *Baseline 2030 scenario* (equivalent to a 3.2% reduction). The scenario with the largest reduction of NO_x emissions was the *Vehicle Fleet Electrification scenario* which reduced NO_x emissions by 6.0 ± 1.7 kt (equivalent to a 91.5% reduction). Electrification scenarios showed the most significant decreases in NO_x emissions.

In the behavioural change scenarios, reductions in NO_x emissions (Figure 4.2) ranged from 0.04 ± 0.01 kt relative to the *Baseline 2030 scenario* (equivalent to a 0.6% reduction) in the *Cycle Lane 10 scenario* to a reduction of 2.2 ± 6.2 kt relative to the *Baseline 2030 scenario* (equivalent to a 32.6% reduction) in the *Car Redu 50 scenario*.

4.2.1.3 Particulate matter

The technological change scenarios (Figure 4.3) resulted in PM₁₀ emission reductions which ranged from a reduction of 1.5 ± 0.2 t of PM₁₀ emissions relative to the *Baseline 2030 scenario* (equivalent to a 0.3% reduction) in the *Electric Bus scenario* to a reduction of 53.5 ± 8.0 t of PM₁₀ emissions relative to the *Baseline 2030 Scenario* (equivalent to a 9.1% reduction) in the *Electric Vehicle Fleet scenario*.

Behavioural change scenarios (Figure 4.3) resulted in PM₁₀ emissions reduction which ranged from 3.3 ± 0.5 t of PM₁₀ emissions relative to the *Baseline 2030 scenario* (equivalent to a 0.6% reduction) in the *Cycle Lane 10 scenario*. A reduction of 146.2 ± 21.9 t of PM₁₀ emissions relative to the *Baseline 2030 scenario* (equivalent to a 24.8% reduction) in the *Car Redu 50 scenario*.

On average, non-exhaust PM₁₀ emissions accounted for 92% of total emissions across transport policy scenarios. Since the technological scenarios convert rather than remove vehicles, they have little effect on PM emissions.

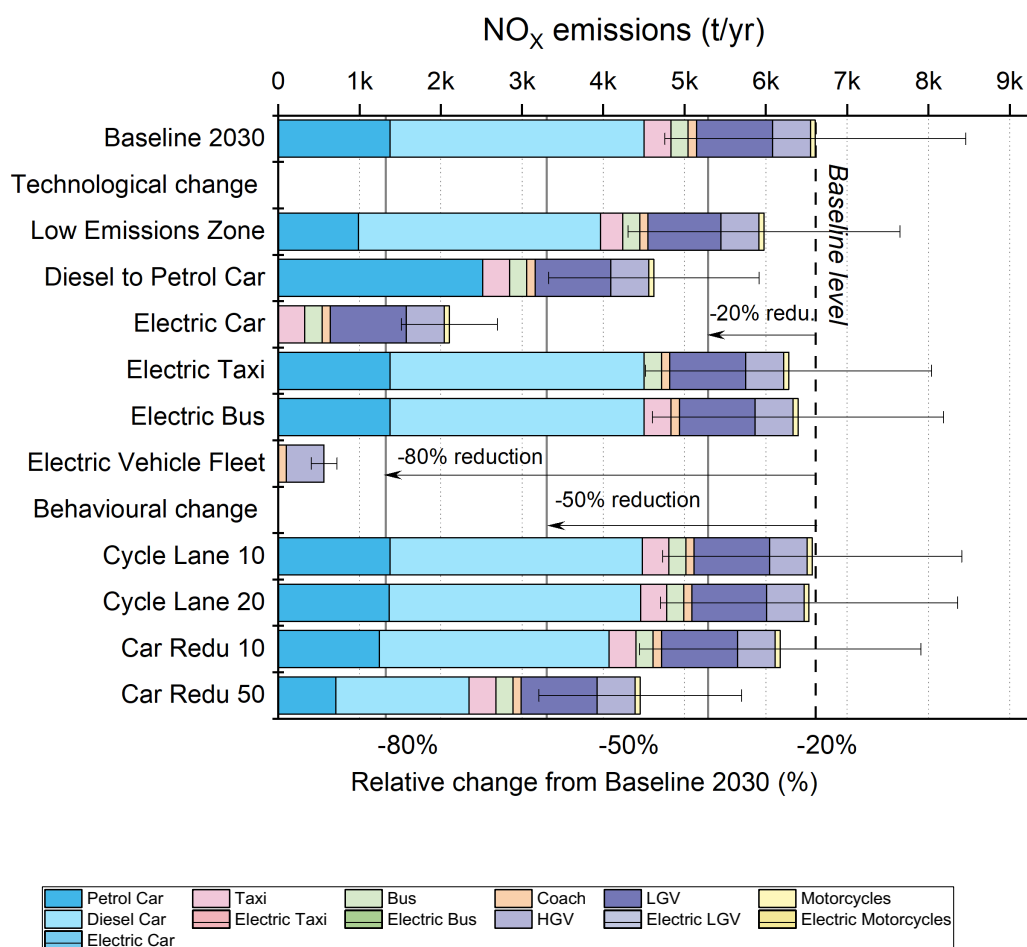


Figure 4.2 Nitrogen oxide (NO_x) emissions (ton/year) projected to 2030 in the technological and behavioural change transport policy scenarios modelled (upper x-axis). Percentage change relative to the baseline 2030 scenario is also shown (bottom x-axis).

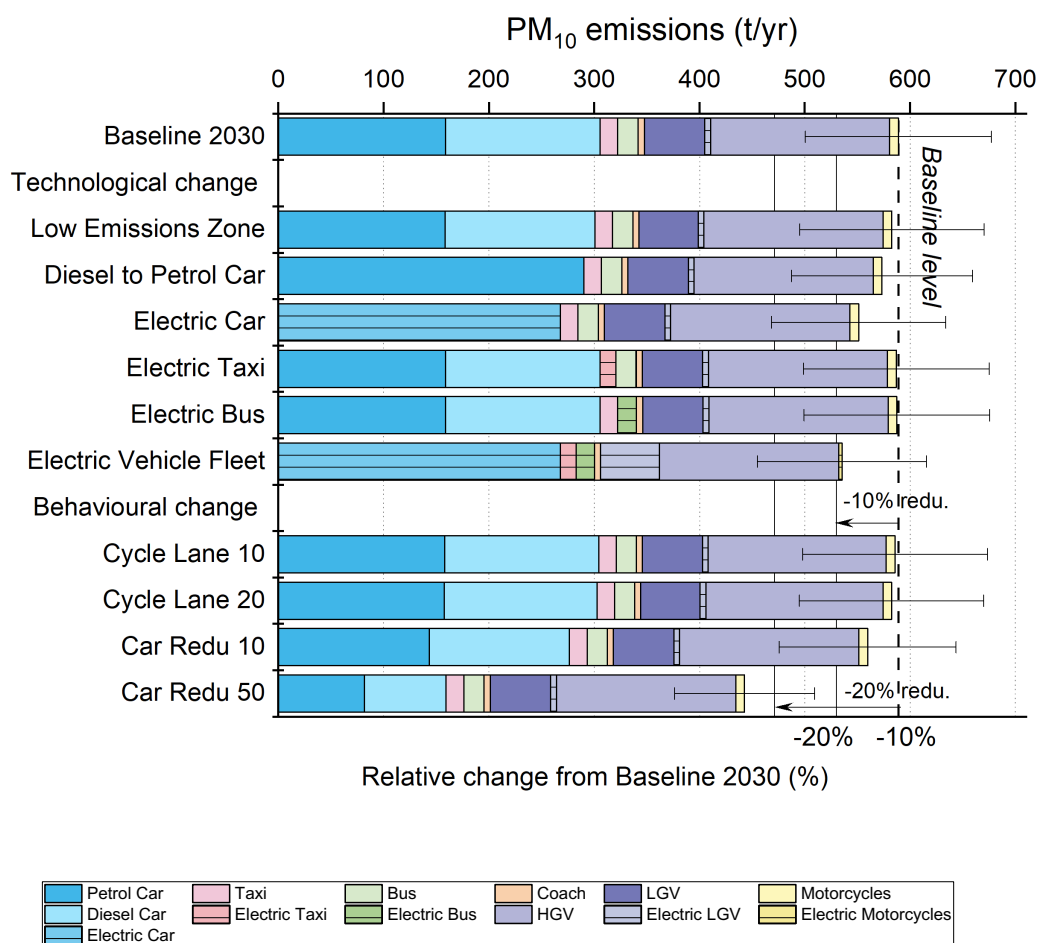


Figure 4.3 Particulate matter (PM₁₀) emissions (ton/year) projected to 2030 in the technological and behavioural change transport policy scenarios modelled (upper x-axis). Percentage change relative to the baseline 2030 scenario is also shown (bottom x-axis).

4.2.1.4 Emissions factors

The average CO₂ emissions factors (Table 4.1) for fossil-fuelled cars are on average around twice as high as CO₂ emissions factors for electric cars. On the other hand, emissions factors (Table 4.1) for particulate matter are only 13% higher for electric cars than for fossil-fuelled cars. This smaller difference between electric and fossil-fuelled cars is because electric cars still account for non-exhaust particulate matter emissions.

As it can be seen in Table 4.1, emission factors per km travelled for buses are naturally higher than for cars, but buses transport 17 to 43 passengers on average in London in contrast to 1.4 passengers per car (GLA, 2014). Then, the passenger-km travelled for buses (that accounts for the number of passengers in a vehicle) is significantly lower than the passenger-km travelled by cars.

Table 4.1 Average CO₂, NO_x and PM₁₀ emissions factors in grams per km travelled and in grams per passenger-km for cars (petrol, diesel, electric) and buses (diesel and electric) from BRUTAL sub-model of UKIAM. The average occupants per vehicle are also indicated (GLA, 2014).

Mode	Average emission factors (g/km)			Average occupants per vehicle	Average emissions factors (g/passenger-km)		
	CO ₂	NO _x	PM ₁₀		CO ₂	NO _x	PM ₁₀
Petrol Car	155.6	0.098	0.0113	1.4	111.1	0.070	0.0081
Diesel Car	132.5	0.269	0.0126		94.6	0.192	0.0090
Electric Car	74.0	-	0.0105		52.9	-	0.0075
Bus	922.9	0.441	0.0400	17 – 44	21.0 – 54.3	0.010 – 0.026	0.0009 – 0.0024
Electric Bus	-	-	0.0369		-	-	0.0008 – 0.0022

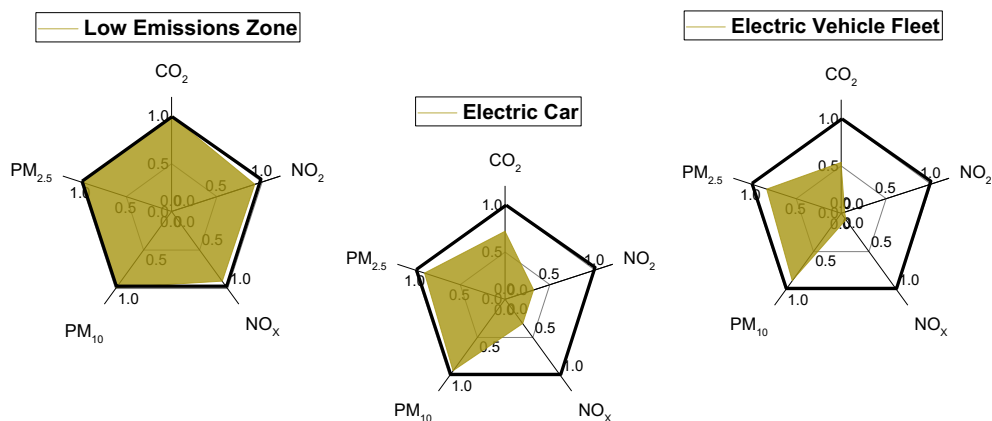
4.2.1.5 All pollutants results: CO₂, NO₂, NO_x, PM₁₀ and PM_{2.5}

The emissions of all the pollutants (CO₂, NO₂, NO_x, PM₁₀ and PM_{2.5}) modelled in each transport policy scenario (Figure 4.4) were normalised to baseline levels and associated with their corresponding implementation cost (the implementation cost was presented in Table 3.1). The transport policy scenarios with the most significant reductions over all the pollutants were: The *Car Redu 50 scenario* and the *Vehicle Fleet Electrification scenario*. Both scenarios entail medium (£100 million - £1 billion) implementation costs.

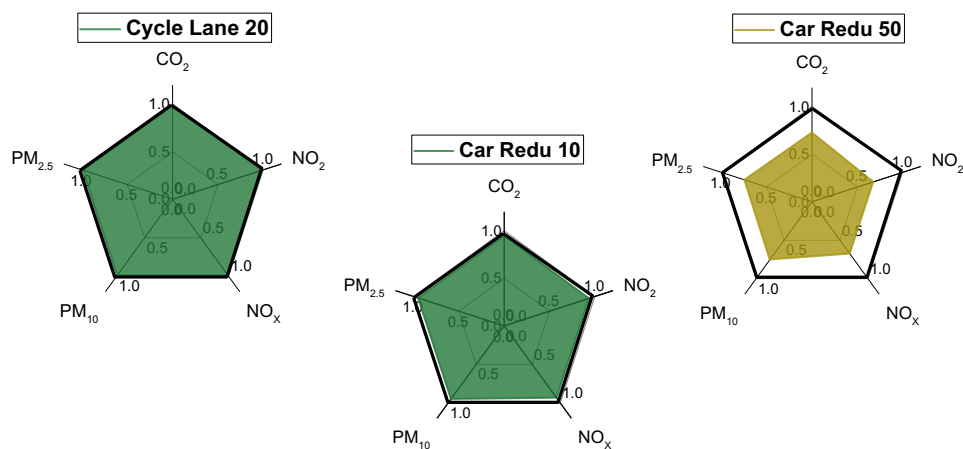
The *Car Redu 50 scenario* (Figure 4.4) brought the most significant reductions of particulate matter emissions. The *Vehicle Fleet Electrification scenario* convey the most substantial reductions of nitrogen oxides and CO₂ emissions. The costliest components for each of these two scenarios were the implementation of the London-wide cycle network needed for the *Car Redu 50 scenario*, and the electric charging infrastructure needed for *Vehicle Fleet Electrification scenario*.

The *Car Redu 10 scenario* demonstrated more significant emissions reductions for particulate matter and CO₂ than the *Low Emissions Zone scenario*, and has a lower implementation cost. Measures needed to accomplish the modal shift needed in the *Car Redu 10* scenario, have a lower cost of implementation. For example, the improvement of local walking routes, the proportion of cycle and walking to work and school and the support the walk London network. In contrast, for the *Low Emissions Zone scenario*, only the implementation of the measure in the central area of London would entail medium range (£100 million - £1 billion) implementation costs.

Technological change scenarios



Behavioural change scenarios



Implementation costs:  Low (<£100m)  Medium (£100m - £1bn)

Figure 4.4 CO₂, NO_x, NO₂, PM₁₀, PM_{2.5} emissions normalised to baseline 2030 levels for selected behavioural and technological change scenarios. The normalised value of 1.0 indicates the baseline emissions level for each pollutant and is highlighted with a black pentagon. The implementation cost is also noted, green (implementation cost < £100 m) and yellow (implementation cost £100 m – £1 bn).

4.2.2 Air pollution exposure

Exposures to the most harmful pollutants for health, NO₂ and PM_{2.5}, were estimated as population weighed annual mean concentrations (PVMC) (Figure 4.5 and Figure 4.6). The resulting PVMC is presented at the ward level for London (Figure 4.5 and Figure 4.6).

4.2.2.1 Baseline 2030

In the baseline 2030 scenario, PVM NO₂ concentrations (Figure 4.5) average $11.5 \pm 3.2 \mu\text{g}/\text{m}^3$ London-wide. The average London-wide PVM PM_{2.5} concentration is $9.3 \pm 1.4 \mu\text{g}/\text{m}^3$ (Figure 4.6).

NO₂ PVM concentrations in Baseline 2030

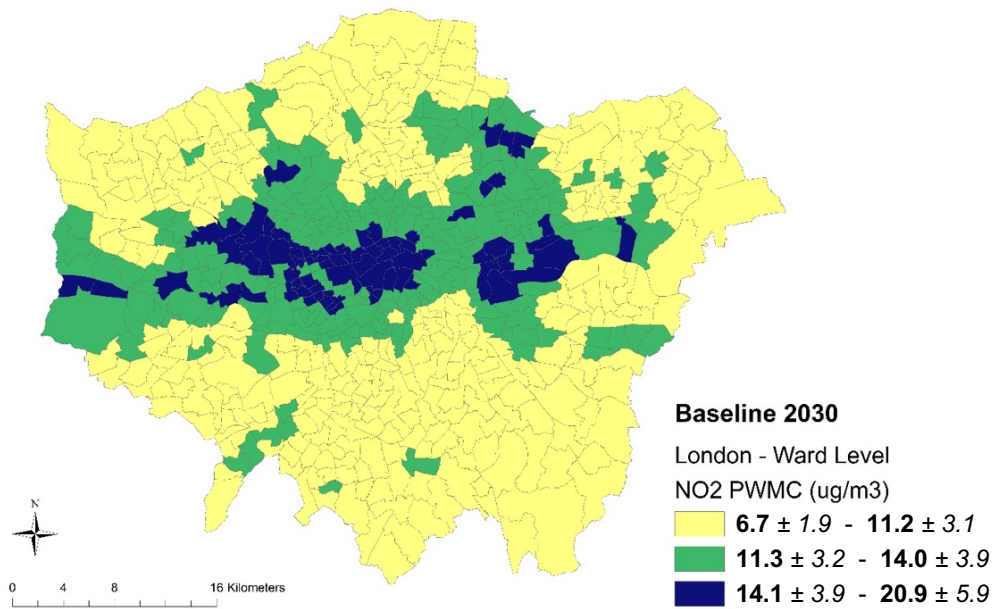


Figure 4.5 NO₂ London-wide population-weighted annual mean concentrations (PVMC) in the baseline 2030 scenario at the ward level.

PM_{2.5} PWM concentrations in Baseline 2030

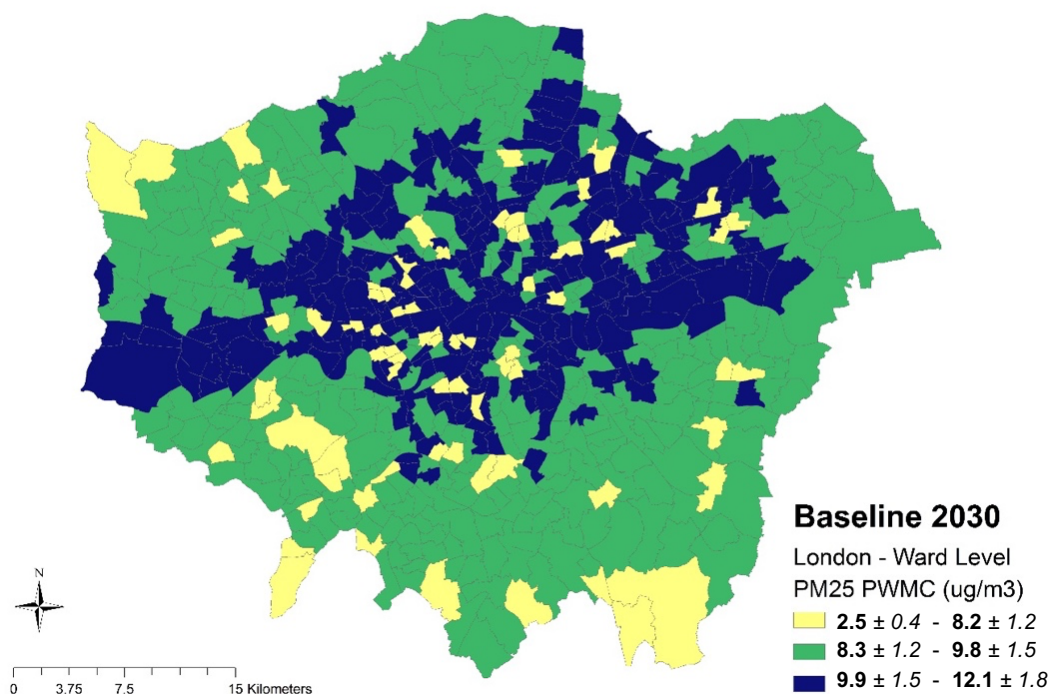


Figure 4.6 PM_{2.5} London-wide population-weighted annual mean concentrations (PWM) in the baseline 2030 scenario at the ward level.

4.2.2.2 Transport policy scenarios

PWM NO₂ and PM_{2.5} concentrations reduction from baseline 2030 are shown for four selected scenarios: two technological change scenarios (*Low Emissions Zone* and *Electric Car*) and two behavioural change scenarios (*Cycle Lane 20* and *Car Redu 50*) (Figure 4.7 and Figure 4.8).

4.2.2.2.1 Exposure to nitrogen dioxide (NO₂)

The *Low Emissions Zone scenario* reduced, on average, London-wide PWM NO₂ concentrations by 3% relative to baseline levels (Figure 4.7). The *Cycle Lane 20 scenario* brought an overall London-wide

reduction of 0.54% PWM NO₂ concentrations relative to baseline levels. In the central part of London (central part of the map), the *Cycle Lane 20 scenario* reduced PWM NO₂ concentration six times more effective than the *Low Emissions Zone scenario*.

The *Electric Car scenario* reduced PWM NO₂ London-wide concentration by 22% relative to baseline levels. The *Car Redu 50 scenario* delivered an 11% London-wide reduction on PWM NO₂ concentration relative to baseline levels.

4.2.2.2.2 Exposure to particulate matter (PM_{2.5})

Regarding the exposure to particulate matter (Figure 4.8), both the *Cycle Lane 20 scenario* and *Low Emissions Zone scenario* reduced London-wide PWM PM_{2.5} by 0.06% relative to baseline 2030 levels. In the central area of London, the *Cycle Lane 20 scenario* reduced PWM PM_{2.5} concentrations 20 times more effective than the *Low Emissions Zone scenario*.

The *Car Redu 50 scenario* resulted in a 0.88% London-wide reduction in PWM PM_{2.5} relative to baseline. The *Electric Car scenario* reduced London-wide PWM PM_{2.5} concentrations by 0.35% relative to baseline levels.

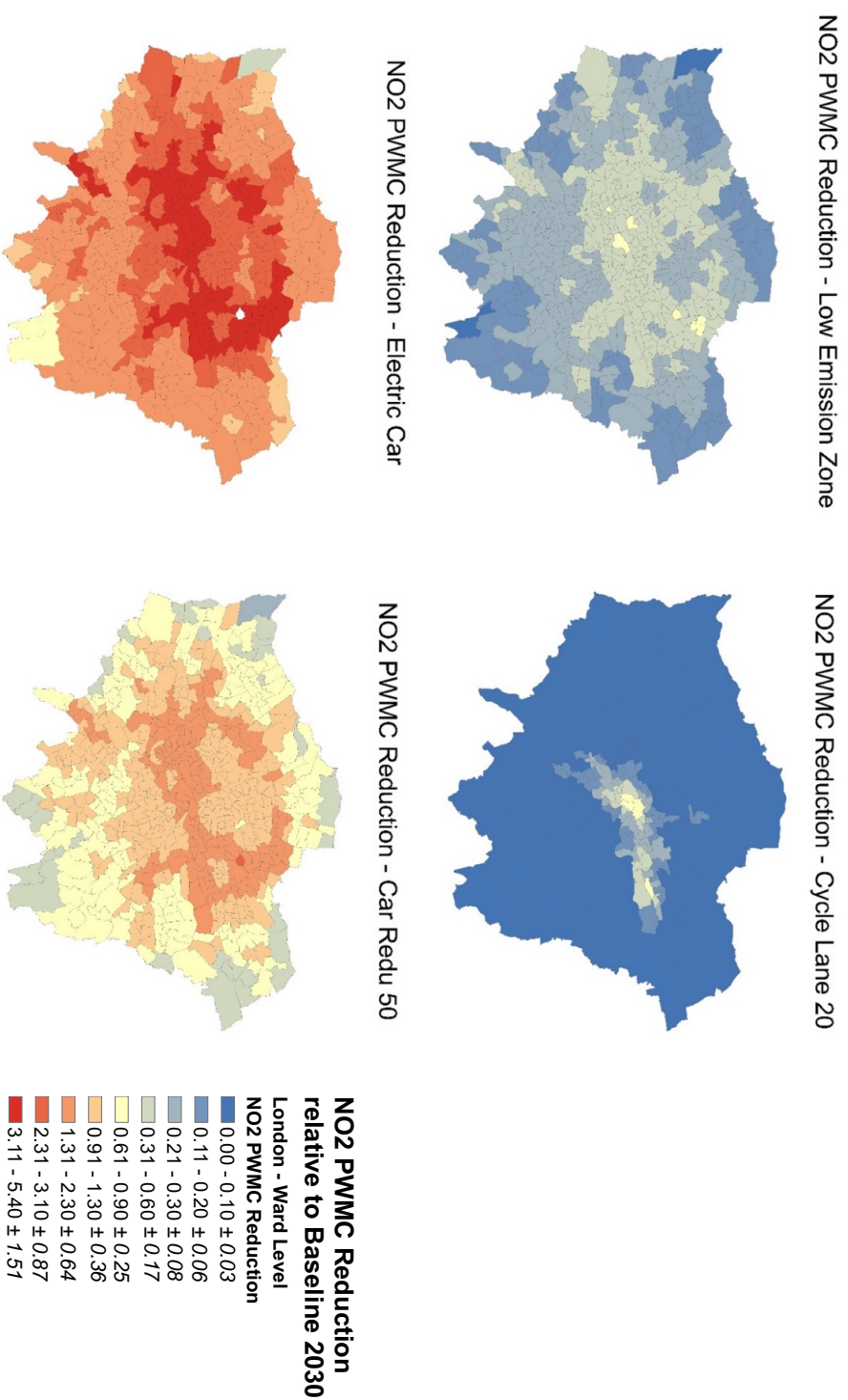


Figure 4.7 Nitrogen dioxide (NO₂) population-weighted mean concentration (PWMC) reductions relative to baseline 2030 levels in selected scenarios.

