An Agent-Based Model framework to simulate active travel-focused transport policy scenarios

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Abstract

The transport sector is a major contributor to climate change, which is considered the most pressing environmental challenge of our time. Consequently, many cities around the globe are introducing sustainable transport legislation to meet the 2015 Paris Agreement of limiting global warming to 2°C and aiming for 1.5°C. To achieve this, policies are sought that can change mobility patterns to reduce emissions rapidly. This could involve a portfolio of measures where a combination of changes to the built environment, human behaviours and financial incentives or penalties are considered.

The work presented in this thesis encompasses efforts to develop and validate a model that simulates a digital representation of the transport mobility, applying Agent-Based Modelling (AgBM) techniques. This model simulates the spatio-temporal interactions of synthetic individuals in the study area during their daily routines, using different transport modes. This validated model is then used as the baseline scenario to simulate different mobility policies and test their efficiency in reducing the number of private and polluting vehicles on the roads in favour of active modes (i.e., walking and cycling) and, therefore, reducing greenhouse gas emissions.

The developed model is described and demonstrated for the Tyne and Wear region, showing its transport mobility during a regular day in 2019 (a pre-pandemic scenario with 'normal' mobility behaviours) and the potential estimated results that could be obtained when different mobility policies modifying the characteristics of the built environment and/or human behaviours are applied. The methodologies followed use open access datasets and open-source tools, when possible, being feasible to replicate the results and adapt them to any other region in the country.

This thesis aims to help in the development and understanding of the urban transport mobility applying AgBMs, where spatio-temporal and human socio-demographic characteristics are considered through the simulation of active transport modes.

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Chapter 1. Introduction

The answers you get depend on the questions you ask. Thomas S. Kuhn

"*Climate change is the most pressing environmental challenge of our time*" (DfT, 2020b). Leaders from different organisations, institutions and governments around the globe have cited this quote, but have rarely gone deeper into its definition and the present and potential future consequences. Fortunately, a vast research effort has been undertaken to better understand the challenges we are already facing. Unfortunately, in many cases, they have been either ignored or misinterpreted by politicians, decision makers and vested-interest groups to undermine the scientific consensus for their own benefit (van der Linden *et al.*, 2017).

1.1. Climate change

The United Nations (UN) define climate change as a long-term shift in temperatures and weather patterns, caused by changes in the sun's activity or large volcanic eruptions (UN, 2023). Earth's climate has changed several times in history, with eight cycles of ice ages and warmer periods in the last 800,000 years, with the end of the last ice age about 11,700 years ago (NASA, 2023).

However, not only those anomalous and very unlikely effects can produce climate changes. Human activities have also been highlighted by the UN as a main driver, primarily due to the burning of fossil fuels and the generation of greenhouse gas (GHG) emissions, acting as a coverage that alters Earth's energy balance and its climate (The Royal Society, 2023). Scientists have analysed GHG variations in air trapped in ice extracted from Antarctica, resulting in CO_2 concentration beginning to increase significantly in the 19th century after staying in a relatively constant range during the last 800,000 years, even throughout different ice age cycles (The Royal Society, 2023).

The Intergovernmental Panel on Climate Change (IPCC), the United Nations body for assessing the science related to climate change, published their first assessment report in 1990 (IPCC, 1990), strengthening the scientific evidence and demonstrating that anthropogenic climate change was intensifying worldwide (Fanelli, 2014).

1.1.1. Climate change consequences

The sixth IPCC report in 2023 stated that human activities, principally through emissions of GHG, have unequivocally caused global warming. This has increased the global surface temperature about 1.1°C above the pre-industrial period (1850-1900) (IPCC, 2023; The Royal Society, 2023; UN, 2023), being greater over land (1.5°C) than over the ocean (0.88°C) (IPCC, 2023). It has been proved with high confidence that global surface temperature has increased faster since 1970 than in any other 50-year period over at least the last 2,000 years (IPCC, 2023). Figure 1 shows the global GHG emissions in billions of tones from the beginning of the Industrial revolution until the year 2020.