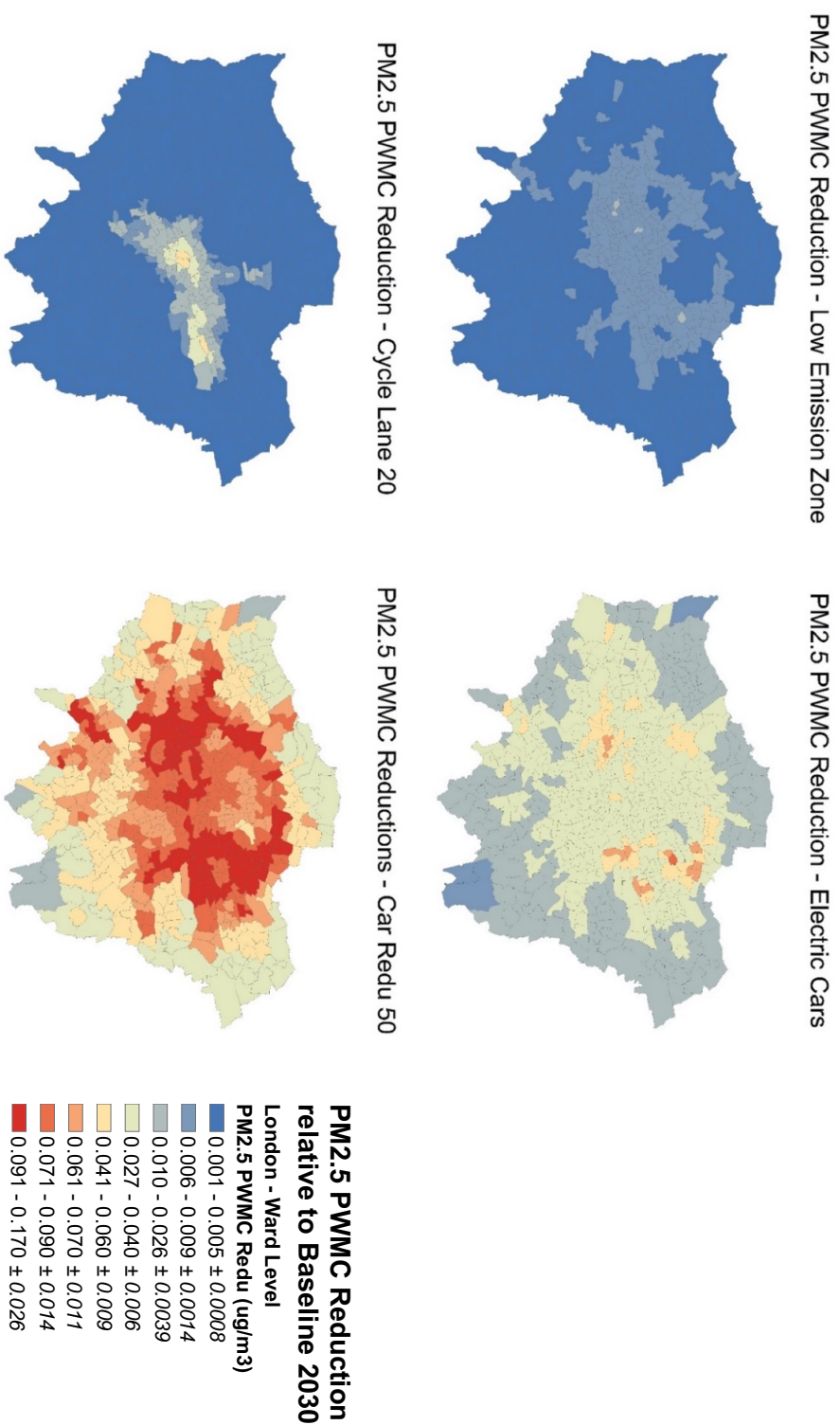


Figure 4.8 Particulate matter (PM_{2.5}) population-weighted mean concentrations (PWMC) reductions relative to baseline 2030 levels in selected scenarios.

4.2.3 Cost assessment

Following the methodology described in Section 3.3.4, the cost assessments (Figure 4.9) calculated accounted for the reduction in air pollutants concentration in each scenario, using the damage cost methodology and the most recent calculations of Carbon offset pricing in London.

Following the methodology described in Section 3.3.4.1, damage costs per unit of air pollutant exposure change for reducing population-weighted mean concentrations (PWMC) were calculated relative to baseline levels (Figure 4.9). The total damage costs in 2017 GBP per population-weighted mean per one $\mu\text{g}/\text{m}^3$ change per person in the technological change scenarios varied from £9 m to £215 m for $\text{PM}_{2.5}$ and NO_2 changes in PWMC (central values).

In the behavioural change scenario, the total damage costs in 2017 GBP per population-weighted mean one $\mu\text{g}/\text{m}^3$ change per person (Figure 4.9) ranged from £6 m to £106 m for $\text{PM}_{2.5}$ and NO_2 changes in PWMC (central values). In all transport policy scenarios (technological and behavioural change scenarios) the damage cost values were significant because of the changes in NO_2 PWMC which showed larger changes in PWMC than changes for $\text{PM}_{2.5}$ PWMC in each transport policy scenario, relative to baseline.

Carbon offset pricing was calculated following the methodology described in Section 3.3.4.2. Carbon offset pricing in each transport policy scenario relative to baseline (Figure 4.9), central values ranged from £16.6 m to £238.8 m in the technological scenarios and varied from £5.6 m to £114.6 m in the behavioural change scenarios. The only transport policy scenario, which resulted in negative carbon offset pricing was the diesel to petrol scenario, which emits more CO_2 emissions than in the baseline scenario.

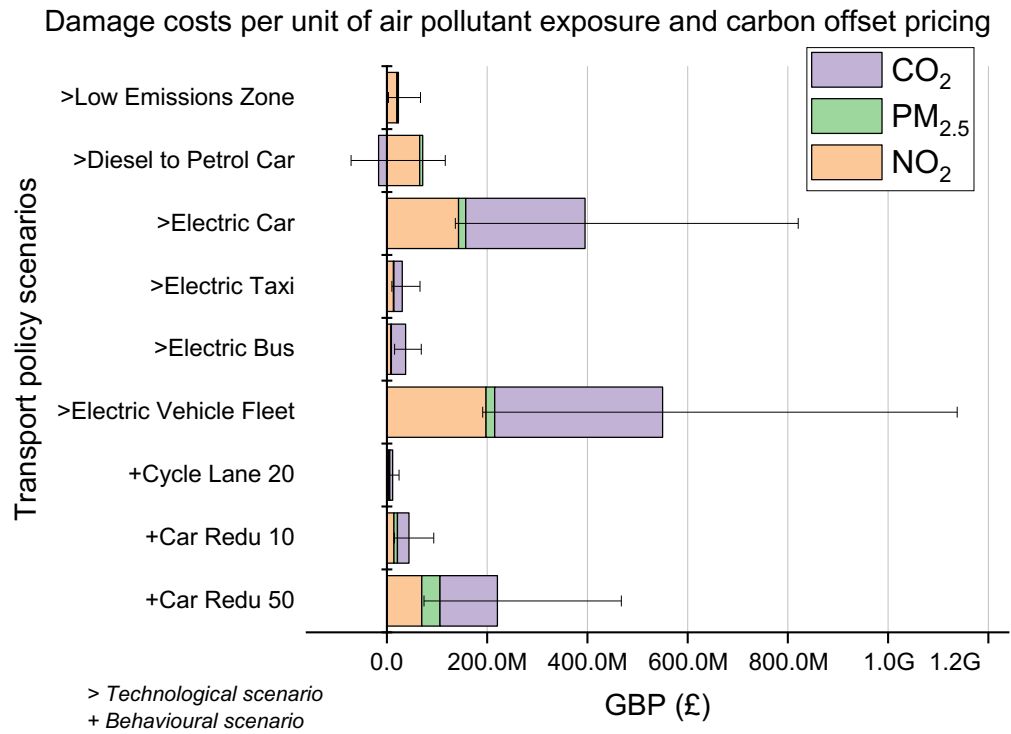


Figure 4.9 Cost assessment of transport policy scenarios, including damage costs per unit of air pollutant exposure for reducing population-weighted mean NO₂ and PM_{2.5} concentrations (PWC) and carbon offset pricing.

4.2.3.1 Damage costs per unit of air pollutant exposure and source apportionment of pollution sources

The source apportionment of pollution sources by vehicle type as population-weighted mean concentrations (PWMC) is presented in Table 4.2. In the baseline scenario, NO₂ PWMC is 60% higher for diesel cars than for petrol cars while for PM_{2.5}, PWMC is only 15% higher for diesel cars than for petrol cars. These damage costs (Table 4.2) have been averaged across London, but in practice would depend on where the km of travel was, i.e. would be higher in more densely populated inner London than in outer London.

In the *Electric Car scenario* source apportionment PM_{2.5} PWMC (Table 4.2) from electric cars is 0.2 µg/m³. Diesel cars have the highest damage costs per km travelled by car for NO_x and PM_{2.5}. Petrol cars have the highest damage cost per km travelled by car for CO₂. When the damage costs are calculated per passenger-km travelled (Table 4.2), buses show substantially lower damage costs than cars.

Table 4.2 Source apportionment by vehicle type (petrol, diesel and electric car and diesel bus) of NO₂ and PM_{2.5} population-weighted mean concentrations. CO₂, NO₂ and PM_{2.5} damage costs in pence: per km travelled and per passenger-km travelled, for cars (petrol, diesel and electric) and buses.

*Source apportionment NO₂ and PM_{2.5} PWMC correspond to the Baseline scenario for bus, petrol and diesel cars, and correspond to the Electric Car scenario for electric cars.

**Damage costs per passenger-km travelled assume an average 1.4 occupants per car and 17 to 44 passengers per bus.

Mode	Source apportionment* PWMC (µg/m ³)		Damage cost (pence) per km travelled			Damage cost (pence) per passenger-km travelled**		
	NO ₂	PM _{2.5}	CO ₂	NO ₂	PM _{2.5}	CO ₂	NO ₂	PM _{2.5}
Petrol car	1.19	0.11	1.04	0.47	0.35	0.80	0.34	0.25
Diesel car	3.09	0.13	0.85	1.48	0.48	0.65	1.06	0.35
Electric car	0.00	0.20	0.47	0.00	0.35	0.36	0.00	0.25
Bus	0.28	0.02	5.91	3.22	1.55	0.35 - 0.13	0.19 - 0.07	0.09 - 0.04

4.3 Discussion

4.3.1 Principal findings

4.3.1.1 CO₂ and air pollution emissions

Technological change scenarios are very efficient at reducing CO₂ emissions. The CO₂ emissions from electricity generation do not outweigh net reductions of CO₂ emissions by electric vehicles. Moreover, carbon emissions from electricity generation become a significant percentage of total emissions in the vehicle electrification scenarios (representing 40% of total CO₂ emissions in the *Electric Car* scenario and 63% of total carbon emissions in the *Electric vehicle Fleet scenario*). CO₂ from charging electric vehicles represents the current UK energy mix, and would reduce in the future with growth of renewable energy. Also, the scenarios were developed before UK announcements about not allowing any new petrol/diesel cars after 2040.

The *Low Emission Zone scenario*, a scenario modelled at the London-wide level, reduced London-wide CO₂ emissions by 0.2%. The construction of cycle lanes as modelled in the *Cycle Lane 20 scenario* despite being localised over 50 km of streets in the central area of London, reduced London-wide CO₂ by 0.7%. The *Diesel to Petrol Car scenario* is the only scenario that exceeds CO₂ emissions from the baseline 2030 levels due to a high carbon emission factor (155 g/km) from petrol cars.

Technological change scenarios are also very efficient at reducing NO_x emissions. The *Low Emission Zone scenario* reduced London-wide NO_x by 9.6%. The *Diesel to Petrol Car scenario* delivers a significant London-wide NO_x emissions reduction of 30% relative to baseline levels (but substantially increases the carbon emissions as mentioned above).

Behavioural change scenarios illustrate the most significant reduction in particulate matter emissions. For particulate matter emissions, the *Low Emission Zone scenario* and the *Cycle Lane 20* have a similar London-wide PM emissions reduction impact cycle lane scenario is reducing emissions of a

limited number of wards. On average, non-exhaust PM₁₀ emissions account for 90% of total PM₁₀ emissions and PM_{2.5}, non-exhaust emissions account for 86% of total PM_{2.5} emissions in all the transport policy scenarios. Also, particulate matter emissions are driven by non-exhaust emissions that can most effectively be reduced by reducing the number of vehicles and replacing motorised modes with active modes of transport (as in the behavioural change scenarios). Electric vehicles fail to mitigate non-exhaust emissions.

4.3.1.2 Spatial analysis

Significant local benefits can be overlooked when observed from a London-wide perspective, and this highlights the importance of the spatial analysis of transport policies. For example, the construction of cycle lanes in the central area of London showed one of the most significant impacts on reducing NO₂ and PM_{2.5} concentration in the most polluted areas in London even if the London-wide effect of this policy was small compared to other scenarios. This is an example of why it is important to interpret the impacts of emissions abatement strategies from an appropriate spatial perspective. Setting city-wide emissions abatement targets can overlook essential local benefits.

4.3.1.3 Cost assessment

The economic benefit of only electrifying taxis in London (£30 m) surpasses the investment cost of £18 m that TfL has proposed to implement its electric vehicle scheme (TfL, 2017c). TfL's electric vehicle scheme aims to build an extensive network of rapid charging points for electric vehicles with specific charging points exclusive for taxis (TfL, 2017c). The £4.5 m of London Mayor's funding, obtained from the Office for Low Emission Vehicles for installing charging points for electric vehicles across London, represents only 1% of the economic benefits that the electrification of cars could bring (£395 m) (London Assembly, 2018a). The only scenario with monetised losses (or favourable cost) for CO₂ emissions is the switch from diesel to petrol cars due to the increase of CO₂ emissions. The economic benefits resulting from the *Car Redu 50 scenario*, will significantly increase cycle trips in London and is of the same order of magnitude (£220 m) as the annual £169 m budget

per year that the London Mayor has committed to increasing cycle infrastructure in London (London Assembly, 2018b).

4.3.2 Uncertainties

The model validation presented in Section 3.3.1.4 showed that particulate matter concentrations modelled with the UKIAM model tend to underestimate $PM_{2.5}$ background concentrations by approximately 15%. The same validation exercise showed that the UKIAM model tends to underestimate NO_2 background concentrations by approximately 30%. The NO_2 background concentrations underprediction is attributed to nitrogen oxide underestimation of COPERT emissions factors used in the UKIAM model. This underestimation of $PM_{2.5}$ and NO_2 could result in getting conservative results model with the UKIAM. The model validation was used to set error bars to the PM and NO_x results from this chapter.

Moreover, as presented and discussed in Section 3.3.1.6, the analysis made in this dissertation included a comparison between 2030 emissions projections of the UKIAM-BRUTAL model and the model used for the London Atmospheric Emissions Inventory (LAEI). The 2030 emissions projection comparison between the two models showed the following results: For CO_2 , the UKIAM-BRUTAL projects overall CO_2 emissions to be 13% higher than total CO_2 emissions reported in the LAEI model in 2030. For CO_2 emissions, this 13% difference with the LAEI model was used to set error bars for the results presented in this chapter. For NO_x emissions, the UKIAM-BRUTAL model predicts 24% higher emissions than the LAEI model in 2030.

For particulate matter emissions, the differences between the 2030 projections by the UKIAM-BRUTAL model and the LAEI model are higher. Exhaust PM_{10} emissions projected to 2030 are 34% lower in the UKIAM-BRUTAL model than in LAEI model. The most critical difference between 2030 emissions projections by the UKIAM-BRUTAL model and LAEI model is for non-exhaust particulate matter emissions. The LAEI model projects 2030 brake wear non-exhaust PM_{10} emissions to be 5.6 times higher than the UKIAM-BRUTAL model. In contrast, tyre wear non-exhaust PM_{10} emissions 2030 projections are more in agreement. UKIAM-BRUTAL 2030 tyre wear non-exhaust PM_{10} emissions are only 22% lower than LAEI 2030 tyre wear non-exhaust PM_{10} emissions estimates.

This important difference between the UKIAM-BRUTAL model and the LAEI model in 2030 brake wear non-exhaust PM₁₀ emissions projections is explained by the fact that the UKIAM-BRUTAL model does not use speed dependant emissions factors for brake wear analysis. In urban areas like London, where the high levels of traffic congestion occur along with repetitive use of car breaks, using speed dependant emissions factors is important to estimate emissions accurately.

As mentioned in Section 3.3.1.6 the uncertainty analysis developed as part of this dissertation, helped to distinguish this uncertainty of the UKIAM-BRUTAL model and the model is currently being improved to correct this and use speed-dependent emissions factors for estimated non-exhaust PM emissions. Since the version of UKIAM I used to model these results, BRUTAL has been updated to include speed-dependent tier 2 emission factors which have indeed shown greater emissions in more congested areas of London. And also a new version of the LAEI has been produced and is being compared with updated NAEI emissions in updating UKIAM.

4.3.3 Strengths and limitations

This study is unique because it provides an in-depth holistic analysis of both carbon and air quality (emissions and concentration), impacts of transport policies in London for the entire vehicle fleet. Moreover, it stands out because it includes the analysis of both, technological and behavioural change transport scenarios which are usually studied independently, with some exceptions (Woodcock *et al.*, 2009; Kollamthodi & Watkiss, 2005). The findings of this study expand on previous studies using the BRUTAL model (Oxley *et al.*, 2012) that have shown that reducing travel demand and the replacement of older vehicles by electric vehicles are effective strategies to reduce both urban air pollution and greenhouse gas emissions in cities.

At present, this is the only study that has evaluated damage cost per vehicle-km travelled, and per vehicle, passenger-km travelled for public and private modes of transport which is an essential way to demonstrate the environmental and health damage that different modes of transport can have.

A limitation of the research is that the viability of the transport policy scenarios was not assessed and the actual viability of the scenarios could be questionable. The rapid vehicle electrification assumed

in the technological change scenarios has never been seen before. The vehicle electrification would need to be accompanied by a massive scrapping scheme to replace fossil-fuelled vehicles with electric vehicles. The behavioural change scenarios assessed an ambitious rate of car reduction that has never been seen before in a large city like London. However, the analysis of the chosen transport policy scenario does help us to evaluate the effect that the transport policies could achieve.

The building of the transport scenarios responded to policies established in the Mayor's Transport Strategy, but each scenario is not necessarily comparable with the other. In an attempt to do a more comparable analysis, the assessment of emission factors and damage costs by km travelled and by passenger-km travelled was calculated.

Non-exhaust particulate matter modelled emissions by the BRUTAL-UKIAM model only accounts for tyre, brake wear and use emissions factors that are not speed-dependant. This limitation of the modelling of non-exhaust air pollutant emissions and concentrations is reflected in the underestimation of non-exhaust particulate matter emissions compared to other models like the one used by the LAEI where re-suspension and road wear non-exhaust emissions are accounted for in addition to tyre and brake wear non-exhaust emissions (King's College London, 2018; Moody, 2018). Further development of BRUTAL is in progress to refine this using speed dependent Trier 2 emissions factors for electric vehicles and allowing for regenerative braking as well as using higher emissions in more congested areas.

4.3.4 Concluding remarks

London has the challenge of achieving longer-term sustainability, reducing carbon emissions and controlling the current levels of air pollution. The road transport sector plays a key role in this challenge, and the uncertainty of the effect of transport policies and the continuing failure to improve air pollution is an important barrier. Our study indicates that vehicle electrification is effective at reducing carbon and nitrogen oxides but fails to reduce particulate matter emissions because electric vehicles still emit non-exhaust emissions. The contribution of particulate matter from the road transport sector can most effectively be reduced by behavioural change strategies. Behavioural strategies that reduce the number of motorised vehicles and promote travel mode shifts to active travel

(walking, cycling and public transport) have the significant potential to reduce particulate matter from the road transport sector.

Damage costs showed that although electric vehicles do offer a reduction of costs from diesel or petrol cars for carbon and nitrogen dioxide, they do not reduce damage costs from particulate matter. The motorised mode of transport with the lowest damage costs is public transport.

The health impact assessment of the transport policy scenarios is presented in the next chapter. The health assessment evaluates the health benefits of reducing air pollution exposure as well as the health benefits of increased physical activity in the behavioural change scenarios.

Chapter 5

Health impact assessment modelling of transport
policy scenarios in London

5.1 Overview

Following the modelling of CO₂ emissions and air quality with the UKIAM-BRUTAL model presented in the previous chapter, this chapter presents the health impact assessment (HIA) modelling of the transport policy scenarios defined for London. Health impacts of PM_{2.5} and NO₂ air pollution exposure (as air pollution inhalation and for changes in air pollution concentration) and physical activity were assessed.

The following section, section 5.2, presents the results of the HIA modelling, including the results of the sensitivity analysis. Section 5.3 presents the discussion of the results, including the critical assessment of principal findings, comparison with other studies, limitations and strengths and policy implications.

5.1.1 Methods overview

The methodology used in this chapter follows the framework for health impact assessment (HIA) modelling presented in chapter 3, section 3.5 (see figure 3.22). Health impacts from changes in air pollutants concentrations (see section 3.5.1.1), from air pollution inhalation (see section 3.5.1.2) and from physical activity (3.5.2) were calculated following the methodology presented in each respective section. The health impact assessment commensurate to the reduction in exposure to PM_{2.5} and NO₂ concentrations relative to baseline 2030 levels was calculated using the annual mean concentrations output values from the modelling with UKIAM-BRUTAL (presented in chapter 4) for each transport policy scenario.

The HIA modelling assumptions and sensitivity analysis was presented and described in detail in section 3.5.3. The description of input variables and the justification of choices for the HIA modelling was presented in section 3.5.4.

5.2 Results

This section presents the health impact assessment results (Figure 5.4) for the transport policy scenarios in London. The next sections present the modelling results for the effects of changes in exposure to air pollution on the whole population (Section 5.2.1.1), then effects on those undertaking active travel by their inhalation of air pollution (Section 5.2.1.2), and then their benefits of the physical activity during active travel (Section 5.2.2).

5.2.1 Air pollution

5.2.1.1 Changes in air pollution concentration

The results for the estimated health effects in terms of deaths prevented in the general population for exposure to air pollution in the different transport policy scenarios are shown in Figure 5.1.

5.2.1.1.1 Particulate matter (PM_{2.5})

Health impacts (quantified as preventable deaths) in the general population of London in 2030 due to changes in particulate matter (PM_{2.5}) population-weighted mean concentrations (PWMC) (Figure 5.1), varied from 1 to 12 deaths prevented per year (uncertainty range: 0 – 16) in the technological change scenarios, relative to baseline 2030 levels. In the behavioural change scenarios, air pollution health impacts ranged from 1 to 26 deaths prevented per year (uncertainty range: 1 – 33), relative to baseline 2030 levels.

5.2.1.1.2 Nitrogen dioxide (NO₂)

Health impacts in the general population of London in 2030 due to reductions of nitrogen oxide (NO₂) population-weighted mean concentrations (PWMC) (Figure 5.1) ranged from 7 to 180 deaths prevented per year (uncertainty range: 5 – 241) in the technological change scenarios and fluctuated from 2 to 64 (uncertainty range: 1 – 85) deaths prevented per year in the behavioural change scenarios, relative to baseline 2030 levels.

5.2.1.1.3 PM_{2.5} and NO₂

Since the NO₂ RR coefficient adjusted for PM_{2.5} was used (see section 3.5.4 for details), the health impacts for the changes in PWMC of PM_{2.5} and NO₂ could be added (Figure 5.1). Total health impacts (quantified as deaths prevented per year) for reductions of PWMC concentrations from PM_{2.5} and NO₂, varied from 8 to 193 deaths prevented per year (uncertainty range: 5 – 257) for the technological change scenarios and from 2 to 89 deaths prevented per year (uncertainty range: 2 – 118) in the behavioural change scenarios, relative to baseline 2030 levels.

Total health benefits for reductions of PM_{2.5} and NO₂ PWMC in London 2030

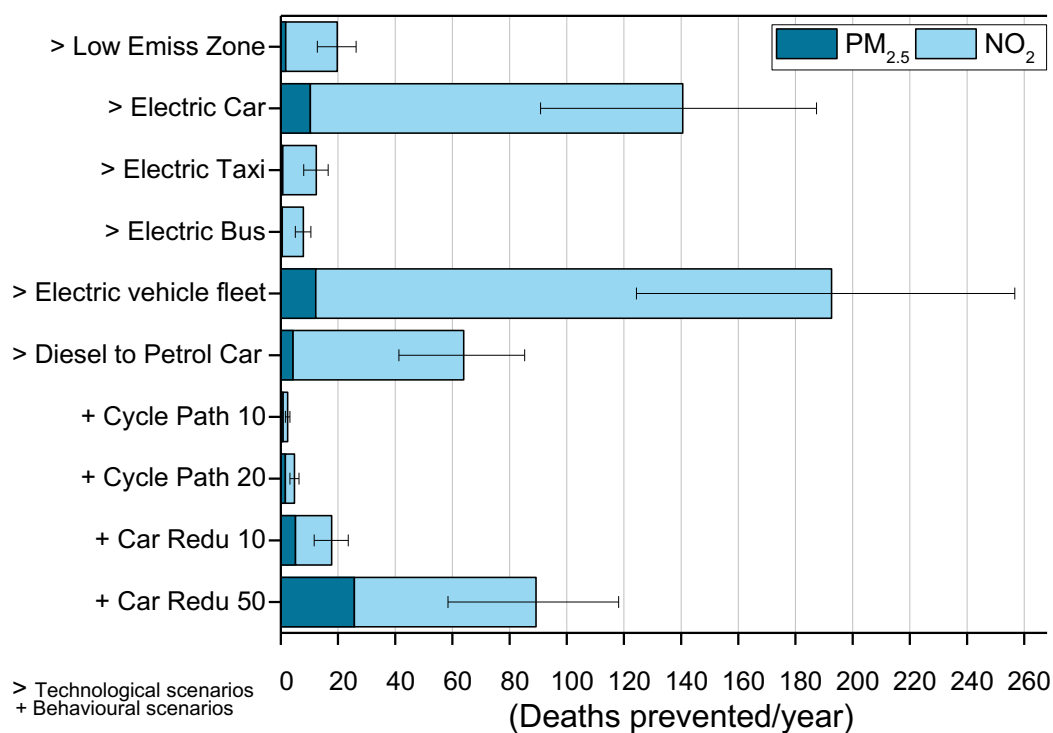


Figure 5.1 Total health impacts (deaths prevented per year) in the general population of London in 2030 due to changes in of particulate matter (PM_{2.5}) and nitrogen oxide (NO₂) population-weighted mean concentrations (PWMC) relative to baseline 2030.

5.2.1.2 Air pollution inhalation

Changes in air pollution inhalation relative to baseline 2030 levels are due to changes in the level of physical activity in addition to air pollution changes. Thus, only the behavioural change scenarios had changes in air pollution inhalation because physical activity was increased in these scenarios as a result of changes from transport modes to active modes (walking, cycling and public transport).

5.2.1.2.1 Particulate matter (PM_{2.5})

Health impacts due to the inhalation of PM_{2.5} air pollution (Figure 5.2) in the behavioural change scenarios varied from -203 to -10 deaths caused per year (uncertainty range: -385 to -3) (negative values indicate deaths caused), relative to baseline 2030 levels.

5.2.1.2.2 Nitrogen dioxide (NO₂)

Health impacts for the inhalation of NO₂ pollution (Figure 5.2) in the behavioural change scenarios ranged from -1 to 9 deaths per year (uncertainty range: -10 to 15) (positive values indicate deaths prevented, negative values indicate deaths caused), relative to baseline 2030 levels.

5.2.1.2.3 PM_{2.5} and NO₂

Total health impacts for the inhalation of PM_{2.5} and NO₂ pollution (Figure 5.2) in the behavioural change scenarios varied from -194 to -12 deaths caused per year (uncertainty range: -394 to -3) (negative values indicate deaths caused), relative to baseline 2030 levels.

Health impacts of PM_{2.5} and NO₂ pollution inhalation, London 2030

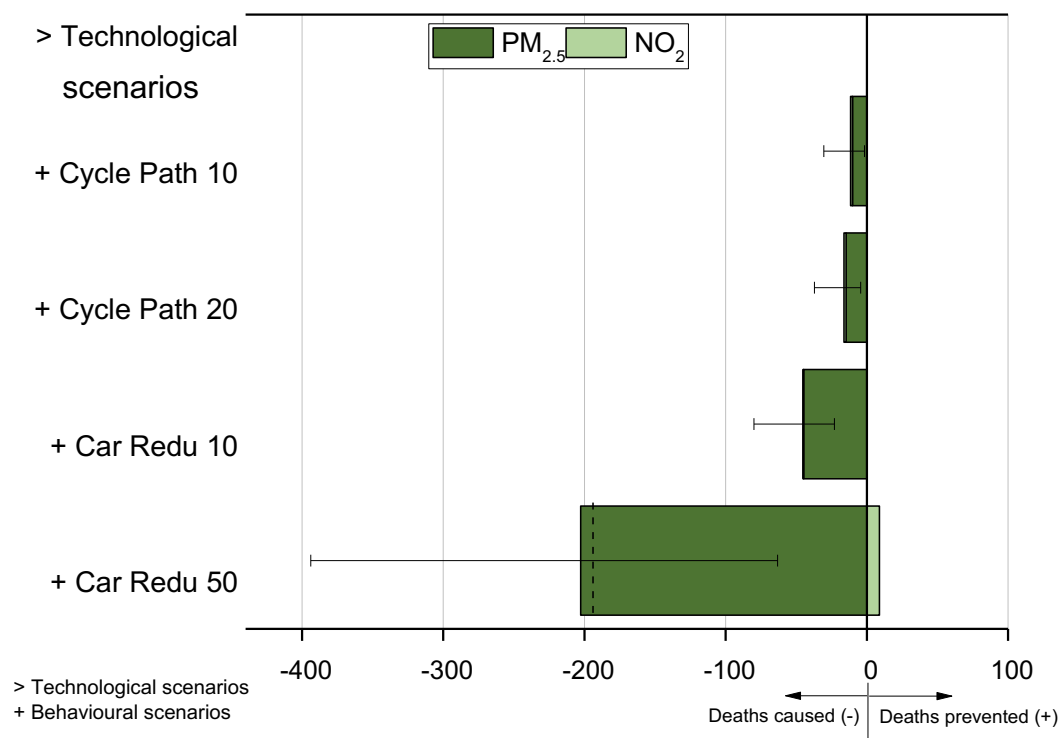


Figure 5.2 Total health impacts (quantified as the number of deaths caused (-) or prevented (+) per year) for PM_{2.5} and NO₂ pollution inhalation in the technological and behavioural change London 2030 transport policy scenarios relative to baseline 2030.

5.2.2 Physical activity

Health impacts arising from the increase in physical activity (Figure 5.3) in the behavioural change scenarios ranged from 3,126 to 379 deaths prevented per year (uncertainty range: 258 – 3,999), relative to baseline 2030 levels. There are no health benefits of physical activity in the technological change scenarios because there are no changes to active travel modes of transport (walking, cycling, public transport), only a technological change in the vehicles used to travel.

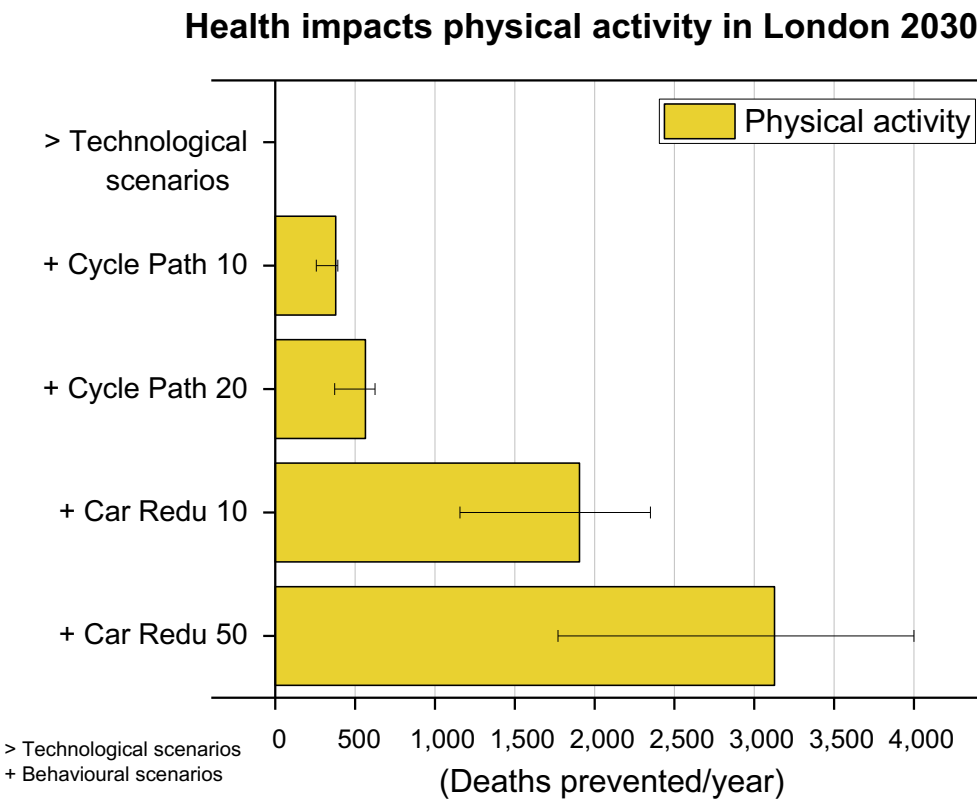


Figure 5.3 Health impacts of physical activity (quantified as the number of deaths prevented (+) per year) in the technological and behavioural change London 2030 transport policy scenarios, relative to baseline 2030.

5.2.3 Total health impacts

The estimated total health impacts (Figure 5.4) from changes in PMWC ($\text{PM}_{2.5}$ and NO_2), air pollution inhalation ($\text{PM}_{2.5}$ and NO_2) and physical activity ranged from 370 to 3,022 deaths prevented per year (uncertainty range: 348 – 4,606) in the behavioural change scenarios, relative to baseline 2030. In the technological change scenarios, total health impacts from changes in PMWC ($\text{PM}_{2.5}$ and NO_2) varied from 8 to 193 deaths prevented per year (uncertainty range: 5 – 257), relative to baseline 2030.

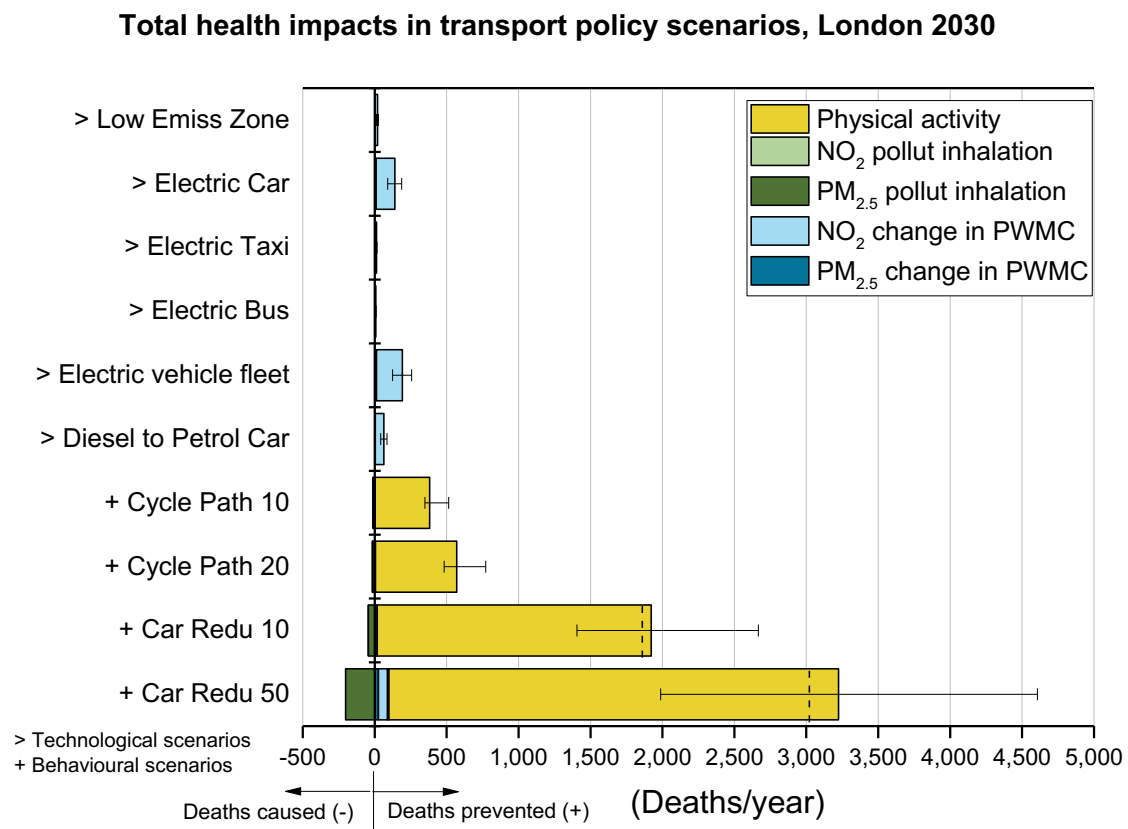


Figure 5.4 Total health impacts resulting from adding health impacts from the changes in PMWC ($\text{PM}_{2.5}$ and NO_2), air pollution inhalation ($\text{PM}_{2.5}$ and NO_2) and physical activity, in the transport policy scenarios in London, relative to baseline 2030. Dotted lines indicated the resulting number of deaths per year after subtracting the number of death causes from the number of deaths prevented.

5.2.4 Sensitivity analysis

Following methods described in section 3.5.3, the sensitivity analysis (Figure 5.5) exemplified by the 50% reduction of cars scenario (Car Redu 50 scenario), showed that of all the variables tested (Table 3.26 and Table 3.27) the results were most sensitive to the following variables: i) The relative risk associated with physical activity (walking and cycling) and mortality. ii) Changes in background $PM_{2.5}$ and NO_2 concentrations. iii) The total number of days per week when active travel modes were used. iv) And, the average duration of the active mode trip.

The variables which brought the smallest variation in the total result (Figure 5.5) were the following: i) Exposure conversion ratios inputs. ii) The number and duration of each trip by car, rail, and underground. iii) The underground concentrations. iv) And, the minute ventilation rates.

The sensitivity of the results to different exposure-response function (ERF) distributions was assessed (Figure 5.5), for both physical activity and mortality ERF. The sensitivity analysis showed that a non-linear ERF distribution applying a 0.25 power resulted in a significant variation (52%) from the mean value (= 3,022 deaths prevented) which were calculated with an ERF normal distribution. A log-normal ERF distribution resulted in a 2% difference from the mean value (= 3,022 deaths prevented) which were calculated with an ERF normal distribution.

The results are much more sensitive to variations of ERF distributions and RR coefficients of physical activity (variations ranged between 1,653 - 4,589 deaths prevented) than variations of air pollution (variation ranged between 2,892 - 3,404 deaths) (Figure 5.5).

Variations in air pollution exposure and mortality RR coefficients (Figure 5.5) from the two-pollutants' ($PM_{2.5}$ and NO_2) mutually adjusted RR coefficients differed by 1% to 5.4% from the mean value used in this dissertation (mean value of 3,022 deaths). The most significant variation (9.2%) from the mean value (mean value of 3,022 deaths) resulted from the use of a single-pollutant unadjusted RR coefficient for NO_2 .

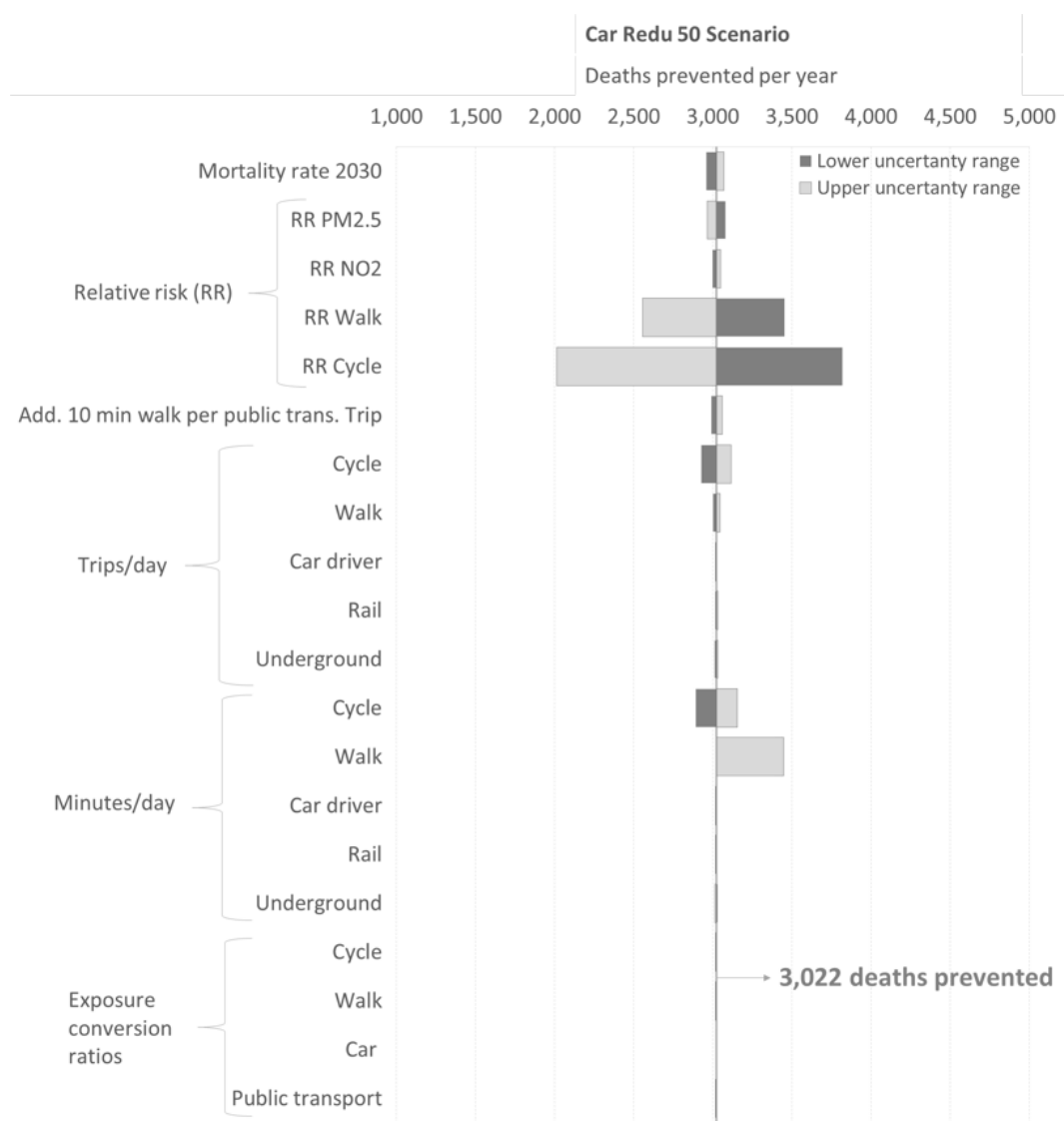


Figure 5.5 Sensitivity analysis of the contribution of input valuables to the uncertainty of the output result for the 50% reduction of cars scenario (Car Redu 50 scenario) (mean value of 3,022 death prevented per year relative to baseline 2030). Note: Scale 1,000 to 5,000 deaths prevented per year.

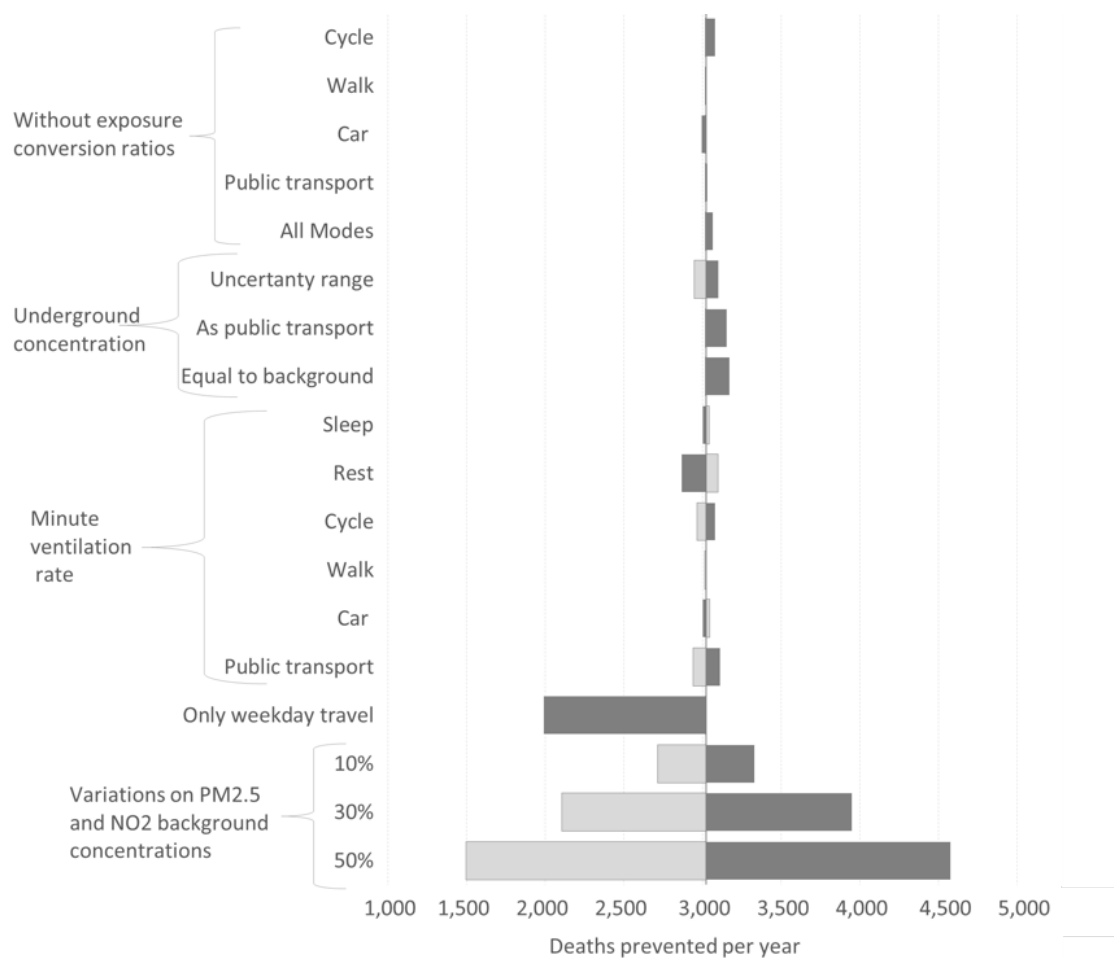


Figure 5.5 (Continued) Sensitivity analysis of the contribution of input valuables to the uncertainty of the output result for the 50% reduction of cars scenario (Car Redu 50 scenario) (mean value of 3,022 death prevented per year relative to baseline 2030). Note: Scale 1,000 to 5,000 deaths prevented per year.

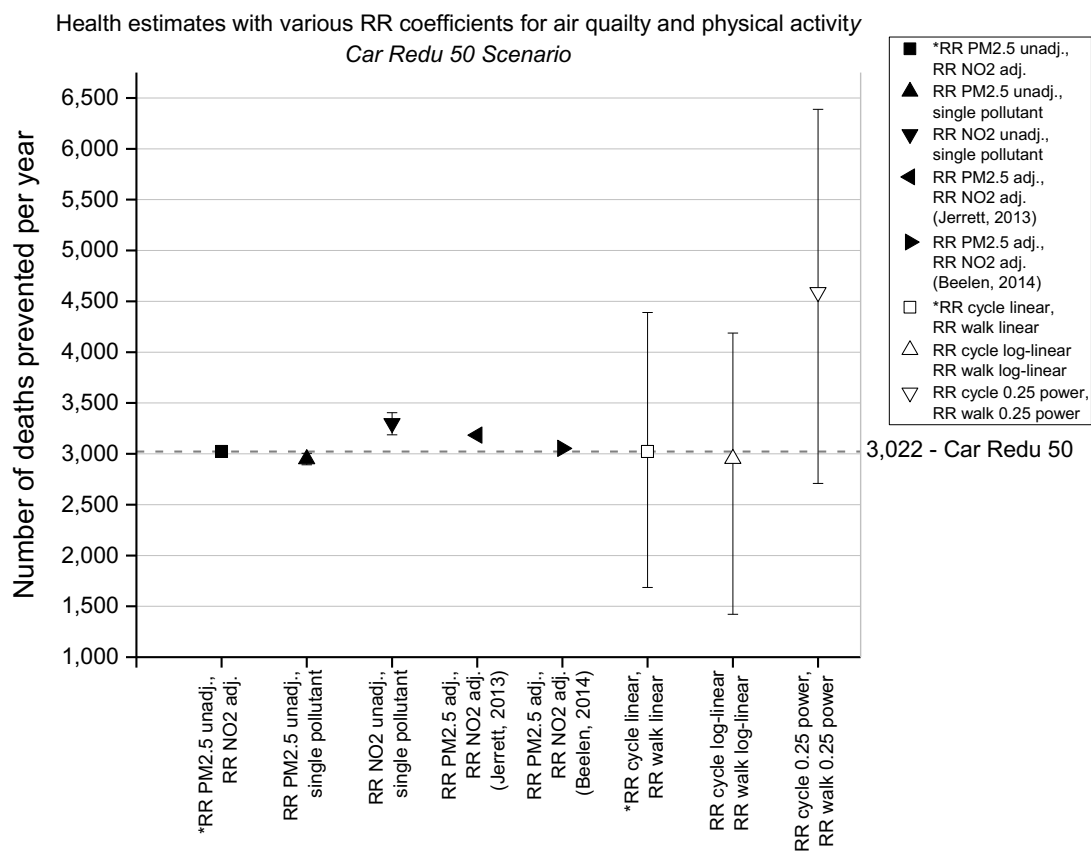


Figure 5.6 Health impacts estimations with various RR coefficients using as an example, the Car Redu 50 scenario, results are relative to baseline 2030. Unadjusted for single pollutant and adjusted for the air pollutants mixture (PM_{2.5} and NO₂), air quality RR coefficients were used (filled coloured symbols) (COMEAP, 2018). For physical activity, RR coefficients from different exposure-response functions distributions (linear, log-linear and 0.25 power) were used from (unfilled coloured symbols) (Kelly *et al.*, 2014).