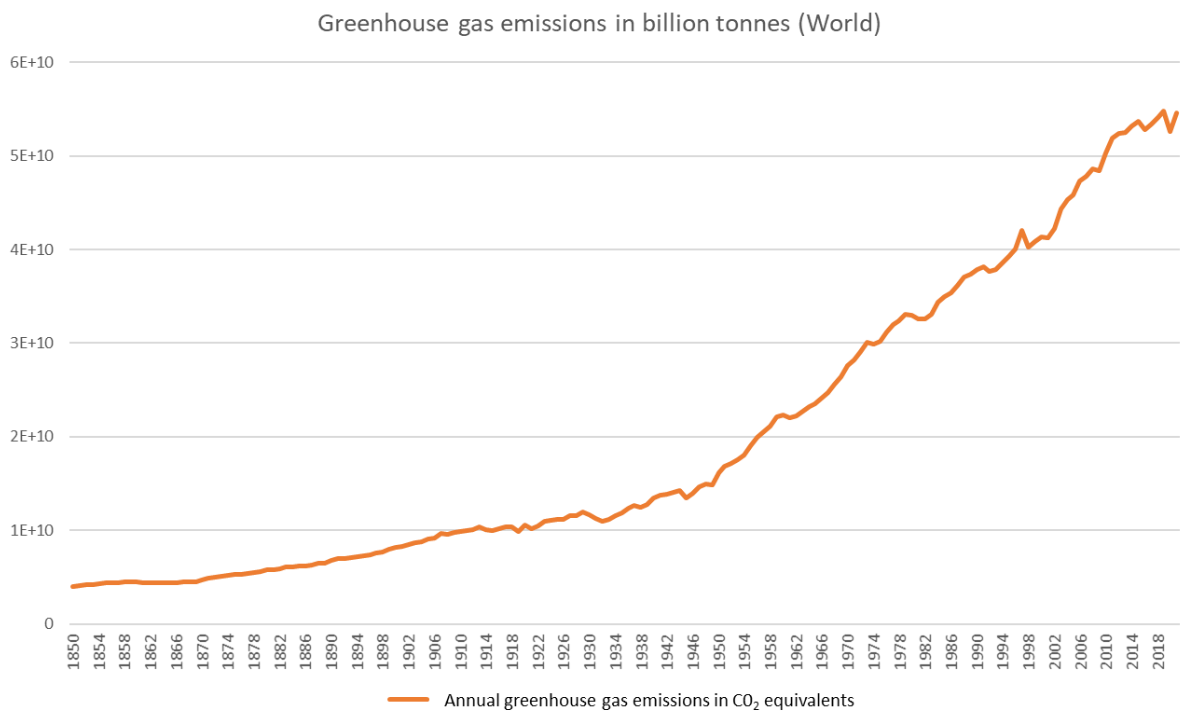


Figure 1 World Greenhouse gas emissions over time (Ritchie et al., 2020).

These effects have been producing substantial damages and increasingly irreversible losses in every region across the globe in terrestrial, freshwater, cryospheric, coastal and open ocean ecosystems (IPCC, 2023). Direct effects of burning fossil fuels have affected human health and the ecosystem due to the air pollution generated (Orru *et al*., 2017). In 2020, the European Environment Agency published that in the European Union, 96% of the urban population was exposed to levels of fine particulate matter above the health-based guideline level set by the World Health Organization (European Environment Agency, 2022). Recently, researchers from Harvard University, in collaboration with the University of Birmingham, the University of Leicester and University College of London, estimated that exposure to particulate matter from fossil fuel emissions accounted for 8.7 million premature deaths annually (Vohra *et al.*, 2021), with an even larger number of hospitalisations and days of sick leave (Orru *et al*., 2017).