Note: The results from the RR coefficients used in this dissertation are shown with a squared symbol and an asterisk (*). Scale 1,000 to 6,500 deaths prevented per year.

5.3 Discussion

5.3.1 Principal findings

The health benefits in the behavioural change scenarios were on average 20 times larger than the health benefits in the technological change scenarios. Health benefits in the behavioural changes scenarios were driven by health benefits of physical activity which accounts for 98% of the health benefits. The results highlight the importance of taking a holistic approach since the accounting of physical activity changes the picture making the behavioural scenarios much more beneficial than the technological scenarios.

The health benefits of physical activity from cycling and walking and the reduction of air pollution (NO_2 and $\text{PM}_{2.5}$) concentration, in the behavioural change scenarios, were large compared with the risks from inhalation of air pollutants (average benefit: risk ratio 32).

The technological scenarios do not remove vehicles from the road, and only address exhaust PM emissions which are small compared with the non-exhaust PM emissions. However, these measures have large effects on NO_x emissions and hence on NO_2 . The health benefits from NO_2 reduction are greater than those from $\text{PM}_{2.5}$ reduction for the technological scenarios. This emphasises the importance of considering the benefits of reducing NO_x as well as $\text{PM}_{2.5}$, whereas many studies only focus on $\text{PM}_{2.5}$. There are uncertainties in the combined effects, but I have used the appropriate RR to consider both together, and the sensitivity analysis was performed to assess this uncertainty.

Since the transport policy scenarios offer larger reductions of NO_2 concentrations than reductions of $\text{PM}_{2.5}$ concentrations. Therefore, health benefits associated with the decrease in air pollution exposure by the reduction in NO_2 annual mean concentrations were on average eight times larger than health benefits associated with the decrease in air pollution exposure by the reduction in $\text{PM}_{2.5}$ annual mean concentrations in the transport policy scenarios.

The health benefits of decreasing air pollution through the reduction of $\text{PM}_{2.5}$ annual mean concentrations brought about by the behavioural change scenarios were 1.7 times larger than the technological change scenarios. For reduction in NO_2 annual mean concentrations, the health benefits of technological change scenarios were 3.4 larger than in the behavioural change scenarios. Health

benefits estimates in the technological change scenarios showed that the highest portion of preventable deaths was attributable to a decrease in air pollution exposure through the reduction in NO₂ annual mean concentrations.

5.3.2 Comparison to other studies

The results presented in this chapter corroborate the findings of previous publications assessing the health benefits of different transport strategies. Similar to the research presented in this dissertation, Woodcock *et al.*, 2009, found considerable larger health benefits (30 times larger) in behavioural change scenarios which increased active travel, rather than technological change scenarios with lower-carbon-emissions motor vehicles in London.

The order of magnitude of the health benefits presented in this dissertation is similar to the published research of Woodcock *et al.*, 2009, has been used for comparison because this study had the most similarities in the construction of scenarios and methodology. Woodcock *et al.*, 2009, found that 4,541 premature deaths per year in 2030 could be prevented in London in a behavioural changes scenario with ambitious increases in active travel. Similarly, this dissertation found that ambitious increases in active travel (in the Car Redu 50 Scenario) could prevent 3,215 premature deaths per year in 2030 in London.

Consistent with the results presented in this dissertation, Woodcock *et al.*, 2009, found that health benefits for reducing PM_{2.5} concentrations are higher in behavioural change scenarios than in technological change scenarios. However, health benefits from PM_{2.5} air pollution reduction are one order of magnitude higher in Woodcock *et al.*, 2009, (air pollution health benefits $\sim 10^3$) than in this dissertation (air pollution health benefits $\sim 10^2$).

This difference can be explained by the use of different models to estimate PM_{2.5} concentrations, especially on how PM_{2.5} non-exhaust concentrations were modelled. Also, the higher health benefits for air pollution reduction obtained by Woodcock *et al.*, 2009, could be related to their projection of a less clean Baseline 2030 and therefore could have a higher difference in the delta concentrations between the baseline and the scenario which would result in higher health benefits for reductions in air pollution (PM_{2.5}) concentrations.

Another study consistent with the results of this dissertation and with a comparable methodological approach is Woodcock *et al.*, 2009. This study found that the highest portion of preventable deaths could be attributed to increases in physical activity (resulting in 1,154 deaths prevented; 95% CI: 858 – 1,577) and reductions in air pollution (PM_{2.5}) concentrations (resulting in 659 deaths prevented; 95% CI: 386 – 834) followed by the noise, heat, and access to green spaces health impacts.

The scenarios modelled in this dissertation are different and not comparable to Mueller *et al.*, 2017. However, the health benefits of physical activity in the scenarios with the highest increase in active

travel are of the same order of magnitude (1×10^3) as in this dissertation. For example, the Car Redu 10 scenario in this dissertation forecast 1,923 preventable deaths; 1,405 – 2,666). Different to our study, Mueller *et al.*, 2017, used a curvilinear exposure-response function, applying a 0.25 power transformation, for the association of physical activity and mortality. This curvilinear type of exposure-response function was assessed in the study in the sensitivity analysis.

Health impacts of reductions in air pollution (PM_{2.5}) concentrations are one order of magnitude higher in Mueller *et al.*, 2017, than in our study, as one would expect. Mueller *et al.*, 2017, estimated 659 preventable deaths from reductions in air pollution (PM_{2.5}) concentrations. In our study, 26 preventable deaths from reductions in air pollution (PM_{2.5}) concentrations in the Car Redu 50 scenario were found.

This difference is explained by the magnitude of the difference in concentrations considered in each study. In the Mueller *et al.*, 2017, study, the contra factual scenario was the current PM_{2.5} concentration in Barcelona of 17.77 µg/m³, which means a delta in concentrations of 7.77 µg/m³ to meet the 10 µg/m³. In our study, the PM_{2.5} concentrations in each scenario were compared to a baseline 2030 (PM_{2.5} concentration of 8.72 µg/m³) with deltas in PM_{2.5} concentrations of, for example, 0.120 µg/m³ Car Redu 50 scenarios.

If the transport policy scenarios in our study had been compared to current levels in London (PM_{2.5} concentration average of 12 µg/m³ approx.), the difference in concentration would have been higher and so would the preventable deaths from reductions in exposure to PM_{2.5} air pollution. The association between PM_{2.5} and mortality in Mueller *et al.*, 2017, was quantified using a linear exposure-response function as in our study.

The results of this dissertation are also in agreement with results from several studies which have found that the health benefits of active transport modes (walking and cycling) are larger than the risks of exposure to air pollutants (for example, Mueller *et al.*, 2017, and Rojas-Rueda *et al.*, 2011).

Studies which have assessed health impacts from inhalation of air pollutants (PM_{2.5}) in the analysis of an implemented active travel policy have also found that the negative effects of pollutants inhalation are outweighed by the much more significant benefit of an increase in physical activity. Rojas-Rueda *et al.*, 2011, also assessed the health impacts of road traffic injury. Accounting only for their results of physical activity and air pollution inhalation, the ratio of benefits against risks results in a benefit/risk ratio of 96 (-12.46 deaths/year for physical activity divided by 0.13 death/year of air pollution inhalation).

The benefit/risk ratio from our results lay in the same order of magnitude. If we account only for physical activity benefits against PM_{2.5} pollution inhalation risks, the ratios are the following for the behavioural change scenarios: benefit/risk ratio of 15 in the Car Redu 50 scenario and a benefit/risk ratio of 43 in the Car Redu 10 scenario.

5.3.3 Strengths and limitations

Grounding this analysis in real-life policies and assessing the effects of implemented or planned transport policies is an important strength of this study. The modelling of air pollution concentration for each transport policy scenario which was used to estimate the health benefits of the transport policies is an asset of this study.

In particular, the modelling of reduction of air pollution concentrations in scenarios which implement a shift from motorised transport to cycling and walking used to estimate health impacts is a significant strength of this research. A novelty of this analysis is to include the assessment of health impacts from NO₂ air pollution exposure. The majority of studies only account for PM_{2.5} neglecting important benefits from the reduction of air pollution.

The estimations of health effects of the transport policies showed considerable health benefits on all-cause mortality arising from behavioural change scenarios which increased physical activity. However, health impact assessments involve multiple assumptions with uncertainties in the estimation of health impacts. A sensitivity analysis (Figure 5.5) was carried out to assess the stability of the results and test the impacts of the main assumptions and data choices in this dissertation.

An important finding from the sensitivity analysis, exemplified by the Car Redu 50 scenario, was that from all the parameters tested, the total health impacts were always beneficial (preventable deaths) and of the same order of magnitude (1×10^3).

The sensitivity analysis (Figure 5.5) showed that our results were significantly sensitive to dose-response functions. As discussed in the Methods chapter, the exposure-response functions for physical activity and air pollution were obtained from the most recent meta-analyses. The evidence for the mortality effects of physical activity and PM_{2.5} air pollution exposure is stronger than for NO₂ air pollution exposure because more research has been done on physical activity and PM_{2.5} air pollution exposure.

There are still investigations about which is the best approach to quantify health benefits from the air pollution mixture of pollutants, for example, PM_{2.5} together with NO₂ air pollution exposure, without the double-counting of deaths (COMEAP, 2018). For this reason, the most up-to-date estimates (at the time of the analysis) of different exposure-response functions and their corresponding (adjusted and unadjusted) RR coefficients were used to study different outcomes (Figure 5.6) (COMEAP, 2018).

For the Car Redu 50 scenario, the mean value obtained using an adjusted RR coefficient for NO₂ and an unadjusted RR coefficient for PM_{2.5} was 3,022 deaths prevented per year (uncertainty range: 1,987 – 4,606). The range obtained using different RR coefficients for PM_{2.5} and NO₂ assessment (Figure 5.7) varied between 2,892 and 3,404 deaths prevented per year.

As shown in the sensitivity analysis (Figure 5.5), the results were much more sensitive to the exposure-response functions related to physical activity. Curvilinear exposure-response functions (Figure 5.6) were studied and the results assessed for the Car Redu 50 scenario (mean value of 3,022 deaths prevented per year) showed that the range of values obtained when using curvilinear exposure-response functions was between 1,717 and 6,470 deaths prevented per year.

However, not all assumptions and data inputs could be tested in the sensitivity analysis. For example, it is possible that people who are more sedentary benefit more from the increase in active travel modes than physically active people who exercise. Also, the benefits of physical activity may be related to the baseline levels of physical activity and general health of the people shifting to active travel modes.

Another variable which is difficult to quantify and which has an effect on the variation of exposure to air pollution is the ability of travellers to choose a less-congested road or cycle route, therefore reducing their exposure to air pollution. To study the effect of changes on exposure, the sensitivity analysis included the assessment of unitary exposure conversion ratios for cycling and walking were, estimating the exposure in active modes as the background concentration. As discussed before, variation to the conversion ratios had a minor effect on the stability of results.

Finally, as discussed in the previous section, health benefit estimations from the reduction of air pollution concentrations depend on the contextual setting and on the definition of the baseline (counterfactual) scenario from which different transport strategies are compared to.

Moreover, the percentage of changes in background concentrations have a significant effect on driving results (as shown in the sensitivity analysis). The high percentage of changes in background concentration were testes (10%, 30%, and 50%), and the results were sensitive to these changes.

This highlights the importance of accurately measure and project background concentrations. Future research should assess the sensitivity of results to different background concentrations actually measured for London or reported in other studies, rather than the sensitivity to these range of percentages.

5.3.4 Policy implications

Effective policies that increase the shift to active travel modes and reduce motorised transport are needed to achieve the significant health benefits of behavioural change policies assessed in this chapter. Much of the attention has been given to the implementation of technological change policies such as the low emissions zones and vehicle electrification by the London authorities.

However, technological policies, even if they did reduce air pollution, have the critical limitations of not offering the same health benefits that an increase in physical activity levels would. The investment made in policies which increase motorised transport should be diverted to the improvement of the walkability and cyclability of the city so that active modes are the easiest and most comfortable transport choice for any short trip.

5.4.5 Conclusions

The most significant health benefits are achieved through the replacement of trips by motor vehicles with active travel modes which increase the level of physical activity. The negative impacts of health from the inhalation of air pollutants do not outweigh the positive health benefits from physical activity. Technological change policies do offer health benefits through the reduction in exposure to air pollution, but the health benefits are much smaller than those of active travel.

Although different assumptions and uncertainties surround the health impact modelling results, it is highly likely that the health benefits associated with active travel are significant and these benefits should be considered in the development of transport policies in cities.

Chapter 6

CO₂ and air pollution emissions evaluation and health
impact assessment modelling of transport policy
scenarios in Mexico City

6.1 Overview

This chapter presents the results and the discussion of the results for the CO₂ and air pollutant emissions evaluation and the health impact assessment modelling (HIA) of the transport policy scenarios in Mexico City. Section 6.2 presents the results, including the CO₂ and air pollutants emissions evaluation (Section 6.2.1) and HIA results (Section 6.2.2).

Section 6.3 presents the discussion and critical assessment of the results including, the analysis of the principal findings, the comparison to previous studies, the strengths and limitations, the policy implications and concluding remarks.

6.1.1 Methods overview

The methods used to arrive at the results presented in this chapter were presented and discussed in Chapter 3. The transport policy scenarios developed for Mexico City (Figure 3.3) were described in detail, including the assumptions used to develop each scenario, in Section 3.2.2.

The methodological approach used for the CO₂ and air pollutants (PM_{2.5}, PM₁₀, NO_x) emissions evaluation in Mexico City was presented in Section 3.3.2. As this section explains, the latest emissions inventory from Mexico City (Section 3.3.2.1) was used to develop the baseline scenario (describing current conditions). Discussion of the reported uncertainties in the inventory was presented in section 3.3.2.1.1. The emissions evaluation for the transport policy scenarios in Mexico City included the assessment of particulate matter non-exhaust emissions from electric vehicles (Section 3.3.2.2) and the evaluation of CO₂ emissions from electricity generation (Section 3.3.3.1, Table 3.6).

Section 3.4 presented the translation of transport policy scenarios as inputs for the modelling framework. The transport policy scenarios for Mexico City (in the same way as the scenarios for London) were defined in terms of the vehicle fleet composition (Section 3.4.1.2, Table 3.12). Then, the travel patterns for each transport policy scenarios in Mexico City was presented in Section 3.4.2.3 (see Table 3.19).

The health impact assessment modelling framework used for the analysis of Mexico City's transport policy scenarios was presented in Section 3.5 (see Figure 3.22). For each transport policy scenario in Mexico City, the health effects of air pollution inhalation (Section 3.5.1.2) and physical activity were accounted for (Section 3.5.2). Air pollution concentrations used in the HIA modelling for Mexico City were taken from data that came from monitoring stations (Section 3.3.2.1). The assumptions, sensitivity analysis, input variables and justification of choices for the HIA modelling were presented in Section 3.5.3 and 3.5.4.

6.2 Results

6.2.1 CO₂ and air pollutants emissions evaluation

The following sections describe the net emissions per transport policy scenario, and the emissions reduced (mitigated) relative to baseline (current) levels, and the equivalent percentage reduction for each transport policy scenario, and each pollutant.

6.2.1.1 Carbon dioxide (CO₂)

Net CO₂ emissions in the technological change scenarios (Figure 6.1), which estimated the electrification of just one vehicle type (Electric Car, Electric Taxi, And Electric Bus scenarios), varied from 13.2 to 14.8 megatonnes of CO₂ emissions per year (Mt/y) (uncertainty range: 12.3 – 15.8 Mt/y of CO₂). Electrifying cars plus electrifying taxis plus electrified buses resulted in 6.0 Mt/y of CO₂ emissions mitigated (uncertainty range: 5.6 – 6.4 Mt/y of CO₂). This reduction in emissions (6.0 Mt/y of CO₂) corresponds to a 37% reduction of CO₂ emissions relative to baseline levels when all percentage reductions from the three scenarios are added together (Electric Car, Electric Taxi, Electric Bus).

The remaining technological change scenario, the electric vehicle fleet scenario (Figure 6.1), resulted in a total of 7.5 Mt/y of CO₂ net emissions (uncertainty range: 7.0 – 8.0 Mt/y of CO₂), which is equivalent to a reduction relative to the baseline of 53% (corresponding to 8.6 Mt/y of CO₂ emissions mitigated; uncertainty range: 8.0 – 9.2 Mt/y of CO₂). Clearly, this scenario reduces more CO₂ net emissions than the Electric Car, Electric Taxi, and Electric Bus scenarios because apart from cars, taxis and buses, it includes the electrification of additional vehicle types (vans, LGVs and motorcycles).

CO₂ emissions from behavioural change scenarios (Figure 6.1), which focused on cars and reduced old cars on the road (Old Car Redu scenario) or reduced km travelled by car by 10% (Car Redu 10 scenario), varied from 15.0 to 15.4 Mt/y of CO₂ net emissions (uncertainty range: 14.0 – 16.4 Mt/y of CO₂), respectively. These two scenarios (Old Car Redu and Car Redu 10) resulted in between 0.8 to 1.1 Mt/y

of CO₂ emissions mitigated (uncertainty range: 0.7 – 1.2 Mt/y of CO₂), which corresponds to a percentage reduction between 5% and 7% relative to baseline levels.

Furthermore, the remaining behavioural change scenarios (Old Taxi Redu, Old Bus Redu) (Figure 6.1) showed that reducing old taxis only resulted in 0.072 Mt/y of CO₂ emissions mitigated (uncertainty range: 0.068 – 0.077 Mt/y of CO₂), equivalent to a reduction of 0.4% relative to baseline. Nevertheless, the Old Bus Redu scenario resulted in total emissions of 14.6 Mt/y of CO₂ net emissions (uncertainty range: 13.7 – 15.6 Mt/y of CO₂), corresponding to a reduction of 9% relative to baseline (1.5 Mt/y of CO₂, uncertainty range: 1.4 – 1.6 Mt/y of CO₂). In comparison with the technological change scenarios, the Electric Bus scenario reduced CO₂ emissions by a similar percentage (11%), relative to baseline.

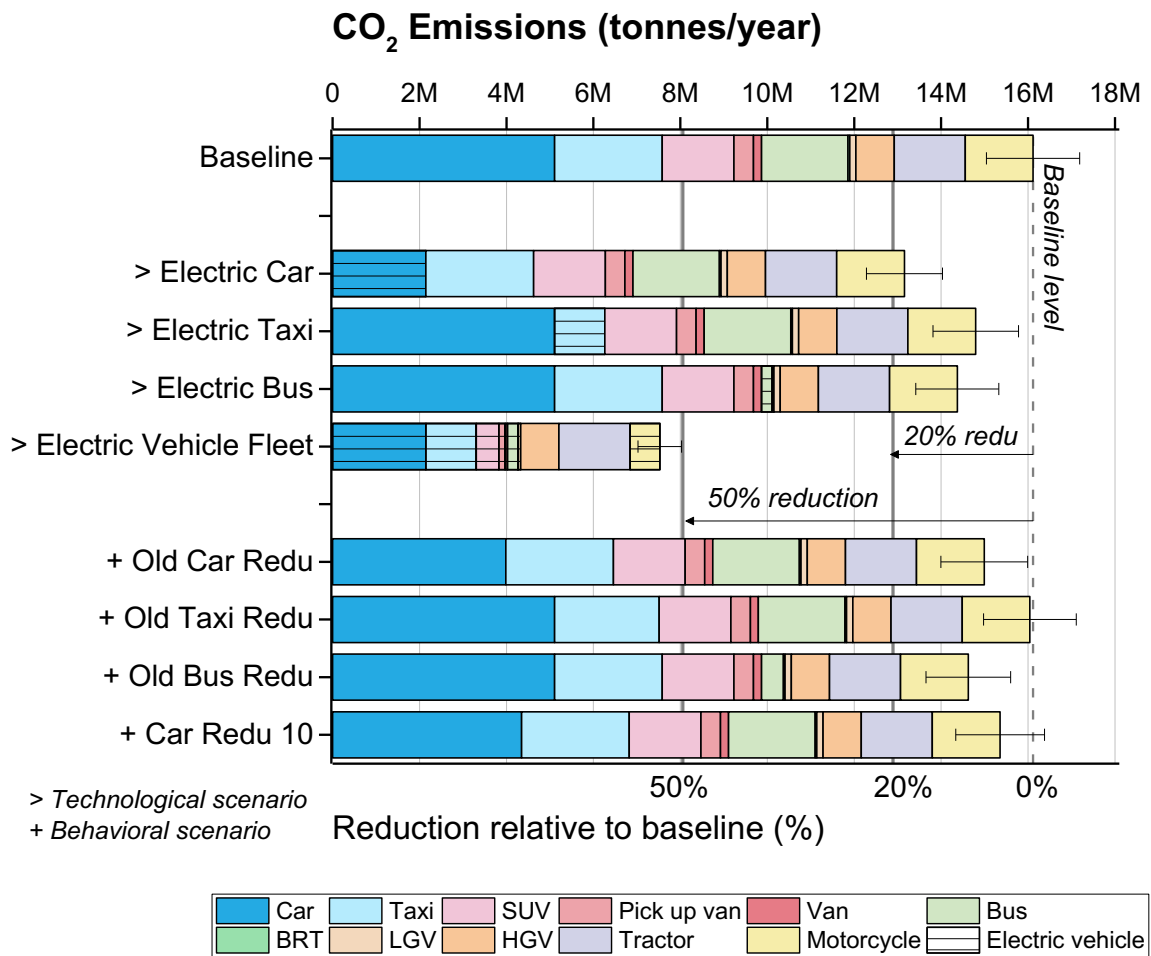


Figure 6.1 CO₂ emissions (tonnes per year) (upper x-axis) per vehicle type in the baseline, technological (>) and behavioural (+) change transport policy scenarios for Mexico City. Percentage (%) reductions relative to baseline levels (dotted line) are indicated in the bottom x-axis.

6.2.1.1.1 Emissions from electricity used by electric vehicles

According to the results shown in the previous section, technological change scenarios, which include vehicle electrification, appear to have the largest effect on mitigating CO₂ emissions in comparison with behavioural change scenarios.

In this context, exhaust emissions by cars in the baseline scenario (5.1 Mt/y of CO₂) accounted for 32% of total CO₂ emissions in the baseline. In contrast, in the Electric Car scenario where cars are electric and therefore, do not emit exhausted CO₂ emissions, the additional CO₂ emissions from the use of electricity by electric cars accounted for 16% of total CO₂ (2.1 Mt/y of CO₂). This indicates that the technological change scenarios resulted in a CO₂ emissions reduction even after accounting for the additional emissions from electricity used by electric vehicles (Table 6.1).

In the baseline, CO₂ exhaust emissions from buses and taxis accounted for 13% and 15%, respectively, of total CO₂ emissions (corresponding to 2.0 and 2.5 Mt/y of CO₂, respectively). When these two vehicle types are electric (Electric Bus and Eclectic Taxi scenario), the additional CO₂ emissions from electricity accounted for 0.2% and 1.2% of total CO₂ emissions in these two scenarios, respectively.

Moreover, the vehicle fleet accounted for 84% (corresponding to 12.9 Mt/y) of CO₂ exhausted emissions from the baseline. When the vehicles are electrified (Electric Vehicle Fleet scenario), the additional CO₂ emissions from electricity account for 67% (corresponding to 5.0 Mt/y) of CO₂ emissions from electricity use.

Table 6.1 CO₂ exhausted emissions in megatonnes per year (Mt/y) in the baseline per vehicle type and CO₂ emissions from electricity use per electric vehicle type in the technological scenarios. The percentage (%) of CO₂ exhaust emissions per vehicle type relative to baseline and CO₂ emissions for electricity used per electric vehicle type relative to total CO₂ emissions in each scenario is indicated.

Baseline	Total CO ₂ exhaust emissions in baseline and per vehicle type (Mt/y)	Percentage of CO ₂ exhaust emissions per vehicle type relative to total CO ₂ emissions in baseline (%)
Total	16.1	100
Car	5.1	32
Taxi	2.5	15
Bus [†]	2.0	13
Vehicle fleet [*]	12.9	84
Technological change scenarios	CO ₂ emissions from electricity use per electric vehicle type (Mt/y)	Percentage of CO ₂ emissions from electricity use per electric vehicle type relative to total CO ₂ emissions in its corresponding scenario (%)
Electric Car	2.1	16
Electric Taxi	1.2	8
Electric Bus [†]	0.2	2
Electric Vehicle Fleet [*]	5.0	67

Note: ^{*}To allow comparison, the vehicle fleet in this table includes the following vehicle types: car, taxi, SUV, pick up van, van, bus, BRT and LGV, and motorcycle. These were the vehicle types which were electrified in the Electric Vehicle Fleet scenario.

[†]The bus category includes minibuses, buses and BRT from the Mexico City vehicle fleet.

6.2.1.2 Nitrogen oxide (NO_x)

NO_x emissions (Figure 6.2) from the technological change scenarios which included the electrification of only one vehicle type (Electric Car, Electric Taxis, or Electric Bus) varied from 38.7 to 47.5 kilotonnes of NO_x emissions per year (kt/y) (uncertainty range: 35.7 – 51.2 kt/y of NO_x emissions), relative to baseline levels (current levels). The total emissions mitigated, which are the added reduced emissions from each of these three scenarios (Electric Car, Electric Taxis, or Electric Bus), resulted in a reduction of 29.3 kt/y of NO_x emissions (uncertainty range: 27.0 – 31.6 kt/y of NO_x emissions reduced) relative to baseline levels, which corresponds to a 56% reduction from baseline.

From the technological change scenarios, the electrification of the entire Electric Vehicle Fleet scenario alone resulted in a reduction of 14.6 kt/y of NO_x emissions (uncertainty range: 13.5 – 15.8 kt/y of NO_x emissions). This is equivalent to a reduction (in the Electric Vehicle Fleet scenario) of 37.8 kt/y of NO_x reduced emissions (uncertainty range: 34.9 – 40.8 kt/y of NO_x emissions reduced) relative to baseline levels, a reduction of 72%.

From the behavioural change scenarios (Figure 6.2), the old taxi scenario resulted in 0.23 kt/y of NO_x emissions mitigated (uncertainty range: 0.21 – 0.24 kt/y of reduced NO_x emissions) relative to the baseline, a reduction of 0.4%. At the same time, NO_x emissions in the scenarios studying the impacts of cars (Old Car Redu and Car Redu 10 scenarios) varied from 46.5 to 48.1 kt/y of NO_x emissions (uncertainty range: 42.8 – 50.1 kt/y of NO_x emissions), respectively. The corresponding emissions reduction from baseline in these car scenarios (Car Redu 10 and Old Car Redu) ranged from 4.3 to 6.0 kt/y of reduced NO_x emissions (uncertainty range: 4.0 – 6.5 kt/y of reduced NO_x emissions), a reduction between 8% and 11% relative to baseline, respectively.

Furthermore, the Old Bus Redu scenario resulted in 48.1 kt/y of NO_x emissions (uncertainty range: 44.4 – 51.9 kt/y of NO_x emissions). The Old Bus Redu scenario resulted in 4.3 kt/y of reduced NO_x emissions (uncertainty range: 4.0 – 4.7 kt/y of reduced NO_x emissions) relative to baseline levels, a reduction of 21%, which is the largest mitigation of NO_x emissions achieved in the behavioural change scenarios.

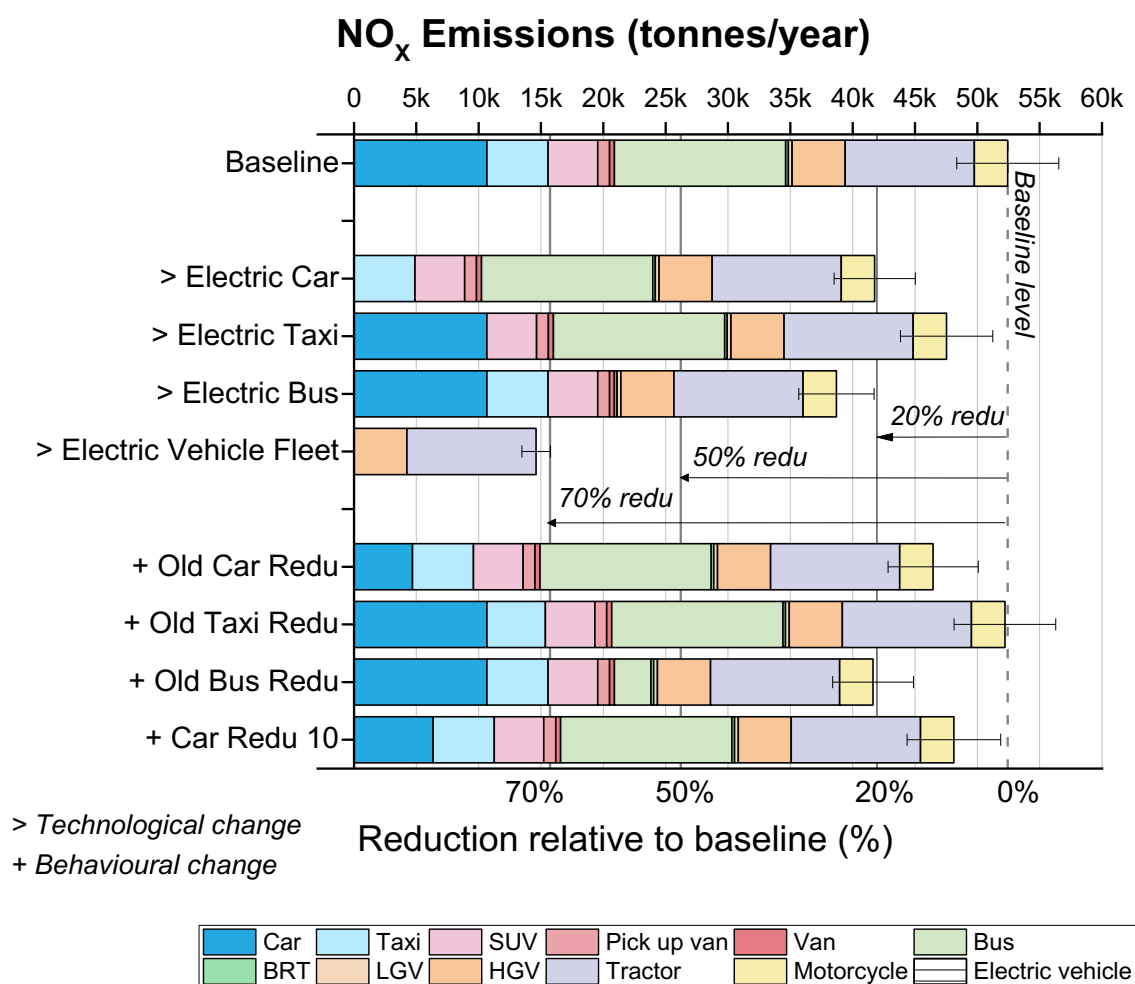


Figure 6.2 NO_x emissions (tonnes per year) (upper x-axis) per vehicle type in the baseline, technological (>) and behavioural (+) change transport policy scenarios for Mexico City. Percentage (%) reductions relative to baseline levels (dotted line) are indicated in the bottom x-axis.

6.2.1.3 Particulate matter of 2.5 μm in diameter ($\text{PM}_{2.5}$)

In this chapter, $\text{PM}_{2.5}$ emissions were also evaluated as part of the overall aim of this thesis, where technological change scenarios total $\text{PM}_{2.5}$ emissions (Figure 6.3) from the scenarios which electrified cars, taxis and buses (Electric Car, Electric Taxis, or Electric Bus) showed a range in net $\text{PM}_{2.5}$ emissions of 2.0 to 2.8 kilotonnes per year (kt/y) (uncertainty range: 1.9 – 3.1 kt/y of $\text{PM}_{2.5}$).

The Electric Taxi and the Electric Car scenario reduced $\text{PM}_{2.5}$ emissions by 1 to 3 % relative to baseline, respectively. These two scenarios, Electric Taxi and Electric Car, $\text{PM}_{2.5}$ emissions mitigated by 0.026 – 0.081 kt/y of (uncertainty range: 0.024 – 0.087 kt/y of $\text{PM}_{2.5}$). The last scenario of this group, the Electric Bus scenario, reduced $\text{PM}_{2.5}$ emissions by 29% (0.83 kt/y $\text{PM}_{2.5}$) relative to baseline, (uncertainty range: 0.76 – 0.89 kt/y of $\text{PM}_{2.5}$).

The most ambitious technological change scenario, the Electric Vehicle Fleet scenario, resulted in net $\text{PM}_{2.5}$ emissions of 1.8 kt/y (uncertainty range: 1.7 – 2.0 kt/y of $\text{PM}_{2.5}$). These net emissions correspond to a reduction of 36% from baseline levels, reducing $\text{PM}_{2.5}$ emissions by 1.03 kt/y (uncertainty range: 0.95 – 1.11 kt/y of $\text{PM}_{2.5}$). Interestingly, this reduction is not significantly larger (only 7% larger) than the electrification of buses (Electric Bus scenario).

Total $\text{PM}_{2.5}$ emissions in the behavioural change scenarios (Figure 6.3) which removed old cars and reduced km travelled by cars by 10% (Old Car Redu and Car Redu 10 scenarios) varied from 2.7 to 2.8 kt/y of $\text{PM}_{2.5}$ emissions (uncertainty range: 2.5 – 3.0 kt/y of $\text{PM}_{2.5}$). The corresponding emissions reduction from baseline in these scenarios (Old Car Redu and Car Redu 10) varied from 0.11 – 0.13 kt/y of $\text{PM}_{2.5}$ emissions reduced (uncertainty range: 0.10 – 0.14 kt/y of $\text{PM}_{2.5}$), a reduction between 4% and 5% relative to baseline.

In the behavioural change scenarios which removed old taxis (Old Taxi Redu) or old buses (Old Bus Redu), the $\text{PM}_{2.5}$ net emissions resulted in 2.9 and 2.2 kt/y of $\text{PM}_{2.5}$ net emissions, respectively (uncertainty range: 2.6 – 3.1 kt/y of $\text{PM}_{2.5}$ and uncertainty range: 2.0 – 2.4 kt/y of $\text{PM}_{2.5}$, respectively). The Old Taxi Redu scenario reduced emissions by only 0.2 % relative to baseline, corresponding to 0.007 kt/y of $\text{PM}_{2.5}$ emissions mitigated (uncertainty range: 0.006 – 0.008 kt/y of $\text{PM}_{2.5}$), whereas interestingly, the Old Bus Redu scenario reduced 24% relative to baseline, corresponding to a reduction of 0.68 kt/y of $\text{PM}_{2.5}$ emissions mitigated (uncertainty range: 0.62 – 0.73 kt/y of $\text{PM}_{2.5}$).

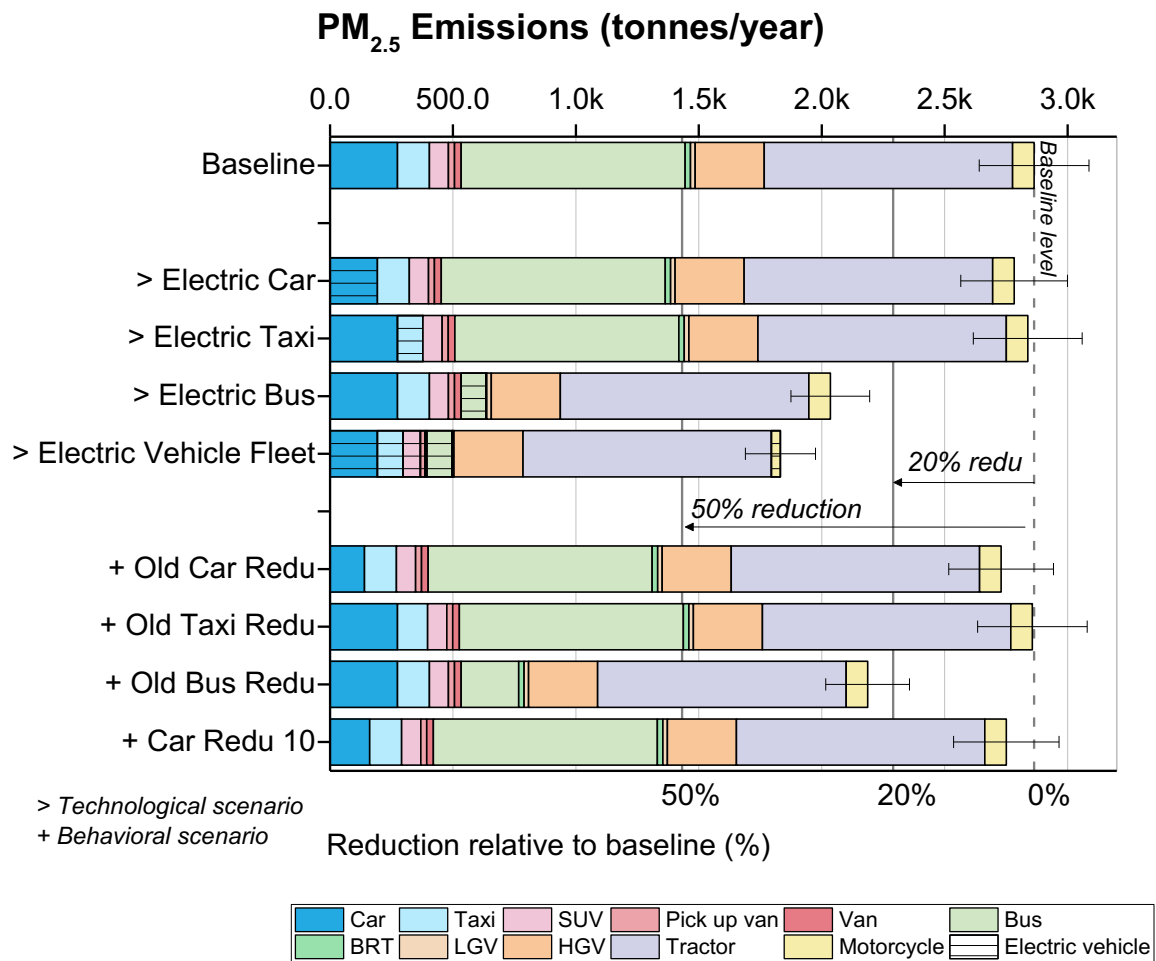


Figure 6.3 PM_{2.5} emissions (tonnes per year) (upper x-axis) per vehicle type in the baseline, technological (>) and behavioural (+) change transport policy scenarios for Mexico City. Percentage (%) reductions relative to baseline levels (dotted line) are indicated in the bottom x-axis.

6.2.1.3.1 Particulate matter (PM_{2.5}) non-exhaust emissions from electric vehicles

It is important to acknowledge that even if electric cars have zero exhaust PM emissions, electric cars do not mitigate PM non-exhaust emissions due to brake and tyre wear. These emissions need to be accounted for in order to make a fair comparison with conventional vehicles. All the PM results presented include non-exhaust emissions.

The PM_{2.5} non-exhaust emissions (Table 6.2) in the Electric Car technological change scenario resulted in 0.193 kt/y, which represents 7% of total emissions from the Electric Car scenario. Comparing the Electric Car results to the baseline (where exhaust PM_{2.5} emissions from cars accounted for 0.274 kt/y or 10%), the net avoided PM_{2.5} emissions from cars in the Electric Car are 0.08 kt/y. Proportions of non-exhaust emission from taxis remain at a similar percentage to the baseline, 4% in the Electric Taxi scenario vs 5% in the baseline.

The contribution to PM_{2.5} emissions from buses and the vehicle fleet changes drastically in the Electric Bus and Electric Vehicle Fleet scenario, relative to baseline levels. In such a baseline, buses contributed to 33% of total PM_{2.5} emissions. In the Electric Bus scenario, the contribution from buses dropped to 4%. Similarly, in the Electric Vehicle Fleet scenario, PM_{2.5} emissions from the vehicles fleet contribute only 9% of the total emissions, in contrast to the contribution of the vehicles analysed, which accounted for 55%.

Table 6.2 Net PM_{2.5} emissions in kilotonnes per year (kt/y) in the baseline and non-exhaust PM_{2.5} emissions from electric vehicles in the technological change scenarios. The percentage (%) of PM_{2.5} emissions per vehicle type relative to baseline and the percentage of non-exhaust PM_{2.5} emissions from electric vehicles relative to total PM_{2.5} emissions in each technological change is indicated.

Baseline	Net PM _{2.5} emissions in baseline per vehicle type (kt/y)	Percentage of PM _{2.5} emissions per vehicle type relative to net PM _{2.5} emissions in baseline (%)
Total	2.864	100
Car	0.274	10
Taxi	0.126	5
Bus [†]	0.948	33
Vehicle fleet*	1.117	55
Technological change scenarios	PM _{2.5} non-exhaust emissions from non-exhaust (kt/y)	Percentage of PM _{2.5} non-exhaust emissions per electric vehicle type relative to net PM _{2.5} emissions in its corresponding scenario (%)
Electric Car	0.193	7
Electric Taxi	0.104	4
Electric Bus [†]	0.104	4
Electric Vehicle Fleet*	0.244	9

Note: *To allow comparison, the vehicle fleet in this table includes the following vehicle types: car, taxi, SUV, pick up van, van, bus, BRT and LGV, and motorcycle. These were the vehicle types which were electrified in the Electric Vehicle Fleet scenario.

[†]The bus category includes minibuses, buses and BRT from the Mexico City vehicle fleet.

The same analysis presented in this table for PM₁₀ was done, and similar proportions of non-exhaust emissions were obtained. For this reason, only results for PM_{2.5} are presented.

6.2.1.4 Particulate matter of 10 µm in diameter (PM₁₀)

Considering now larger particulate matter; net PM₁₀ emissions in the technological change scenarios (Figure 6.4), which electrified only one vehicle type (Electric Car, Electric Taxis, or Electric Bus), ranged from 4.55 to 5.37 kilotonnes per year (kt/y) of total PM₁₀ emissions (uncertainty range: 4.20 – 5.79 kt/y of PM₁₀).

The percentage reduction in each scenario was the following: Electric Taxi reduction of 5% (mitigation of 0.27 kt/y of PM₁₀; uncertainty range 0.25 – 0.29); Electric Car reduction of 13% (mitigation of 0.75 kt/y of PM₁₀; uncertainty range 0.69 – 0.81) and; Electric Bus reduction of 19% (mitigation of 1.09 kt/y of PM₁₀; uncertainty range 1.01 – 1.18), all relative to baseline levels, indicating a comparable contribution from cars and buses.

The most ambitious technological change scenario, the Electric Vehicle Fleet scenario, resulted in net PM₁₀ emissions of 3.14 kt/y (uncertainty range: 2.90 – 3.39). These net emissions correspond to a reduction of 36% from baseline levels, reducing PM₁₀ emissions by 2.50 kt/y (uncertainty range: 2.30 – 2.69). Interestingly, this emissions reduction is similar to the mitigation resulting from electric cars and buses, which shows the important weight of these vehicle types.

Total PM₁₀ emissions in the behavioural change scenarios (Figure 6.4), which removed old cars and reduced km travelled by cars by 10% (Old Car Redu and Car Redu 10 scenarios) varied from 5.33 to 5.40 kt/y of PM₁₀ emissions (uncertainty range: 4.91 – 5.83 kt/y). The corresponding emissions reduction from baseline in these scenarios (Old Car Redu and Car Redu 10) varied from 0.24 – 0.32 kt/y of PM₁₀ emissions reduced (uncertainty range: 0.22 – 0.34 kt/y), equivalent to a reduction between 4% and 6% relative to baseline.

In the behavioural change scenarios, which removed old taxis (Old Taxi Redu) or old buses (Old Bus Redu), the PM₁₀ net emissions resulted in 5.62 kt/y and 4.75 kt/y of PM₁₀ net emissions, respectively (uncertainty range: 5.18 – 6.06 and 4.38 – 5.12, respectively). The Old Taxi Redu scenario only reduced emissions by 0.4 % relative to baseline, corresponding to 0.020 kt/y of PM₁₀ emissions mitigated (uncertainty range: 0.019 – 0.022), whereas the Old Bus Redu scenario reduced emissions by 16% relative to baseline, corresponding to a reduction of 0.090 kt/y of PM₁₀ emissions mitigated (uncertainty range: 0.83 – 0.97 kt/y).

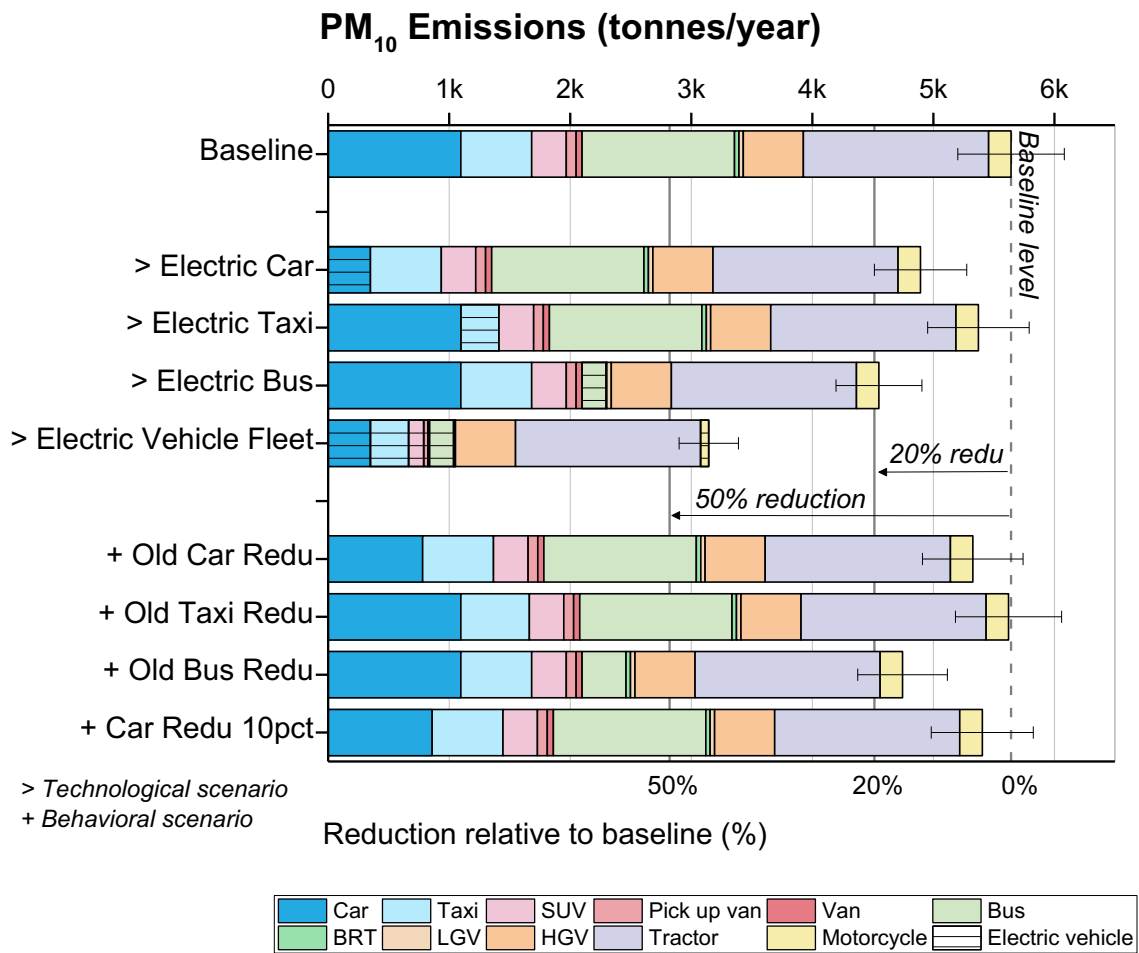


Figure 6.4 PM₁₀ emissions (tonnes per year) (upper x-axis) per vehicle type in the baseline, technological (>) and behavioural (+) change transport policy scenarios for Mexico City. Percentage (%) reductions relative to baseline levels (dotted line) are indicated in the bottom x-axis.

6.2.1.5 Emissions reduction per vehicle replaced

Until now, interesting results in terms of net emissions and emissions reductions from baseline levels have been shown for the technological and behavioural change scenarios. This section presents the average emissions reduced through the replacement of a vehicle from the street.

The average amount of emissions mitigated per vehicle replaced by an electric vehicle (Table 6.3), varied between 2.10 and 33.13 tonnes of CO₂ emissions per year (tonnes/year). 2.1 tonnes when replacing an internal combustion vehicle for an electric vehicle and 33.13 tonnes when replacing a diesel bus for an electric bus. In terms of air pollution, emissions reductions per bus replaced with an electric vehicle resulted in the following: 261.71 kg/y of NO_x emission per bus replaced; 16.39 kg of PM_{2.5} emissions per bus replaced, and 22.09 kg/y emission per bus replaced.

Strikingly, these results suggest that reductions of emissions per vehicle replaced by active travel (walking and cycling) in the behavioural change scenarios resulted in higher reductions of emissions than in the technological change scenarios. The replacement of a car or a bus by a bicycle or walking varied from 3.13 to 39.94 tonnes per year (tonnes/year) of CO₂ emissions, respectively. Air pollution emissions reductions per bus replaced with bicycle or walking resulted as follows: 289.80 kg/y of NO_x emission per bus replaced; 16.39 kg of PM_{2.5} emissions per bus replaced, and 22.09 kg/y emission per bus replaced.

Table 6.3 Average emissions (CO₂, NO_x, PM_{2.5}, PM₁₀) mitigated (reduced) per vehicle replaced in the technological change scenarios (vehicles are replaced with electric vehicles) and behavioural change scenarios (vehicles are replaced by active travel (walking, cycling and public transport)).

Scenarios	Vehicle replaced	New vehicle/mode of transport (replacement)	Average emissions mitigated per vehicle replaced			
			CO ₂ (t/y)	NO _x (kg/y)	PM _{2.5} (kg/y)	PM ₁₀ (kg/y)
Technological change scenarios						
			Per vehicle replaced			
Electric Car	Diesel/petrol car	Electric car	2.10	8.19	0.14	0.71
Electric Taxi	Diesel/petrol taxi	Electric taxi	8.92	36.61	0.58	3.67
Electric Bus	Diesel/petrol bus	Electric bus	33.13	261.71	16.39	22.09
Average in Electric Vehicle Fleet	Average diesel/petrol vehicle	Average electric vehicle	3.54	16.82	0.65	1.52
Behavioural change scenarios						
Old Car Redu	Diesel/petrol car	Active travel	3.13	16.70	0.37	0.88
Old Taxi Redu	Diesel/petrol taxi	Active travel	15.83	49.40	1.53	4.44
Old Bus Redu	Diesel/petrol bus	Active travel	39.94	289.80	18.17	24.03
Car Redu 10	Diesel/petrol car	Active travel	2.96	16.87	0.44	0.93

6.2.2 Health impact assessment

Following the assessment of CO₂ and air pollutants emissions from the transport policy scenarios, this section presents the results of the health impact assessment modelling for Mexico City. It is important to notice (as explained in section 3.3.2) that it was not possible to model air pollution for Mexico City due to lack of resources. Thus, health impacts for the variations of PM_{2.5} and NO₂ concentration in each scenario were not accounted for.

The health impacts estimated and presented in this section were air pollutants (PM_{2.5} and NO₂) inhalation and physical activity. Only behavioural change scenarios (in which transport modes were changed to active travels) had variations relative to baseline levels on air pollutants inhalation during walking or cycling as well as an increase of physical activity for the use of active modes of transport.