Furthermore, an increase in frequency and intensity of extreme weather and climate events (Stott, 2016) has been also proved, as the National Academies of Science concludes in 2016 (National Academies of Sciences, Engineering, 2016). An example is droughts, due to decreased precipitation and increased evaporative demand under warmer temperatures (Dai *et al*., 2018). More frequent and intense droughts lead to drier surfaces, warmer temperatures and lower relative humidity, developing a loop worsening the effects produced by climate change (Dai *et al*., 2018). Other side-effects from droughts are global food and water insecurities that will affect millions of people (IPCC, 2023), which could threaten global peace (Hanjra and Qureshi, 2010) due to changes in water supply and demand (Döll and Siebert, 2002) and food shortage (Arnell *et al.*, 2004; Hanjra and Qureshi, 2010), with their complementary economic consequences. Other examples of climate events that can be increased in number and intensity are floods (Knox, 2000; Botzen and Van Den Bergh, 2008; Mirza, 2011; Wilby and Keenan, 2012) and forest fires (Gillett *et al.*, 2004; Flannigan *et al.*, 2006, 2009; Abram *et al.*, 2021).

Unfortunately, citing the IPCC in their sixth report, global warming will continue to increase in the near term in nearly all considered scenarios and modelled pathways. Based on estimations from the IPCC, approximately 3.3 to 3.6 billion people are nowadays highly vulnerable to climate change (IPCC, 2023) and it is expected that this figure will increase, as it is projected that 68% of the world's population will live in urban areas by 2050 (UN, 2018).

The question to answer now is not if climate change will increase temperature and if its consequences will affect the planet and every living being on it. The question to address is to what extent we can limit global warming and its consequences. Different urban strategies need to be followed to limit global warming and the future consequences.

1.1.2. Worldwide GHG emissions

Based on statistical data from 2016, the sectors that contribute the most to GHG emissions globally were: energy use in industry (24.2%), agriculture, forestry and land use (18.4%), energy use in buildings (17.5%), transport (16.2%), direct industrial processes (5.2%), and waste (3.2%) (Ritchie *et al*., 2020). These figures are not consistent between countries, with significant differences between high and low-income countries. High-income countries produce the most GHG emissions (both globally and per capita) from electricity, heat and transport (e.g., European Union, United States and the UK), while in low-income countries it is from agriculture and land use change and forestry (e.g., African and South American countries), although divergences occur between them depending on their main economic sectors.

Considering countries only from the Organization for Economic Co-operation and Development (OECD), the average main GHG emissions in 2019 were generated by energy industries (28%), transport (23%), manufacturing industries (12%), agriculture (10%), industrial processes (7%) and waste (3%) (OECD, 2020). In the UK context, transport is the largest GHG emitter (27% in 2019), followed by residential energy use (20%) and energy use in industry (19%) (OECD, 2023).

1.2. The need to reduce transport GHG emissions

The UN consider cities as key contributors to climate change, estimating 75% of all global CO_2 emissions are produced due to urban activities (UN Environment Programme, 2023). As Wamsler *et al.* (2013) highlight, climate change poses a serious threat to sustainable urban development, placing many cities at risk. Robert Glasser, UN Special Representative of the Secretary-General for Disaster Risk Reduction, states that the impact of climate change and disasters is likely to be severe in urban centres where exposure is high due to population density and a heavy concentration of critical infrastructure (UNISDR, 2017; European

Environment Agency, 2023b; IPCC, 2023). Consequently, cities are considered key actors for leading climate change mitigation efforts (Hoornweg *et al.*, 2011; Kennedy *et al*., 2014).

Analysis and models developed by IPCC suggest that limiting warming to 2°C or lower by 2100 involves rapid and deep and, in most cases, immediate GHG emissions reductions in all sectors (IPCC, 2023), besides other adaptive and resilient measures being implemented. One of those sectors that has to be decarbonised fast is transport, especially in developed countries (e.g., the UK, Spain, France, Denmark, Austria (Ritchie *et al*., 2020a)) as it is one of the largest contributor sectors.

Therefore, many cities around the globe are introducing sustainable transport legislation that can change mobility patterns to reduce emissions rapidly. This could involve a portfolio of measures where a combination of changes to the built environment, human behaviours and financial incentives or penalties are considered. Examples of these strategies are electric cars (Gibbins *et al.*, 2007; Teoh *et al.*, 2018); encouraging active modes for a healthier mobility (Wimbush *et al*., 1998; Nielsen and Haustein, 2019); improving cycling conditions (Buehler *et al.*, 2017); providing economic rewards (Polydoropoulou *et al.*, 2019; Máca *et al.*, 2020); implementing Low Traffic Neighbourhoods (LTNs) (Aldred and Goodman, 2020; Goodman *et al.*, 2021) or low emission zones (Panteliadis *et al.*, 2014; Ku *et al.*, 2020); and enabling alternative transport modes such as e-bikes (Philips *et al.*, 2022) and e-scooters (Gössling, 2020), among many others.

1.3. Transport modelling and AgBMs

Different transport models have been developed and used in the last few decades (mainly four-step models (FSM)) to test and estimate the efficiency of transport mobility policies before their implementation in the real world. Currently, novel approaches such as the use of Agent-Based Models (AgBMs), are being considered principally in transport research but also within pioneer governmental transport departments (e.g., Switzerland, Germany) and industries (e.g., Arup CML).

AgBMs, unlike previous approaches, have some benefits that make them the appropriate models to test policies for a more sustainable transport sector. They allow the spatio-temporal simulation of the interactions between individuals and the environment (e.g., road and public network), considering characteristics of the built environment (e.g., road type and surface) but also of the individuals (e.g., age, sex, income). This approach provides a microscopic representation of the decisions made by individuals, and enables their behaviours and the implications of their explicit interactions (Wise *et al*., 2017) in the transportation system to be revealed (Kagho *et al.*, 2020).

1.4. Aim of the doctoral thesis

The analysis of the climate crisis has given a broad but concise summary of the current and expected future consequences the world will face if measures to address the climate emergency are not established, based on reputable and reliable scientific sources. This implies the need to identify and apply measures to enable citizens to adapt their routines to more decarbonised daily lives. Within the transport sector, a more sustainable daily mobility is required, where the use of private and polluting vehicles is shifted to public and active modes.

New methods and models to test urban mobility policies have been developed. This is the case of AgBMs, which allow consideration of more attributes and characteristics, as well as the interactions of the individuals in space and time. These models could provide an innovative approach and analyse the efficiency of the policies from several perspectives. Firstly, the characteristics of the built environment (e.g., road type and condition) can be considered to estimate how safe routes are when cycling or walking, which are key components in the route and transport mode decision, as defined by the 'spatial cognition' concept. Secondly, AgBMs allow the simulation, in space and time, of the interactions between agents and the built environment, which could help identifying more efficient policy implementations based on the different agents' behaviours. Lastly, as disaggregated socio-demographic attributes (e.g., sex, age, income) from each individual are known, different mobility patterns and behaviours within society could be considered.

This doctoral thesis encompasses efforts to contribute to a more sustainable transport sector, applying AgBMs techniques. Therefore, the aim is:

***To explore the potential of AgBMs to simulate urban mobility policy scenarios, in space and time, to enable a mode shift to active travel considering the built environment and socio-demographic attributes*.**

This is in line with Active Travel England (ATE), whose goal is to achieve 50% of trips in towns and cities to be walked, wheeled or cycled by 2030 (ATE, 2023a). This thesis aims as well to contribute to achieving this global goal, which has highlighted the significant role of research and innovation in transport decarbonisation.

This is an important challenge, as several barriers need to be faced, such as safety improvements, the effects of climate, the willingness of policy implementations and the need for a change in human behaviours. Three of them are identified as critical: safety, policy implementation and human behavioural change, as they affect three different but fundamental components to achieve the goal: the built environment characteristics, the need to analyse the success or failure of active travel policies to convince stakeholders, and the human perspective. The remaining challenge (weather conditions), although fundamental too, could be considered as an extension, where different weather conditions could be analysed when safety improvements, policy implementations and changes in human behaviour are implemented. As such, the effects of weather were currently out of scope for this project but may be included in future research.

Different cities have different challenges, data and solutions, but a general-purpose architecture and modelling framework could address these and hence there is inherent transferability. Consequently, the methodology developed in this thesis can be adapted and replicated to any other region in England, using open-access data and open-source tools, when possible, as part of the Responsive Research and Innovation component.

The developed methodology is applied to the Tyne and Wear region, as it is the main urban area within the North East (NE) of England and due to the amount of accessible data that Newcastle University and other bodies linked to the University store in terms of mobility. The timeframe chosen was the year 2019 because it was the last year with ‘normal’ human mobility behaviours, as the following years since the COVID-19 pandemic do not represent a stable situation of human mobility.