6.2.2.1 Air pollution: inhalation of air pollutants

Health impacts for air pollutants (PM_{2.5} and NO₂) inhalation (Figure 6.5) are due to changes in the level of physical activity relative to baseline levels. Thus, only the behavioural change scenarios had variations in air pollutants inhalation. This is because physical activity was increased in these scenarios due to changes from transport modes to active modes (walking, cycling and public transport).

In the technological change scenarios, there are no variations in air pollutant inhalation (relative baseline) because there is no increase in physical activity in these scenarios since they do not include changes to active travel modes of transport, only a technological change in the vehicles used to travel. Information on average background concentrations for PM_{2.5} and NO₂ were used from the information reported at monitoring stations in Mexico City, as explained before (section 3.3.2.3).

6.2.2.1.1 Particulate matter (PM_{2.5})

Health impacts due to the inhalation of PM_{2.5} air pollution (Figure 6.5) in behavioural change scenarios which reduced the old cars or reduced km travelled by car by 10% (scenarios Old Car Redu and Car Redu 10) and replaced those trips with active modes, ranged from -175 to -127 deaths caused per year (uncertainty range: -243 to -81) (negative values indicate deaths caused), relative to baseline levels, respectively.

Reducing the number of old taxis from the vehicle fleet (Old Taxi Redu) and transforming these journeys into increased active travel, resulted in -28 deaths caused per year (uncertainty range: -39 to -18) due to PM_{2.5} pollution inhalation relative to baseline. The additional behavioural change scenario which assessed the impact of reducing old buses (Old Bus Redu scenario) and replacing those trips with active modes caused -89 death per year (uncertainty range: -123 to -57) due to the increase of PM_{2.5} inhalation relative to baseline.

6.2.2.1.2 Nitrogen dioxide (NO₂)

Health impacts for the inhalation of NO₂ pollution (Figure 6.5) in the behavioural change scenarios resulting from the replacement of transport by car to active travel (Old Car Redu and Car Redu 10 scenarios) caused a range of -64 to -46 deaths per year (uncertainty range: -92 to -28) (negative values indicate deaths caused), relative to baseline levels, respectively.

Reduction of travel by old taxis to active travel (Old Taxi Redu scenario) caused -10 deaths per year (uncertainty range: -15 to -6) from the increased inhalation of NO₂ pollution relative to baseline. Compared with -33 deaths per year (uncertainty range: -47 to -20) caused by the fourth behavioural change scenario (Old Bus Redu scenario), due to the increase of NO₂ pollution inhalation relative to baseline.

6.2.2.1.3 Total PM_{2.5} and NO₂

Total health impacts for the inhalation of PM_{2.5} and NO₂ pollution (Figure 6.5) could be added because, as explained in Chapter 3 section 3.5.1, an adjusted relative risk coefficient was used for NO₂. The health impacts for the increase of PM_{2.5} and NO₂ pollution inhalation (relative to baseline) in the behavioural change scenarios resulting from the effect of mode shift from cars to active travel modes (Old Car Redu and Car Redu 10 scenarios) varied from -239 to -173 deaths caused per year (uncertainty range: -335 to -109), respectively.

PM_{2.5} and NO₂ pollution inhalation for the reduction of travel by old taxis to active travel modes (Old Taxi Redu scenario) caused -38 deaths per year (uncertainty range: -24 to -53). The reduction of travel by old buses to active travel modes (Old Bus Redu scenario) caused -122 death per year (uncertainty range: -170 to -77) due to the increase inhalation of PM_{2.5} and NO₂ pollution relative to baseline.

Health impacts of PM_{2.5} and NO₂ pollution inhalation in Mexico City

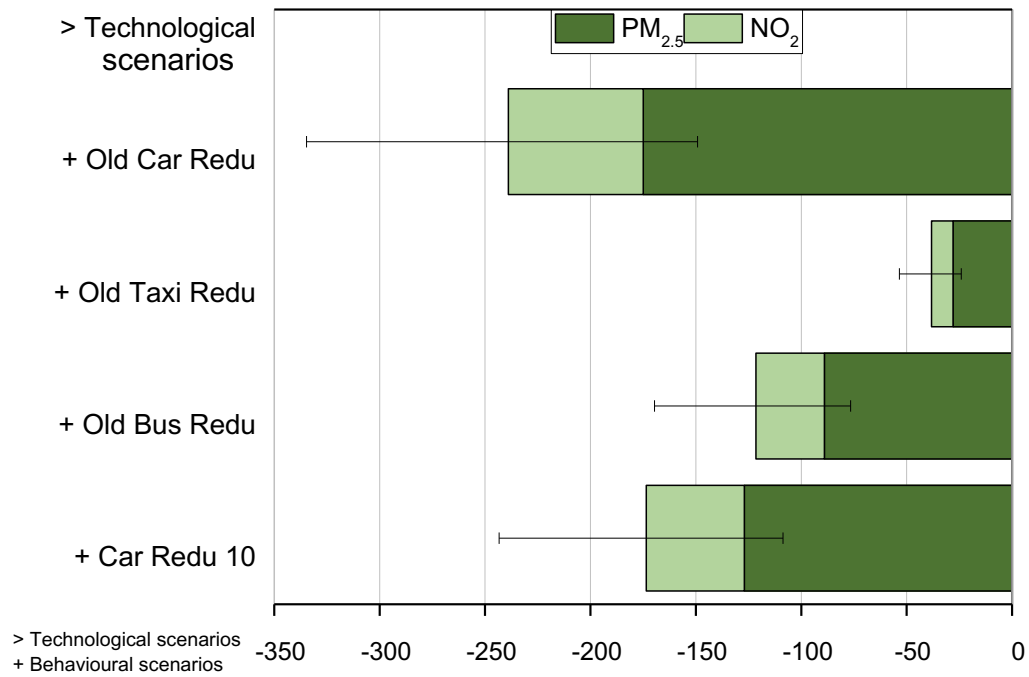


Figure 6.5 Health impacts of PM_{2.5} and NO₂ pollution inhalation (quantified as the number of deaths caused (-) per year) in the transport policy scenarios for Mexico City, relative to baseline.

6.2.2.2 Physical activity

The results in the previous section suggested that the behavioural change scenarios caused at least tens of deaths per year due to the inhalation of air pollutants. However, the health impact assessment has to include the health impacts of physical activity. Such health impacts on the inhabitants of Mexico City are presented in this section.

Health impacts due to the increase in physical activity (Figure 6.6) in the behavioural change scenarios resulting from the change of modes from cars to active travel (Old Car Redu and Car Redu 10 scenarios) ranged from 1,212 to 1,639 deaths prevented per year (uncertainty range: 673 – 2,215), relative to baseline levels.

The increase in physical activity during active travel as a result of the reduction of travel (Figure 6.6) by old taxis (Old Taxi Redu scenario) prevented 249 deaths per year (uncertainty range: 137 – 249). It is apparent from Figure 6.6 that the reduction of travel by old buses to active travel modes, which increased levels of physical activity relative to baseline (Old Bus Redu scenario), prevented 671 deaths per year (uncertainty range: 384 – 899).

There are no health benefits from physical activity in the technological change scenarios because there are no changes to active travel modes of transport (walking, cycling, public transport), only technology changes in the vehicles used to travel.

Health impacts of physical activity in Mexico City

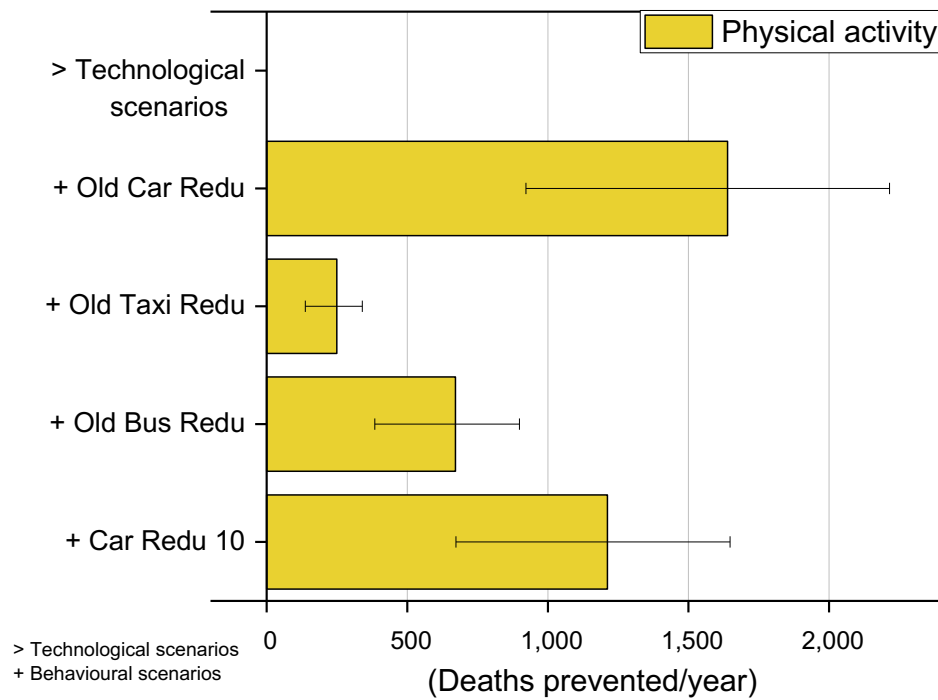


Figure 6.6 Health impacts of physical activity (quantified as the number of deaths prevented per year) in the transport policy scenarios in Mexico City, relative to baseline.

6.2.2.3 Total health impacts

From the results presented here, it is apparent that the total health impacts (Figure 6.7), resulting from the increase in air pollutants (PM_{2.5} and NO₂) inhalation and increased physical activity in the behavioural change scenarios, resulted in more significant health benefits (deaths prevented) than risks (deaths caused). The health benefits from the increase in physical activity were larger (seven times larger on average) compared with the risk for inhalation of air pollutants (for both PM_{2.5} and NO₂).

The reduction of travel by old cars (Old Car Redu scenario) (Figure 6.7) resulted in net health benefits of 1,400 deaths prevented per year (uncertainty range: 588 – 2,066), with a benefit (for physical activity) versus risk (inhalation of PM_{2.5} and NO₂) (risk ratio: 7). The second scenario resulting from the reduction of cars and an increase in active travel combined with a reduction of km travelled by car of 10% (Car Redu 10 scenario), resulted in total health benefits of 1,039 (uncertainty range: 430 – 1,539), with a risk ratio of 7, which indicates the same proportion between benefits and risk in these scenarios (Old Car Redu and Car Redu 10).

Reduction of travel by old taxi (Old Taxi Redu scenario) (Figure 6.7) increased health benefits by preventing 211 deaths per year (uncertainty range: 83 – 316), also with a risk ratio of 7. Moreover, the health benefits of reducing travel by old buses (Old Bus Redu scenario) prevented 549 deaths per year (uncertainty range: 215 – 316): risk ratio of 6 (similar proportion of benefits and risks as in the rest of the behavioural change scenarios).

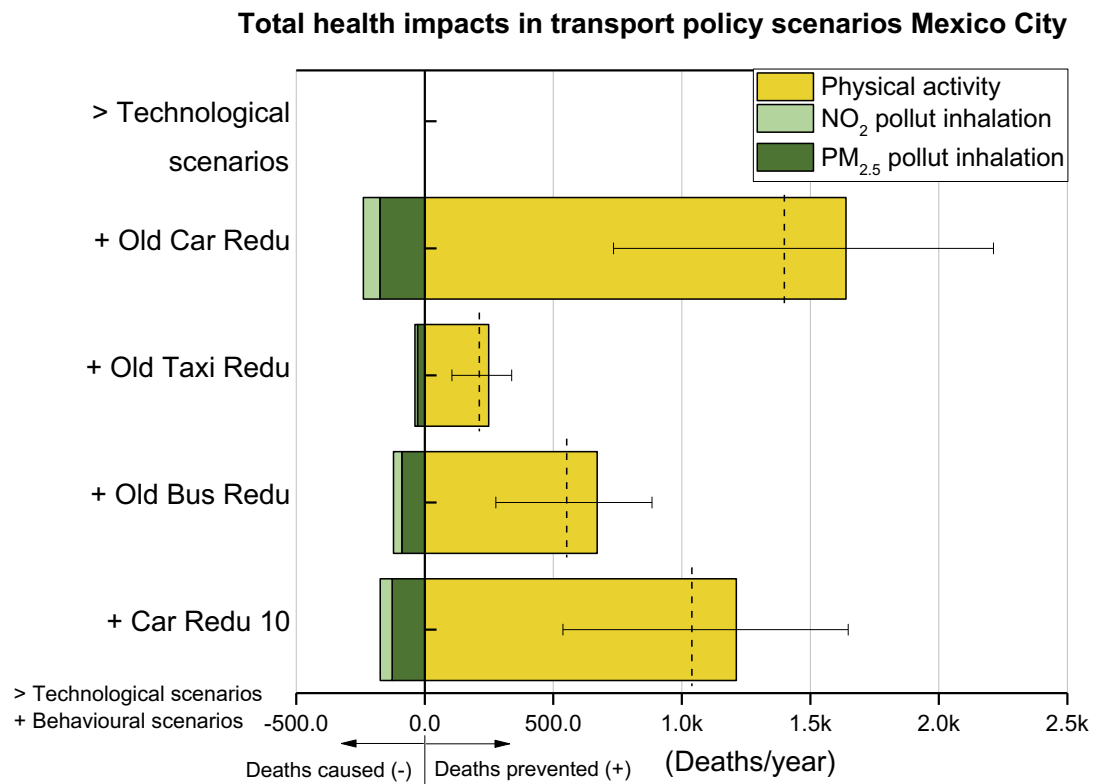


Figure 6.7 Total health impacts resulting from adding negative (-) health impacts (deaths caused) from air pollutants (PM_{2.5} and NO₂) inhalation and positive (+) health impacts (deaths prevented) from the increase in physical activity in the transport policy scenarios in Mexico City, relative to baseline levels.

Dotted lines indicated the net number of deaths (prevented) per year after subtracting the number of death caused by the number of deaths prevented.

6.3 Discussion

This section presents the discussion of results for the transport policy scenarios in Mexico City, including discussion about principal findings, comparison to previous studies, strengths and limitations, policy implications and concluding remarks.

As mentioned in the results section, it is important to notice that the assessment approach for the emission estimates in Mexico City was a simple approximation limited by the lack of data and modelling resources and the results and its discussion should be assessed accordingly.

6.3.1 Principal findings

Air pollution and CO₂ emissions assessment were shown in this chapter for different technological and behavioural change scenarios in Mexico City. Additionally, the health impacts of such scenarios were also estimated. The principal finding from the results presented in this chapter will be discussed below.

Technological change scenarios that assessed the electrification of the vehicle fleet (Electric Vehicle Fleet scenario) performed well in reducing NO_x (reduction of 72%) and CO₂ emissions (reduction of 53%), even after accounting for CO₂ emissions from the electricity use of electric vehicles. Particulate matter emissions from this scenario (Electric Vehicle Fleet) reduce PM emissions by an average of 40% after accounting for PM non-exhaust emissions from electric vehicles. Please refer to the summary of Table 6.4.

Moreover, all the technological change scenarios resulted in reductions relative to baseline levels for all of the pollutants assessed; CO₂, NO_x, PM_{2.5}, PM₁₀ (Table 6.4). Thus, these results indicate that the advantages of electric vehicles outweigh the disadvantages of emitting additional CO₂ for electricity use. This finding is striking because Mexico's electricity generation is firmly dependant on fossil-fuels (600 g CO₂/kWh). Electricity carbon intensity factor for electric vehicles in the context of Mexico are needed to refine the certainty of this result.

Although the introduction of electric vehicles does reduce net CO₂ emissions (including emissions from electricity use) relative to baseline in all technological change scenarios, emissions from electricity use for electric vehicles become the predominant source of CO₂ emissions (Table 6.1). For example, in the Electric Car scenario, CO₂ emissions from electricity use account for 16% of total CO₂ emissions in this scenario. While in the baseline, exhausted emissions from non-electric cars accounted for 32% of total exhaust CO₂ baseline emissions.

This finding highlights the importance of accounting for indirect emissions from electricity use when assessing the impacts of electric vehicles. As has been discussed in (Section 3.3.3.2), not accounting for air pollutants emissions during the electricity generation for electric vehicles is a limitation of the research. However, literature in life cycle carbon dioxide equivalent (CO₂eq) and NO_x emissions from vehicles has shown that life cycle CO₂eq and NO_x emissions from electric vehicles are considerably lower than life cycle CO₂eq and NO_x emissions from petrol and diesel cars. In contrast with electric vehicles, they result in a large amount of tank-to-wheel exhaust emissions during fossil-fuel burning (Rangaraju *et al.*, 2015).

Similar to the significant weight of indirect CO₂ emissions for electricity use in the technological change scenarios, PM non-exhaust emissions from electric cars become a large proportion of net PM emissions in these scenarios (Table 6.2). For example, PM_{2.5} emissions from non-electric cars in the baseline accounted for 10% of net baseline emissions. In the Electric Car scenario, non-exhaust PM_{2.5} emissions accounted for 7% of net emissions in this scenario. Moreover, it is important to highlight the uncertainty on non-exhaust PM emission, which has been discussed in section 3.3.1.

These results show that an effective way of tackling the disadvantages of technological change scenarios which emit additional emissions from electricity use and non-exhaust emissions discussed above is to adopt the behavioural change scenarios where an actual vehicle is taken off the street and replaced by cycling and walking. The behavioural change scenarios assessed the replacement of travel via the old vehicle fleet (which accounts for a significant amount of pollution) with active travel modes in Mexico City. The results have shown that an effective measure to reduce air pollution would be to replace old vehicles, in particular, old buses (older than ten years) that account for 70% of the bus fleet.

The behavioural change scenarios performed well in reducing PM emissions compared to technological change scenarios (Table 6.4). For example, the reduction of old buses with active modes resulted in a reduction of 24% and 16% of PM_{2.5} and PM₁₀, respectively. Instead, the electrification of buses resulted in 29% and 19% of PM_{2.5} and PM₁₀ emissions relative to baseline, respectively. As discussed above,

the reduction of PM emissions in technological change scenarios is attenuated by its non-exhausted emissions, which behavioural change scenarios do mitigate (PM non-exhausted emissions).

Most importantly, the behavioural change scenarios which increase the use of active modes of transport (walking and cycling, and public transport) showed significant health benefits (Table 6.5) due to the increase in physical activity relative to baseline. Technological change scenarios did not result in health benefits because the mode of transport remained motorised, and no active travel was assumed. However, a limitation of this research is that air quality modelling was not done and therefore, changes in air pollution concentrations as a result of introducing cleaner electric vehicles were not accounted for. Thus, health benefits resulting from the variation on concentrations could not be calculated.

Moreover, the health benefits of physical activity from walking and cycling attributed to the replacement of old vehicles in the behavioural change scenarios were larger than the risks from inhalation of air pollutants. Health benefits in the behavioural change scenarios were on average, seven times larger than the risks.

Table 6.4 Summary of emissions reduction relative to the baseline of CO₂, NO_x, PM_{2.5}, PM₁₀ for the transport policy scenarios in Mexico City.

	CO ₂	NO _x	PM _{2.5}	PM ₁₀				
Baseline	16.1 Mt/y	52.4 kt/y	2.9 kt/y	5.6 kt/y				
Scenarios	Reduction relative to baseline							
	CO ₂	NO _x	PM _{2.5}	PM ₁₀				
	Emissions (Mt/y)	Percentage (%)	Emissions (kt/y)	Percentage (%)	Emissions (kt/y)	Percentage (%)		
Technological change scenarios								
Electric Car	3.0	18	10.7	20	2.8	3	4.9	13
Electric Taxi	1.3	8	4.9	9	2.8	1	5.4	5
Electric Bus	1.8	11	13.7	26	2.0	29	4.6	19
Electric Vehicle Fleet	8.6	53	37.8	72	1.8	36	3.1	44
Behavioural change scenarios								
Old Car Redu	1.1	7	6.0	11	2.7	5	5.3	6
Old Taxi Redu	0.1	0.4	0.2	0.4	2.9	0.2	5.6	0.4
Old Bus Redu	1.5	9	10.8	21	2.2	24	4.7	16
Car Redu 10	0.8	5	4.3	8	2.8	4	5.4	4

Note: The uncertainty ranges of the mean values presented in this summary table were shown in the figures and text of the result section 6.2.

Table 6.5 Summary of health impacts (air pollution and physical activity) relative to baseline levels in transport policy scenarios in Mexico City.

Scenario	Air pollution		Physical activity	Total health impacts		Benefits/risk ratio*
	PM _{2.5} inhalation	NO ₂ inhalation				
	(Deaths caused/year)	(Deaths caused/year)		(Deaths prevented/year)	(Deaths prevented/year)	
Technological change scenarios						
Electric Car	0	0	0	0	-	-
Electric Taxi	0	0	0	0	-	-
Electric Bus	0	0	0	0	-	-
Electric Vehicle Fleet	0	0	0	0	-	-
Behavioural change scenarios						
Old Car Redu	-175	-64	1,639	1,400	7	7
Old Taxi Redu	-28	-10	249	211	7	7
Old Bus Redu	-89	-33	671	549	6	6
Car Redu 10	-127	-46	1,212	1,039	7	7

Note: *The benefit/risk ratio is the ratio of physical activity benefit versus risks from inhalation of air pollutants. The uncertainty ranges of the mean values presented in this summary table were shown in the figures and text of the result section 6.2.

6.3.2 Comparison to other studies

The transport policy scenarios modelled in this thesis for Mexico City are not comparable to scenarios presented in other research studies because they have been constructed and defined differently. Although the scenarios are different, some similarities to previous studies were found. For example, Chavez-Baeza & Sheinbaum-Pardo (2014) modelled sustainable technological and behavioural change scenarios in passenger road transport in Mexico City and assessed the reduction of air pollutants and greenhouse gas (GHG) emissions.

Chavez-Baeza & Sheinbaum-Pardo (2014) used a much more sophisticated modelling approach (using the Mobile6 emissions model developed by USA EPA) and modelled more conservative scenarios (some of them might be considered more realistic) than the ones assessed in this chapter. Chavez-Baeza & Sheinbaum-Pardo (2014) most ambitious scenario included the following characteristics: (i) A 3% rise in the average fuel economy of new private cars and taxis, from which 40% of new cars are assumed to be hybrid cars. (ii) An increase in the average fuel economy of diesel buses, increasing from 1.8 km/l in 2016 to 3.2 km/l in 2028 (modelling years from the study are 2008 to 2028). (iii) A modal shift from private cars and minibuses (old, polluting buses) to the Bus Rapid Transit (BRT) transport system.

Chavez-Baeza & Sheinbaum-Pardo (2014) assumed that 30% of passenger-km of trips currently realised through private cars were shifted to BRT. This modal shift implied a reduction in passenger-km of private vehicles from 2% in 2016 to 15% in 2028. This reduction was not estimated as a vehicle reduction, like in this chapter, but as a distance travelled reduction. Additionally, they assumed that new BRT lines substituted old and polluted minibuses.

This scenario (as described in the previous paragraph) modelled by Chavez-Baeza & Sheinbaum-Pardo (2014) resulted in the following reductions of both air pollutants and GHG emissions: 7 % (70.4 kt) in PM₁₀, 15.4% (18.9 kt) in NO_x, and 1. % (354.0 kt) in CO₂eq. This scenario is not comparable with the scenarios modelled in this chapter, but percentage reductions relative to the baseline of the same order of magnitude were found for the Old Car Redu scenario (Table 6.4): 6 % in PM₁₀, 11% in NO_x, and 7% in CO₂. Chavez-Baeza & Sheinbaum-Pardo (2014) modelled CO₂eq, and this chapter presented estimates for CO₂.

However, the proportional reduction from baseline for the three pollutants is of the same order of magnitude. The Old Car Redu scenario presents some similarities to the scenario modelled by Chavez-Baeza & Sheinbaum-Pardo (2014) because by reducing the km travelled by old cars, the average fuel economy of cars similarly increased. Also, km travelled by cars are reduced.

In the same way as for the emissions estimates, for the assessment of health impacts, the health benefits from the increase in physical activity in the Old Car Redu and Car Redu 10 behavioural scenarios were of the same order of magnitude (1×10^3) as results from previous studies (Woodcock *et al.*, 2009; Mueller *et al.*, 2017).

In the research presented in this chapter, the Old Car Redu scenario that reduced all cars older than ten years (same assumption used by Woodcock *et al.*, 2009, for their analysis for Delhi, India) prevented 1,639 deaths (order of magnitude 1×10^3) relative to baseline from physical activity (Table 6.5). The Car Redu 10 scenario reduced km travelled by cars by 10% and resulted in the prevention of 1,212 deaths (order of magnitude 1×10^3) relative to baseline from physical activity (Table 6.5).

Woodcock *et al.*, 2009, found that a small increase in the distance (km travelled) walked (33% increase from baseline 2030) and an increase in distance cycled (164% increase from baseline 2030) would prevent 9,152 premature deaths (order of magnitude 1×10^3) in Delhi, India projected to 2030 (population of 26 million in 2030). In the same study (Woodcock *et al.*, 2009) found that a significant increase in the distance (km travelled) walked (146% increase from baseline 2030) and a significant increase in distance cycled (804 % increase from baseline 2030) would prevent 4,541 deaths (order of magnitude 1×10^3) in London, UK, projected to 2030 (population of 8.6 million in 2030).