This aim is summarised in figure 2, where the three main components (transport decarbonisation, human behaviour and the built environment) are connected to define the research gap identified for this doctoral thesis.

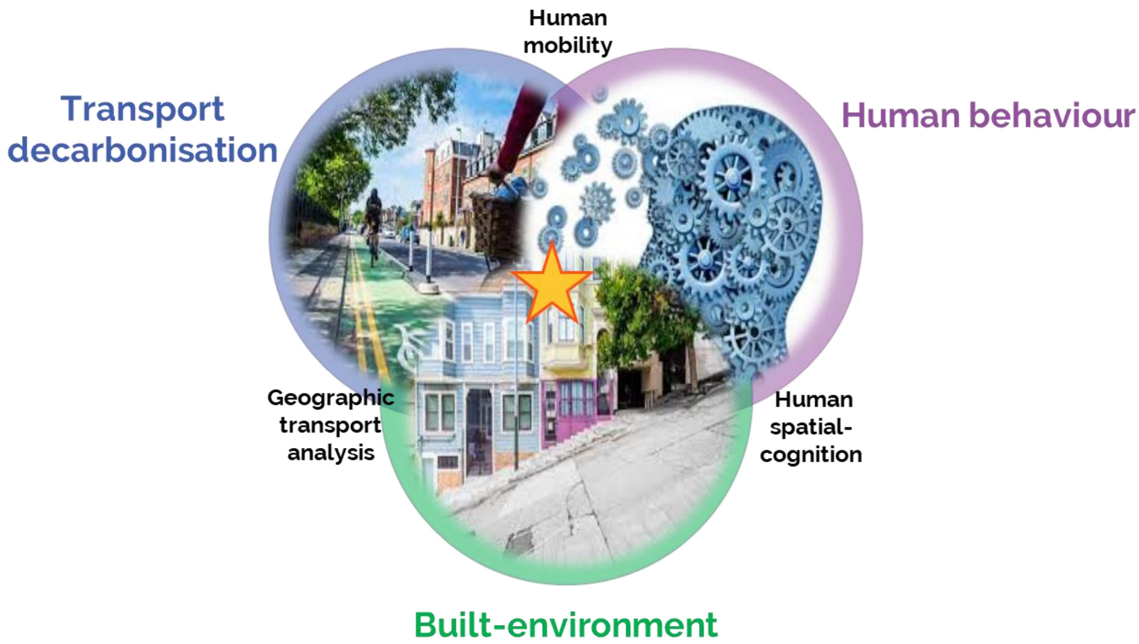


Figure 2 Connection of the three main components of the thesis: transport decarbonisation, human behaviour and built environment.

To the best of the author's knowledge, this is the first time a transport AgBM (MATSim) model has been used to simulate tailored scenarios to reduce the use of polluting private vehicles in favour of active modes in the UK.

1.5. Research gap

Climate change and transport AgBM modelling is an incipient field in research. The literature reviewed in Chapter 2 identified the need to decarbonise the transport sector in favour of active modes and the use of transport AgBMs to test active mobility policies.

The combination of these two components is scarce in research, as a consequence of computational resources and data limitations. However, new tools and datasets, as well as better computational systems are now available, which enable researchers to contribute and find alternative approaches to tackle the climate crisis by simulating the interactions of the individuals in space and time, as well as considering their individual characteristics and their interactions with the environment.

Therefore, the research gap identified in this doctoral thesis is the following:

To develop a transport AgBM model to simulate urban mobility policy scenarios to increase the use of active modes, considering key built environment characteristics for those modes.

The previously identified research gap was defined in more detail when it was observed that a low number of publications considered characteristics of the built environment when applying AgBMs for a modal shift to active modes. Characteristics such as the type of road and surface, the slope and the presence of dedicated cycle paths are the main characteristics considered by most researchers when simulating active mobility policies. Unfortunately, these characteristics could be insufficient, as characteristics such as road length, width, the existence of kerbs, crossing and junctions, among others, are also key components when analysing and simulating the use of active modes. Fortunately, Cyclestreet (2022a) has developed a methodology that classifies road for cycling based on all these attributes, which was incorporated into the design of the models used in this thesis to simulate more realistic scenarios from the cyclists' perspective.

1.6. Objectives

The defined aim of the doctoral thesis was broken down into the following objectives:

- To review the current status of transport mobility in England and the different urban mobility strategies to tackle the decarbonisation of the transport sector.
- To review the different models used in transport research and the current use of AgBMs in simulating urban mobility scenarios.
- To develop a very detailed synthetic travel demand that represents the individuals (i.e., synthetic population) living in the study area based on a set of socio-demographic

attributes with a detailed activity plan, using open access tools and datasets, when possible.

- To develop a combined road and public transport network to allow the individuals from the synthetic population to move between activities, with a special interest in characteristics that support the use of active modes (e.g., bicycle access, road network characteristics, elevation and cycleability rating).
- To calibrate and validate a transport AgBM model that simulates the normal transport mobility during a regular day in the study area. Simulations of cycling routes take into account some of the characteristics implemented in the previously developed network, for a more realistic and accurate understanding of cyclists' behaviours.
- To define, code and simulate a set of urban mobility policies to reduce the number of private and polluting vehicles on the roads in favour of active modes.

1.7. Research questions

The development of this doctoral thesis opens several research questions that need to be answered by the end of it (see section 5.3). These are the following:

- How can open-access data and open-source tools support the development of spatio-temporal scenarios to assess the effectiveness of policy portfolios to increase active travel uptake, taking into account socio-demographic attributes and built environment characteristics?
- What synthetic population attributes are required to capture the behavioural responses of transport users to active travel policies, and how can these attributes be produced using open-source demographic tools?
- Which characteristics of urban infrastructure are important in shaping travel choices, and particularly the use of active travel?

1.8. Doctoral thesis innovations

To conclude, this thesis proposes four novel innovations to simulate transport scenarios with a transport AgBM model in the UK context:

- A new, open-access and very detailed synthetic population methodology for any region in England (see section 3.3.3). This heterogeneous population will allow a wide variety of groups in society to be simulated, providing broader mobility patterns than less detailed alternatives.
- Inclusion of a new network attribute (*quietness*) ranking roads for cycling based on their built characteristics, using open access data from Cyclestreets (Cyclestreets, 2022a) (see section 3.4.4). This parameter quantifies the road quality for cycling, helping to identify the feasibility of synthetic agents for cycling.
- A MATSim bicycle contribution code update to consider characteristics of the built environment (i.e., *quietness* attribute) to simulate more realistic cycling routes. This contribution was developed in conjunction with Dr Ziemke (see section 3.6). This will help better account for infrastructure when making travel decisions when cycling.
- A set of tailored "*stick*" and "*carrot*" scenarios to test urban mobility policies to influence transitions to active travel and reduce the use of private motor vehicles (see section 3.8).

1.9 Thesis structure

The thesis has been structured as follows:

Chapter 2 presents a literature review. Firstly, UK measures to achieve a net-zero transport sector are analysed from governmental and scientific perspectives, highlighting the need to increase active travel in the short and medium term. Secondly, different methodologies for modelling transport mobility policies are reviewed, identifying the advantages of using AgBM to simulate transport scenarios considering characteristics of the population, space, time and the built environment.

Chapter 3 describes in a high level of detail the developed methodology to generate all the required input datasets to calibrate and validate a MATSim model. Furthermore, the model is used to simulate different mobility policy scenarios in order to test their efficiency in increasing the use of active modes.

Chapter 4 groups all results obtained from each of the established objectives, from the development of a synthetic travel demand and network, to the model calibration and validation and the results obtained from each scenario simulated for a more sustainable transport future.

Chapter 5 provides insight on the principal outcomes achieved in the doctoral thesis, as well as discussing the work presented, considering the assumptions and limitations previously acknowledged. Additionally, the research questions identified in chapter 1 are reviewed, providing a realistic and fair view of the level achieved with respect to the established goal of the thesis. Future work that researchers could consider are also identified and described. The implications of research for researchers, practitioners and policy makers are also discussed. Lastly, a conclusion of the doctoral thesis is provided.