Mueller *et al.*, 2017, found that increasing physical activity levels to those recommended by the WHO in Barcelona could prevent 1,154 deaths (order of magnitude 1×10^3). Although different values are expected from these studies because, among other dissimilarities, different cities were studied, different assumptions were made about the construction of the scenarios, different baseline travel patterns in context to the city of study and different exposure-response functions were considered (curvilinear functions in (Woodcock *et al.*, 2009; Mueller *et al.*, 2017), for example). However, it is remarkable that the presented results are still comparable (same order of magnitudes) to the existing literature.

After corroborating findings from previous studies (Rojas-Rueda *et al.*, 2012, 2011, 2016; de Hartog *et al.*, 2010) with this research it was found that the benefits of an increase in physical activity through the use of active travel modes are larger than the adverse effects from exposure to air pollution due to the inhalation of air pollutants.

6.3.3 Strengths and limitations

It is important to mention that the analysis in Mexico City was intended as a first approach to the study of abatement scenarios for road transport and the results come from modelling tools that are not as powerful as those used in the analysis in previous chapters. The present study shows the first steps in the study of the combined effects of CO₂ and air pollutants against the health of transport strategies in Mexico City. The scenarios examined only show possible outcomes of separate interventions. In future work, the scenarios could be redefined.

Not having access to the models and analytical tools leaves various questions open. For example, the PM_{2.5} emission factors are much lower than the PM₁₀ emission factors. NO_x emission factors are higher for petrol cars than diesel cars, and CO₂ emissions factors are higher for diesel cars than for petrol cars, this behaviour is opposite to the emissions factors found in the London modelling exercise. A possible explanation could be related to the fact that diesel cars are a negligible proportion of the car fleet and maybe correspond to the oldest cars. A deeper understanding of the analysis is needed.

The emissions calculation could be done with more powerful modelling tools (if accessible) as has been done before in similar studies for Mexico City which used the Energy and Emissions Model for Mexico developed by EPA, USA (Chavez-Baeza & Sheinbaum-Pardo, 2014). More importantly, modelling the scenarios with a dispersion model, such as the CMAQ used by Mexico City Environmental Ministry (SEDEMA, 2015) could significantly enrich the study by estimating the corresponding particulate matter concentrations reductions generated by the transport policy scenarios. Specific particulate matter concentration results for each scenario could allow us to calculate the health benefits for variations in particulate matter concentration in each transport policy scenario.

The effect of emissions reduction on ozone, which is a significant pollutant in Mexico City, needs to be considered in the analysis. For example, how the reduction of ozone precursors such as NO_x affect ozone concentrations in the valley. Additionally, the health impacts of ozone need to be accounted for in future research.

6.3.4 Policy implications

Different incentives and regulations are required for the penetration of clean vehicles in the Mexico vehicle fleet. Policies to promote the renewal of the vehicle fleet and replace the oldest vehicles with more efficient vehicles are urgently needed. In particular, the renewal of the bus fleet. Buses are intensely driven every day and are the oldest (70% of buses are older than ten years) and the most polluting vehicle in the city. If decision-makers want to improve the health of the population, encouraging active travel is a promising approach.

6.3.5 Concluding remarks

Mexico City has the challenge of tackling its chaotic transportation system and controlling the alarming air pollution levels that are harming the health of its inhabitants. Technological and behavioural change interventions were studied in this chapter in order to evaluate their holistic impacts on CO₂ and air pollutant emissions and health.

CO₂ emission reductions from electric vehicles (which do not emit CO₂ exhausted emissions) in the technological change scenarios are not outweighed by CO₂ emissions from the electricity use from electric vehicles (with the emissions factors used in this study). CO₂ emissions from electricity use do become the primary source of emissions in the technological change scenarios. For example, 67% of total CO₂ emissions come from electricity use from electric vehicles in the Vehicle Fleet scenario. Additionally, accounting for non-exhaust particulate matter emission in the electric vehicles scenarios does not outweigh the reduction from electric vehicles, but it does significantly reduce the percentage from baseline.

Moreover, health benefits from the increase in physical activity due to the use of active travel modes are predominant and on average, seven times larger than the health risks associated with inhalation of air pollution (health benefits for air quality concentrations reduction were not accounted for). Technological change scenarios do reduce CO₂ and air pollutant emissions but these scenarios have the significant disadvantage of not increasing physical activity and therefore, do not have any health benefits as a result of the use of active travel modes.

Chapter 7

Discussion

7.1 Overview

This chapter presents the discussion and critical assessment of the results of this dissertation. In this chapter, the discussion and critical assessment of results are shown in the following sections: principal findings, comparison to other studies, uncertainties and sensitivities, limitations and strengths and future research. The principal findings section assesses the results for London and Mexico City and presents a comparison between the two cities.

7.2 Principal findings

7.2.1 London

Technological change scenarios which introduced electric vehicles to the vehicle fleet (Electric Car, Electric Taxi, Electric Bus, Electric Vehicle Fleet scenarios) are efficient at reducing CO₂ emissions and NO_x and NO₂ emissions and concentrations (Figure 7.1, Figure 7.2, Section 4.3.1). These scenarios reduce CO₂ emissions by up to 46% and NO_x and NO₂ emissions by between 91% and 96%, relative to baseline levels.

It is important to note that in this dissertation, the CO₂ emissions from electricity generation were accounted for and included in the analysis. The research in this dissertation showed that technological scenarios with electric vehicles result in net CO₂ emissions reductions, even after accounting for CO₂ emissions from electricity generation (Figure 4.1). However, CO₂ emissions from electricity generation become a significant percentage of total emissions in the technological change scenarios with vehicle electrification, representing on average half of net CO₂ emissions.

A clear trade-off between air pollution and GHG emissions mitigation analysed in this dissertation was the *diesel to petrol* scenario in which all diesel cars were shifted to petrol cars. By eliminating diesel

cars from the vehicle fleet, NO_x emissions were reduced by 30% while CO₂ emissions were increased by 5% (Figure 4.1, Figure 4.2).

In contrast, technological scenarios which electrify (Electric Car, Electric Taxi, Electric Bus, Electric Vehicle Fleet scenarios) the vehicle fleet, fail to significantly reduce particulate matter emissions and concentrations (Figure 7.1, Figure 7.2, Section 4.3.1). These scenarios only reduced particulate matter emissions by a maximum of 10%, relative to baseline levels. Technological change scenarios which electrify the vehicle fleet do not perform well at reducing particulate matter emissions and concentrations because these scenarios still emit non-exhaust emissions from tyre and brake wear, which accounts for close to 90% of total particulate matter emissions (Section 4.3).

Behavioural change scenarios yielded the most significant reduction in particulate matter emissions and concentrations (Figure 7.1, Figure 7.2, Section 4.3.1). This dissertation's results showed that particulate matter emissions are driven by non-exhaust emissions that can most effectively be reduced by reducing the number of vehicles from the roads and replacing motorised modes with active modes of transport, as in the behavioural change scenarios.

The spatial analysis indicated that significant local benefits could be overlooked when observed from a London-wide perspective, highlighting the importance of the spatial analysis of transport policies. For example, the construction of cycle lanes in the central area of London showed one of the most significant impacts on reducing NO₂ and PM_{2.5} concentration in the most polluted regions of London, even if the London-wide effect of this policy was small compared to other scenarios. Setting city-wide emissions abatement targets can sometimes overlook significant local benefits.

The cost assessment indicated that the highest damage cost per km driven came from diesel cars for NO₂ concentrations (1.48 pence per km driven, three times higher than petrol cars). Particulate matter damage costs are not mitigated by electric vehicles, which have a similar damage cost per km driven to fossil-fuelled vehicles (0.35 pence per km). Offset prices for CO₂ emissions mitigation per km driven were higher for petrol cars (0.80 pence per km driven) and were not mitigated by electric vehicles due to still emitting CO₂ emissions from electricity generation.

Percentage emissions reductions relative to baseline levels in London's transport policy scenarios by pollutant

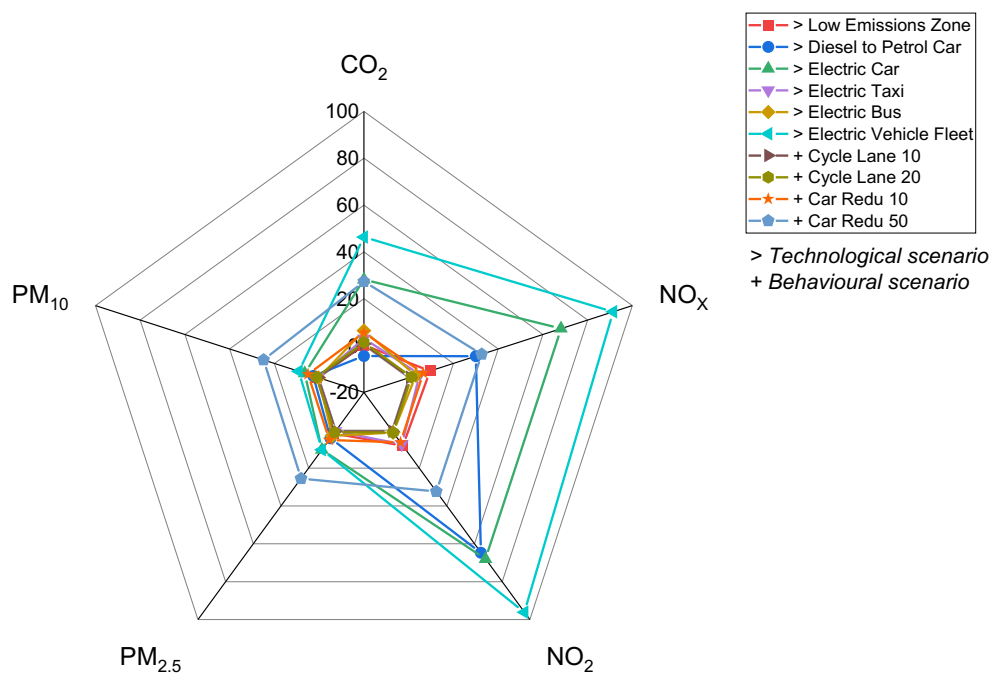


Figure 7.1 Percentage emissions reductions relative to baseline levels in London's transport policy scenarios by pollutant (CO₂, NO_x, NO₂, PM_{2.5}, PM₁₀).

Percentage emissions reductions relative to baseline levels in London's transport policy scenarios

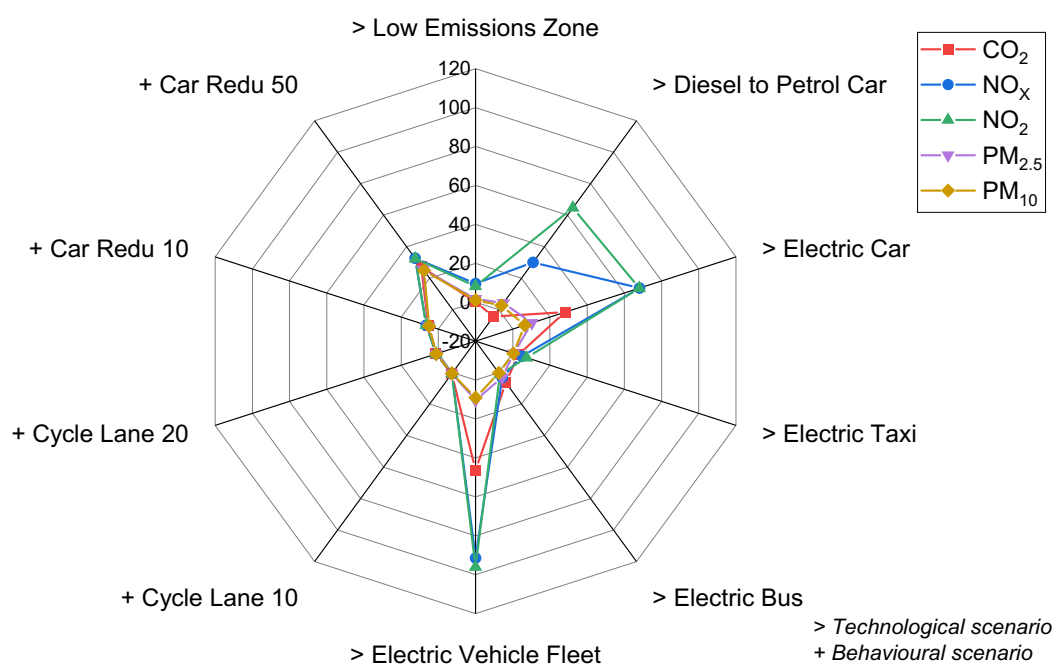


Figure 7.2 Percentage emissions reductions, per pollutant (CO₂, NO_x, NO₂, PM_{2.5}, PM₁₀), relative to baseline levels in London's transport policy scenarios.

The health benefits in the behavioural change scenarios were, on average, 20 times larger than the health benefits in the technological change scenarios (Figure 7.3, Section 4.3.1). Health benefits in the behavioural change scenarios were driven by health benefits of physical activity which account for 98% of the total health benefits. The health benefits of physical activity from cycling and walking and the reduction of air pollution (NO_2 and $\text{PM}_{2.5}$) concentration in the behavioural change scenarios were larger than the risks from inhalation of air pollutants.

As discussed before (Section 4.3), the transport policy scenarios resulted in more considerable reductions of NO_2 concentrations than reductions of $\text{PM}_{2.5}$ concentrations. Therefore, health benefits associated with the decrease in NO_2 air pollution exposure were on average eight times larger than health benefits related to the reduction in $\text{PM}_{2.5}$ air pollution exposure. Health benefits estimates in the technological change scenarios showed that the highest portion of preventable deaths was attributable to the decrease in air pollution exposure resulting from the reduction in NO_2 annual mean concentrations.

The health benefits brought about by decreasing air pollution exposure through the reduction in $\text{PM}_{2.5}$ annual mean concentrations in behavioural change scenarios were 1.7 times larger than those brought about by the technological change scenarios. With respect to a reduction in NO_2 annual mean concentrations, the health benefits of technological change scenarios were 3.4 larger than those in the behavioural change scenarios.

The analysis of travel patterns in London showed that there is a significant number of car trips (approx. 58% of car trips) which are within a walkable or cyclable distance. There is a need for policymakers to implement strategies that facilitate the use of active travel modes for short trips.

Health effects in London's transport policy scenarios

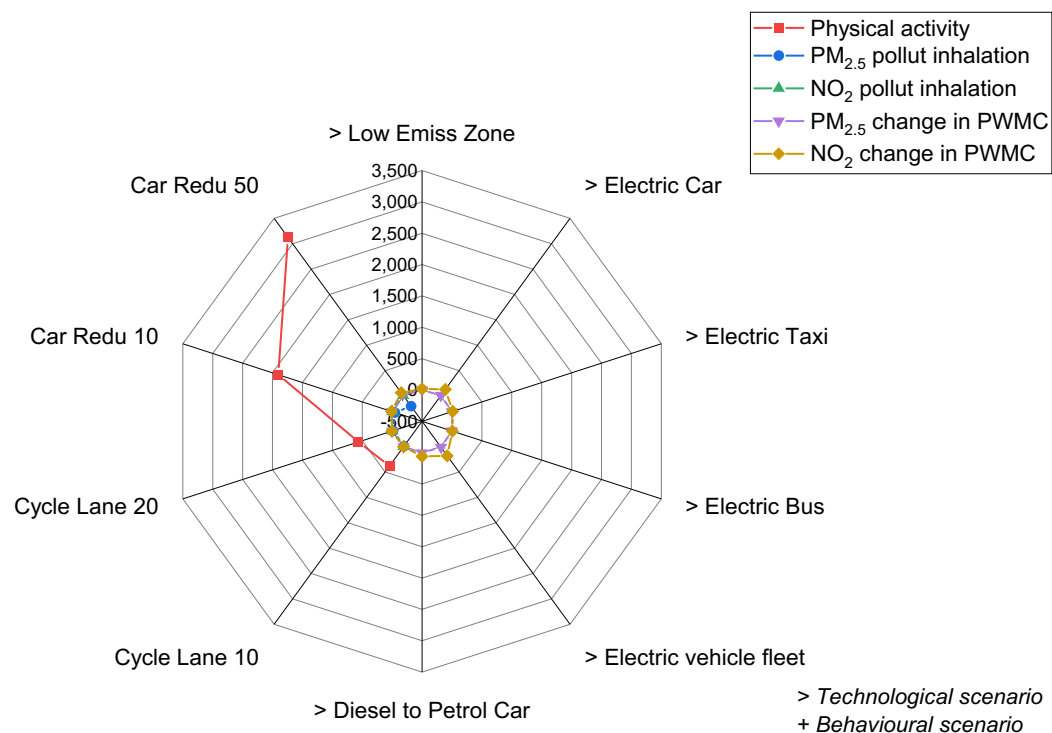


Figure 7.3 Health effects in London's transport policy scenarios.

7.2.2 Mexico City

The transport policy scenarios which had the largest effect on reducing NO_x emissions in Mexico City were the Electric Car, Electric Bus and the Old Bus Redu scenarios (Figure 7.4, Figure 7.5); reducing NO_x emissions by between 20% and 26% at the city level. Buses in Mexico City are an important driver of NO_x emissions. Removing buses older than ten years in the Old Bus Redu scenario had the second largest effect on reducing Mexico City's NO_x emissions (Figure 7.4).

It is important to remember that NO_x is an ozone precursor, and Mexico City's air pollution problem is mainly caused by ozone pollution. Therefore, the results of my dissertation can help inform public policies which aim to reduce air pollution in Mexico City by promoting the renewal of the bus fleet which has been shown to have a substantial effect at reducing NO_x emissions.

Similar to the behaviour of NO_x emissions, the scenarios which electrified or removed old buses in Mexico City, were also efficient at reducing particulate matter emissions (Figure 7.4, Figure 7.5); reducing PM₁₀ and PM_{2.5} emissions by 20% and 30% respectively. It is important to note that these reductions account for PM non-exhaust emissions from electric vehicles. PM non-exhaust emissions from electric cars become a significant proportion of net PM emissions in the technological change scenarios, which include electric vehicles in the vehicle fleet (Table 6.2).

For CO₂ emissions (Figure 7.4, Figure 7.5), the bus scenarios (Electric Bus and the Old Bus Redu scenarios) perform well, reducing CO₂ emissions by around 10%. The scenario with the largest reduction of CO₂ emissions (for a single-vehicle fleet) is the Electric Car scenario, reducing CO₂ emissions by 17%.

Consequently, these results show that the benefits of electric vehicles offset the drawbacks of emitting additional CO₂ from electricity use. This result is interesting since Mexico's electricity generation is strongly dependant on fossil-fuels (600 g CO₂/kWh). Though electric vehicles in the technological scenarios do reduce net CO₂ emissions (including emissions from electricity use) relative to baseline, in all technological change scenarios emissions from electricity generation become the primary source of CO₂ emissions (Table 6.1).

Percentage emissions reductions relative to baseline levels in Mexico City's transport policy scenarios by pollutant

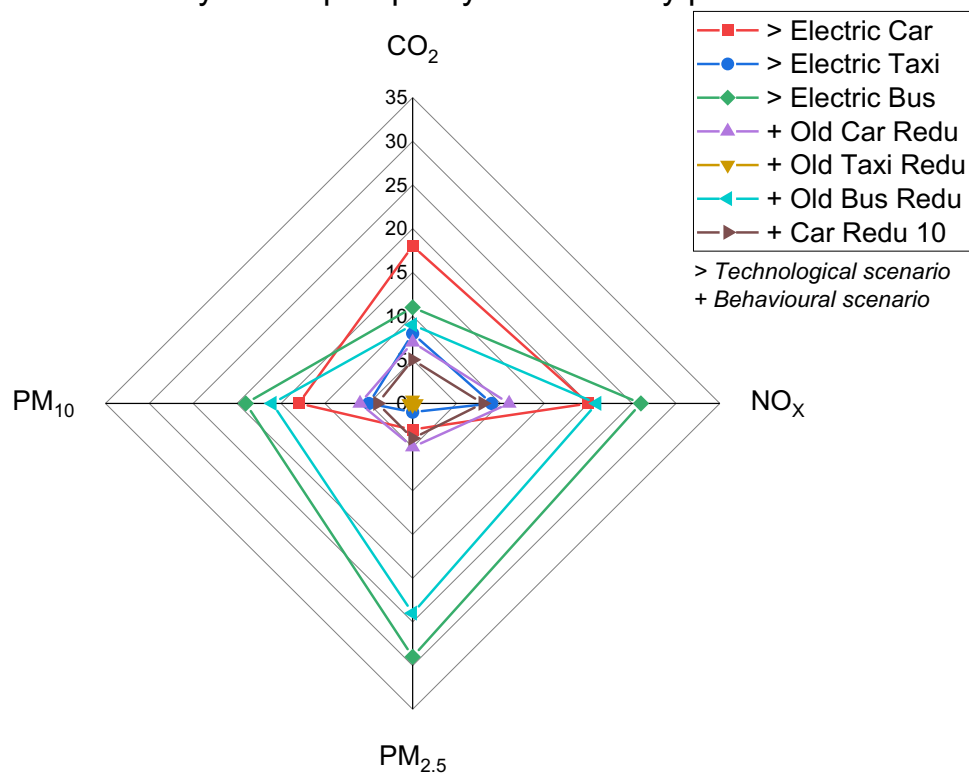


Figure 7.4 Percentage of emissions reductions relative to baseline levels in Mexico City's transport policy scenarios by pollutant (CO₂, NO_x, NO₂, PM_{2.5}, PM₁₀).

Percentage emissions reductions relative to baseline levels in Mexico City's transport policy scenarios

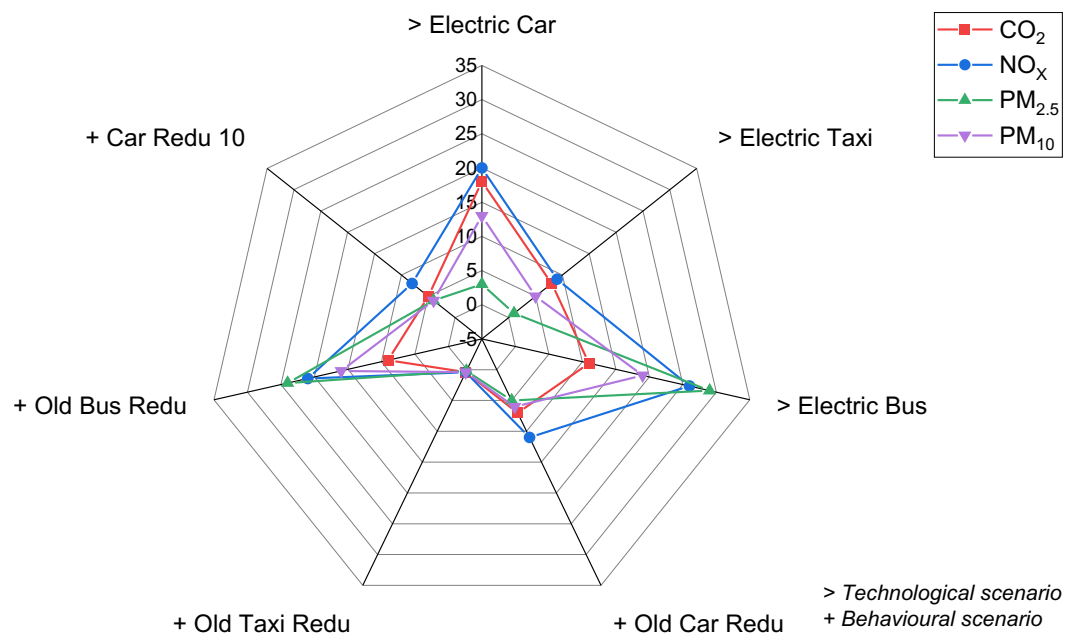


Figure 7.5 Percentage emissions reductions, per pollutant (CO₂, NO_x, NO₂, PM_{2.5}, PM₁₀), relative to baseline levels in Mexico City's transport policy scenarios.

These scenarios (Old Car, Taxi, Bus Redu and Car Redu 10) showed significant health benefits (Figure 7.6) as a result of the increased physical activity relative to baseline. Moreover, the health benefits of physical activity resulting from the replacement of travel by old vehicles in the behavioural change scenarios were more extensive than the risks from inhalation of air pollutants. Health benefits in the behavioural change scenarios were on average, seven times larger than the risks.

Legend:

- Physical activity (Green line with triangles)
- NO2 inhalation (Blue line with circles)
- PM2.5 inhalation (Red line with squares)

Scenarios:

- Technological scenario** (Green line with triangles)
- Behavioural scenario** (Blue line with circles)

Categories:

- > Electric Car
- > Electric Taxi
- > Electric Bus
- > Electric Vehicle Fleet
- + Old Car Redu
- + Old Taxi Redu
- + Old Bus Redu

Scale:

- 1,800
- 1,600
- 1,400
- 1,200
- 1,000
- 800
- 600
- 400
- 200
- 0
- 200

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7.2.3 Comparison between London and Mexico City

7.2.3.1 Comparison between equivalent transport policy scenarios

A detailed comparison between emissions reduction in the four equivalent transport policy scenarios (Electric Car, Electric Taxi, Electric Bus and Car Redu 10) in London and Mexico City is presented in Figure 7.7. The comparison between percentage emissions reduction from baseline levels in the two cities (Figure 7.7) highlights how the city's characteristics (vehicle fleet characteristics) determined the effect on emissions reductions.

For example, in London, 77% of all the kilometres driven in the city are driven by car (Table 3.10). For all pollutants, car emissions are the main source of emissions (Section 4.2.1). In Mexico City, only 40% of all the kilometres driven in the city are driven by car (Table 3.12), representing a smaller share in total emissions (Section 6.2.1). Moreover, in London, 30% of vehicles are diesel vehicles. In contrast, in Mexico City, only 7% of vehicles are diesel (Table 2.7).

These differences in road transport in each city explain, for example, why the Electric Car scenario in London reduced NO_x emissions by considerably more (diesel vehicles have a high NO_x emission factor than petrol vehicles) than in the Electric Car scenario in Mexico City (Figure 7.1, 7.2 and Figure 7.4, 7.5). CO₂ emissions reduction in the Electric Car scenario is higher in London because cars account for a larger share of the road transport sector emissions and also because London electricity generation has a lower emissions factor than that of Mexico City.

The higher percentage reductions of emissions in the Electric Taxi scenario in Mexico City compared to those in the Electric Taxi scenario from London can be related to the fact that taxis account for 22% of kilometres driven in Mexico City (Table 3.12), and account for only 2% of kilometres driven in London (Table 3.10).

The percentage reduction of emissions relative to baseline levels in Mexico City's Electric Bus scenario is considerably higher than in London because, as discussed before, the bus fleet in Mexico City is extremely old and polluted. Kilometres driven by bus in Mexico City account for 4% of total kilometres driven in the city. In London, buses account for half that of Mexico City, 2%, of total kilometres driven in the city.

The percentage reductions relative to baseline levels are most similar in the two cities (London and Mexico City) for the Car Redu 10 scenario. Reductions for CO₂ and PM emission are slightly higher

for the London scenario. For NO_x emissions the reductions relative to baseline levels are higher in the Mexico City scenario because 10% of the oldest cars were reduced, and in Mexico City, a small percentage of these vehicles did not have a catalytic converter which significantly reduces NO_x emissions.

7.2.3.2 General comparison

In both cities, the technological change scenarios, which introduce electric vehicles to the vehicle fleet, proved to be efficient at reducing CO₂ emissions and NO_x emissions (Figure 7.1, Figure 7.4). However, in contrast to London, Mexico City's bus fleet has a significant role to play in reducing emissions due to the very old and polluted bus fleet that Mexico City has.

In both cities, all the technological scenarios with electric vehicles result in net CO₂ emissions reductions (Figure 7.2, Figure 7.5), even after accounting for CO₂ emissions from electricity generation. This is especially surprising for Mexico City, where the electricity carbon intensity is twice as high as in London. However, in both cities, CO₂ emissions from electricity generation become an important proportion of total CO₂ emissions in technological scenarios with electric vehicles.

In both cities, particulate matter emissions are a significant percentage of the emissions in technological scenarios with electrification due to non-exhaust particulate matter emissions. In Mexico City, particulate matter emissions are not driven as strongly by non-exhaust emissions as in London because Mexico City still has a significant portion of exhaust particulate matter emissions from old vehicles.

In London, the behavioural change scenario yielded the most significant reduction in particulate matter emissions and concentrations (Figure 7.2). In Mexico City, different to London, the electric bus scenarios and the old buses reduction scenario translated into the largest reductions of particulate matter emissions (Figure 7.5). This exemplified how a very dirty vehicle type in a city (like buses in Mexico City) can drive particulate matter emissions.

Very clearly, in both cities, the health benefits in behavioural change scenarios were by far the largest (Figure 7.3, Figure 7.6), outweighing the health benefits from technological change scenarios. Moreover, regardless of different travel patterns in the two cities, the health benefits of physical activity were enormous in both settings.

In Mexico City, the health benefits for reducing air quality concentration in the technological change scenarios were not accounted for, because air quality modelling was not performed. Nevertheless, the health benefits of behavioural changes scenarios which increase physical activity resulted in the same order of magnitude (1×10^3) of health benefits as in London, in the most ambitious behavioural change scenarios.

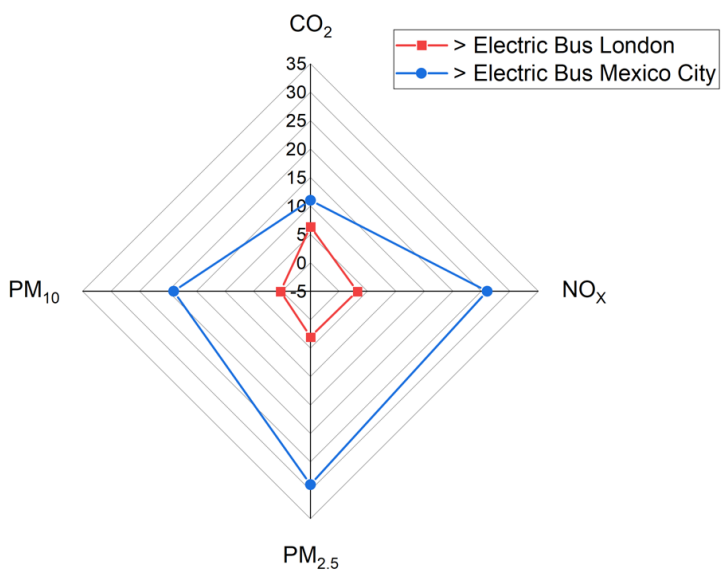
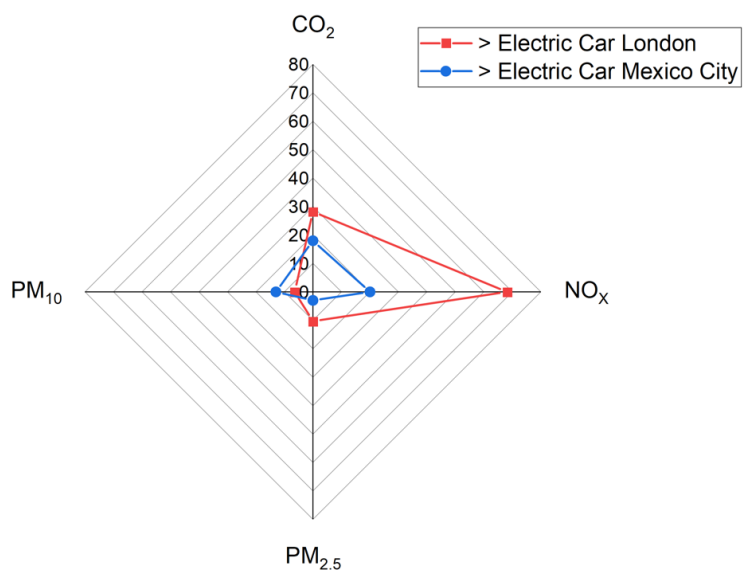


Figure 7.7 Comparison between selected London and Mexico City transport policy scenarios. Percentage reduction of emissions relative to baseline levels in Mexico City's transport policy scenarios by pollutant (CO₂, NO_x, PM_{2.5}, PM₁₀).

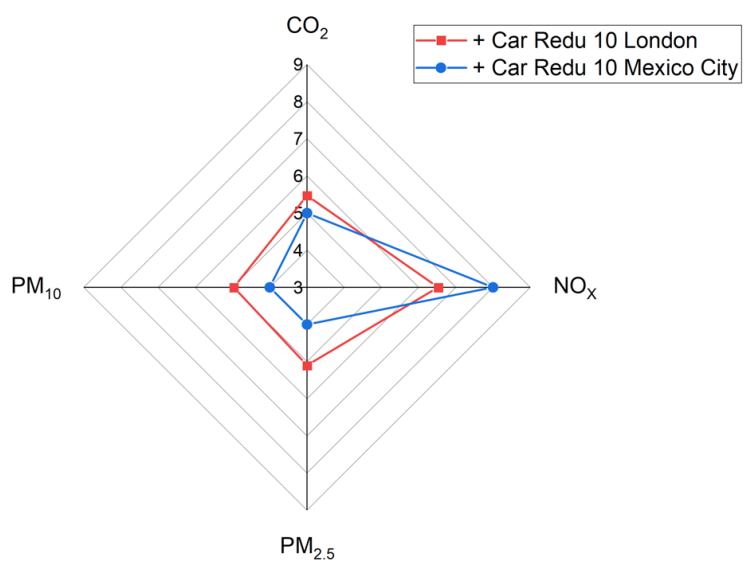
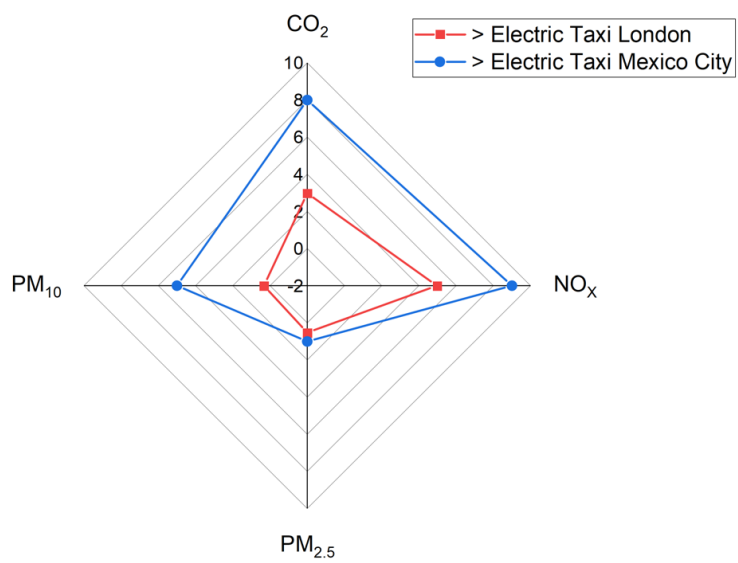


Figure 7.7 (Continued) Comparison between selected London and Mexico City transport policy scenarios. Percentage reduction of emissions relative to baseline levels in Mexico City's transport policy scenarios by pollutant (CO₂, NO_x, PM_{2.5}, PM₁₀).

7.3 Comparison to other studies

7.3.1 London

7.3.1.1 CO₂ emissions and air quality modelling

The research presented in this dissertation encompassed a comparison between 2030 emissions projections of the UKIAM model and BRUTAL sub-model and the model used for the London Atmospheric Emissions Inventory (LAEI) by London authorities (discussed in Section 3.3.1.6). The 2030 emissions projection comparison between these two models was different for each pollutant. For CO₂ and NO_x emissions, the different projections between the two models for the year 2030, ranged from 13% to 24%. Specifically, for CO₂ emissions, the UKIAM-BRUTAL projects on average 13% higher CO₂ emissions than total CO₂ emissions reported in the LAEI model in 2030. For NO_x emissions, the UKIAM-BRUTAL model estimates 24% higher emissions than the LAEI model in 2030.

The projections of the two models for the year 2030 for total particulate matter emissions were the largest and represent the most important source of disparity between the UKIAM-BRUTAL model and the LAEI model. Exhaust PM₁₀ emissions projected to 2030 are 34% lower in the UKIAM-BRUTAL model than in LAEI model.

However, the most critical difference between 2030 emissions projections by the UKIAM-BRUTAL model and LAEI model is for non-exhaust particulate matter emissions. The LAEI model projects 2030 non-exhaust PM₁₀ emissions to be higher than the UKIAM-BRUTAL model. This disparity among how the UKIAM-BRUTAL model and the LAEI model project non-exhaust PM emissions is explained by the fact that the UKIAM-BRUTAL model does not use speed dependant emissions factors for non-exhaust particulate matter emissions. In urban areas like London, where the high levels of traffic congestion occur, using speed dependant emissions factors is important to estimate emissions.

Also, the LAEI includes resuspended dust as due to vehicles, whereas UKIAM and the National Atmospheric Emissions Inventory (NAEI) represent resuspension as urban dust which is kept fixed and not as an emission related to vehicle km. This can be explained as a difference between models, and one which may tend to give conservative estimated benefits of removing vehicles using UKIAM.

7.3.1.2 Health impact assessment modelling

The health impact assessment modelling results presented in this research are in line with results from previous studies evaluating the health effects of transport strategies. One of the studies which is most similar to the research presented in this dissertation, Woodcock *et al.*, 2009, also found that behavioural change scenarios achieved significantly larger health benefits than technological change scenarios. The health benefits results in this dissertation are of the same order of magnitude as in studies with similar methodologies, Woodcock *et al.*, 2009, and Mueller *et al.*, 2017, an order of magnitude of 1×10^3 .

Health benefits arising from reductions in air pollution (PM_{2.5}) concentrations are one order of magnitude higher in Mueller *et al.*, 2017, and Woodcock *et al.*, 2009, than in this study. This difference can be expected, as in these studies, the magnitude of the difference (delta) in PM_{2.5} concentrations between the contra factual and the comparison scenario was higher (see section 5.3.2 for detailed explanation).

The health benefits described in this dissertation are also in agreement with results from several studies which have found that the health benefits of active transport modes (walking and cycling) are larger than the risks of exposure to air pollutants (for example, Mueller *et al.*, 2017) and Rojas-Rueda *et al.*, 2011). Studies which have assessed health impacts from inhalation of air pollutants (PM_{2.5}) during physical activity (Rojas-Rueda *et al.*, 2011), as was done in this dissertation, have also found that the negative effects of the inhalation of pollutants are outweighed by the much more significant benefits resulting from increased physical activity.

7.3.2 Mexico City

7.3.2.1 CO₂ emissions and air quality assessment

The transport policy scenarios modelled in this dissertation for Mexico City were compared to similar studies in the Mexico City setting, (Chavez-Baeza & Sheinbaum-Pardo (2014)), which modelled sustainable technological and behavioural change scenarios in the passenger road transport in Mexico City and assessed the reduction on air pollutants and greenhouse gas (GHG) emissions (see section 6.3.2).

The scenarios modelled by Chavez-Baeza & Sheinbaum-Pardo (2014) resulted in a reduction of both air pollutants and GHG emissions: 7% in PM₁₀, 15.4 % in NO_x, and 1.5% in CO₂eq. These scenarios are not directly comparable with the scenarios modelled in this dissertation since they were developed differently, but the percentage reductions relative to the baseline of the same order of magnitude were found for the Old Car Redu scenario: 6% in PM₁₀, 11% in NO_x, and 7% in CO₂.

7.3.2.2 Health impact assessment modelling

The health benefits from the increase in physical activity in the Old Car Redu and Car Redu 10 behavioural change scenarios in Mexico City were of the same order of magnitude (1×10^3) as results from previous studies (Woodcock *et al.*, 2009; Mueller *et al.*, 2017) (Section 6.3.2).

Moreover, after verifying results from earlier studies (Rojas-Rueda *et al.*, 2012, 2011, 2016; de Hartog *et al.*, 2010) the research presented in this dissertation found that the benefits arising from the increase in physical activity in scenarios which increase the use of active travel modes and therefore increase physical activity, were larger (on average seven times larger) than the adverse effects from exposure to air pollution due to the inhalation of air pollutants.

7.4 Uncertainties and sensitivities

7.4.1 London

7.4.1.1 CO₂ emissions and air quality modelling

In order to critically assess uncertainties from the UKIAM model and its BRUTAL sub-model and its emissions factors were discussed (Section 3.3.1.3); the model validation was presented (Section 3.3.1.4); a review of a model inter-comparison with other urban models was evaluated (Section 3.3.1.5); and the comparison between BRUTAL sub-model and LAEI emissions projections for the year 2030 was made (Section 3.3.1.6).

The version of the BRUTAL sub-model used in this dissertation used COPERT 5 emission factors. The benefit of using COPERT factors in a model is that they have shown a better correlation with real-world emissions, therefore, reducing uncertainty (Kousoulidou *et al.*, 2013; O'Driscoll *et al.*, 2016) (Section 3.3.1.3).

The model validation against measurements from London and national monitoring stations (Section 3.3.1.4) showed that particulate matter concentrations modelled with the UKIAM model tend to underestimate PM_{2.5} background concentrations by approximately 15%. The same validation exercise showed that the UKIAM model tends to underestimate NO₂ background concentrations by about 30%. The NO₂ background concentrations underprediction is attributed to nitrogen oxide underestimation of COPERT emissions factors used in the UKIAM model. The results of this model validation were used to set error bars to the modelled results with UKIAM model.

The study of the UKIAM model made by Defra (2013) included a review of the comparison between urban air quality models in London which were capable of predicting air quality concentrations at the urban scale (Section 3.3.1.5). An important finding in Defra (2013) was that the most significant disparity among the models with regard to particulate matter concentration relates to estimations of non-exhaust particulate matter emissions. Not all the models estimate non-exhaust emissions from the same component. For example, some models such as BRUTAL only include estimates from tyre and

brake wear non-exhaust particulate matter emissions. Other models, in addition to non-exhaust tyre and brake wear, account for particle resuspension (PCM).

As was previously stated, a significant source of uncertainty comes for the modelling of non-exhaust particulate matter emissions. This was shown in the comparison of modelling results for the year 2030 with the BRUTAL sub-model and the LAEI model (Section 3.3.1.6). This analysis highlights the importance of modelling non-exhaust emissions with speed-dependent emissions factors to capture the effect of traffic congestion in urban areas.

7.4.1.2 Health impact assessment modelling

The sensitivity analysis for the health impact assessment modelling (Section 5.2.4, Figure 5.5), showed that for the variables examined (Table 3.26 and Table 3.27) the results were most sensitive to the following variables: i) The relative risk associated to physical activity (walking and cycling) and mortality. ii) Changes in background PM_{2.5} and NO₂ concentrations. iii) The number of days of the week travelled by active modes. iv) And, the average duration of the trip by active modes. These results highlight the importance of correctly modelling changes in background PM_{2.5} and NO₂ concentrations

The sensitivity of the results to different distributions of exposure-response function (ERF) was assessed. As previously discussed (Section 3.5.3 and 3.5.4), the mean value of the results was calculated with an ERF normal distribution. The sensitivity of the results to different ERF distributions showed that a non-linear ERF distribution applying a 0.25 power resulted in a significant (52%) variation of results from the mean value. In contrast, a log-normal ERF distribution resulted in a small difference of 2% from the mean value (Section 5.2.4, Figure 5.6).

Moreover, the sensitivity analysis showed that the results are much more sensitive to variations of ERF distributions and RR coefficients of physical activity (variations ranged between 1,653 - 4,589 deaths prevented) than variations of air pollution (variation ranged between 2,892 - 3,404 deaths) (Section 5.2.4, Figure 5.6).

Additionally, the sensitivity of variations in air pollution exposure and mortality RR coefficients from the two-pollutants (PM_{2.5} and NO₂) was studied. The sensitivity analysis showed that using mutually adjusted RR coefficients resulted in a difference of 1% to 5.4% from the mean value used in this dissertation (mean value of 3,022 deaths). The most significant variation (9.2%) from the mean value resulted from the use of a single-pollutant unadjusted RR coefficient of NO₂.

7.4.2 Mexico City

Uncertainty ranges for the emissions factors established in Mexico City's emissions inventory (Section 3.3.2.1, Table 3.3) were used to model emissions in the different transport policy scenarios in Mexico City. Non-exhaust particle matter emissions factors used for the evaluation of transport policy scenarios in Mexico City emissions were taken as a factor from the UKIAM model from London (Section 3.3.2.2).

Therefore, the uncertainty analysis of the non-exhaust emissions for London also applies to the uncertainties of the analysis of transport policy scenarios in Mexico City. The health impact assessment modelling of transport policy scenarios in Mexico City followed the same methodology and uncertainty approach as the one for London discussed above.

7.5 Strengths and limitations

This research presented in this dissertation is unique because it provides an in-depth holistic analysis of both carbon and air quality impacts of transport policies scenarios in two different settings London and Mexico City. Moreover, it stands out because it includes the analysis of both, technological and behavioural change transport scenarios which are usually studied independently, with some exceptions (Woodcock *et al.*, 2009; Kollamthodi & Watkiss, 2005). Also, grounding the analysis in proposed city transport policies and assessing its effects is an important strength of this dissertation.

An important strength of this research is that, for London, the modelling of air pollution concentration for each transport policy scenario was used to estimate the health benefits of the transport policies. In particular, the modelling of reduction of air pollution concentrations in scenarios which implement a shifting from motorised transport to cycling and walking and then estimating the health impacts of this shift is a significant strength of this research. A novelty of this analysis is to include the assessment of health impacts from NO₂ air pollution exposure in both cities, London and Mexico City. The vast majority of studies only account for PM_{2.5} neglecting important benefits from the reduction of air pollution.

A limitation of the research is that the viability of the transport policy scenarios for London and Mexico City was not assessed and the actual viability of the scenarios could be questionable. The rapid vehicle electrification assumed in the technological change scenarios has never been seen before. In a developed city like London high and rapid vehicle electrification rates could be more feasible and achievable than in a newly developed city like Mexico City with a smaller government budget.

For example, the vehicle electrification would need to be accompanied by a massive scrapping scheme to replace fossil-fuelled vehicles with electric vehicles. The behavioural change scenarios assessed an ambitious rate of car reduction that has never been seen before in a large city like London. However, the analysis of the chosen transport policy scenario does help us to evaluate the effect that the transport policies could achieve.

Also, non-exhaust particulate matter modelled emissions by the UKIAM model only accounts for tyre, brake wear and use emissions factors that are not speed-dependant. This limitation of the modelling of non-exhaust air pollutant emissions and concentrations is reflected in the underestimation of non-

exhaust particulate matter emissions compared to other models like the one used by the LAEI. Further development of BRUTAL is in progress to refine this using speed dependent Tier 2 emissions factors for electric vehicles and allow for regenerative braking as well as higher emissions in more congested areas. This uncertainty of how PM non-exhaust emissions were modelled, also affected Mexico City's analysis where a factor of UKIAM's emissions factors was used to calculate non-exhausted emissions from electric vehicles (due to lack of data).

The estimations of health effects of the transport policies showed considerable health benefits on all-cause mortality coming from behavioural change scenarios which increased physical activity in London and Mexico City. However, health impact assessments involve multiple assumptions with uncertainties in the estimation of health impacts. A sensitivity analysis was carried out to assess the stability of the results and test the impacts of the main assumptions and data choices in this dissertation. An important finding from the sensitivity analysis, was that from all the parameters tested, the total health impacts were always beneficial (preventable deaths) and of the same order of magnitude (1×10^3).

However, not all assumptions and data inputs could be tested in the sensitivity analysis. For example, it is possible that people who are more sedentary benefit more from the increase in active travel modes than physically active people who exercise. Also, the benefits of physical activity may be related to the baseline levels of physical activity and general health of the people shifting to active travel modes.

Additionally, health benefit estimations for the reduction in air pollution concentrations depend on the contextual setting and on the definition of the baseline (counterfactual) scenario from which different transport strategies are compared.

7.6 Future research

Future research should focus on the study of win-win strategies in other sectors, for example, the energy sector. Also, implementation costs and economic benefits of the strategies should be studied more deeply. Studying which policies could bring the largest environmental, social and economic benefits is essential to inform policymakers.

Moreover, the feasibility of the scenarios as well as finding metrics in which the scenarios are comparable. Specific improvements of the modelling with UKIAM would include re-running the transport scenarios with the new version of the model which accounts for speed-dependent non-exhaust particulate matter emissions factors. This should increase non-exhausted particulate matter pollution in the congested areas of central London, for example.

The Mexico City study should be complemented with the use of modelling tools, for example, the use of the CMAQ model, which is the model used by the environmental ministry in Mexico City. A correlation between transport strategies and reduction in air pollution concentrations could give excellent insight into measuring the effect on health in polluted cities and help to inform policymakers of the best transport policies to improve health.

Furthermore, the effect of emissions reduction on ozone which is a significant pollutant in Mexico City needs to be considered in the analysis and how the reduction of ozone precursors such as NO_x affect ozone concentrations in the valley. Additionally, the health impacts of ozone in Mexico City needs to be accounted for in future research.

7.7 Concluding remarks

London and Mexico City have the challenge of achieving longer-term sustainability, reducing CO₂ emissions and controlling the current levels of air pollution. The road transport sector plays a key role in this challenge, and the uncertainty of the effect of transport policies and the continuing failure to improve air pollution is an important barrier. My dissertation indicates that vehicle electrification is effective at reducing CO₂ and nitrogen oxides in both cities but fails to reduce particulate matter emissions because electric vehicles still emit non-exhaust emissions.

The contribution of particulate matter from the road transport sector can most effectively be reduced by behavioural change strategies. Behavioural strategies that reduce the number of motorised vehicles and promote travel mode shifts to active travel (walking, cycling and public transport) have the significant potential to reduce particulate matter from the road transport sector.

Damage costs analysis for London showed that although electric vehicles do offer a reduction of costs from diesel or petrol cars for carbon and nitrogen dioxide, they do not reduce damage costs from particulate matter. The motorised mode of transport with the lowest damage costs is public transport.

Effective policies that increase the shift to active travel modes and reduce motorised transport are urgently needed to achieve the significant health benefits of behavioural change policies in London and Mexico City. Much attention has been given to the implementation of technological change policies such as the low emissions zones in London and the BRT system in Mexico City. However, technological policy, even if it does reduce air pollution, has the critical limitation of not delivering any health benefits. The investment made in policies which increase motorised transport should be diverted to investments in the improvement of the walkability and cyclability of the city so that active modes are the easiest and more comfortable transport choices for any short trip.

The most significant health benefits are achieved through the replacement of trips by motor vehicles with active travel modes which increase the level of physical activity. There is potential to shift short distance trips currently made by motorised vehicles to walking and cycling, which results in the highest health benefits due to increased physical activity. Decision-makers have to promote and facilitate the shift to healthier and environmentally friendly transport modes.

The negative impacts of health from the inhalation of air pollutants do not outweigh the positive health benefits from physical activity. Technological change policies do bring health benefits through a reduction in exposure to air pollution, but the health benefits are much smaller than from active travel. Although different assumptions and uncertainties surround the health impact modelling results, it is highly likely that the health benefits associated with active travel are significant and these benefits should be considered in the development of transport policies in cities.

Developing a systematic approach to assessing transport strategies in cities aimed both at reducing greenhouse gas emissions and air quality pollutants has proved a useful framework for the two cities used as case studies. It could be usefully applied to other cities too to progress in a more holistic analysis to inform policymaking.

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