Chapter 2. Literature Review

You were not made to live as brutes, but to acquire virtue and knowledge. Dante Alighieri

Chapter 1 introduced the current climate crisis, from a detailed description of its origin and current and future expected consequences to the main economic sectors contributing to it. Consequently, the research gap, main objectives and research questions were defined.

This chapter reviews the literature from governmental and scientific perspectives to face the climate emergency, identifying a set of measures that would enable a net-zero transport future. Besides, several transport models are investigated, identifying their advantages and disadvantages in terms of modelling urban transport mobility and their applications to help face the challenge of the climate crisis.

2.1. The UK transport sector

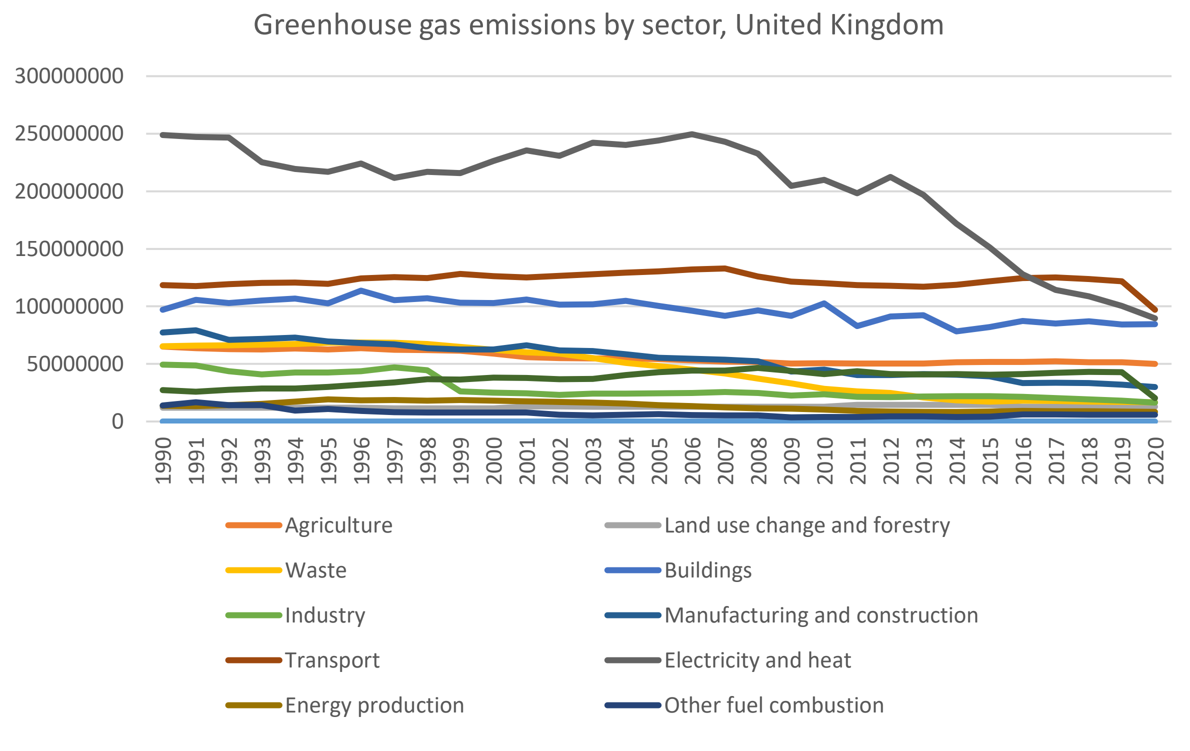


Figure 3 Greenhouse gas emissions by sector in the UK (Ritchie *et al.*, 2020).

The UK possesses one of the strongest records of emissions reduction in the OECD since the early 1990s, where energy industries had the largest source of emissions reductions, shifting from coal to gas and renewable energies (DfT, 2022e; OECD, 2023), achieving a global 48% emission decrease since then (Department for Business, 2023). Unfortunately, transport emissions became the largest contributor sector from 2016 (DfT, 2022e) (see figure 3), although it decreased by 5% between 1990 and 2019 (DfT, 2022e). Despite this decrease, the UK transport sector requires immediate measures to reduce GHG emissions to achieve the goals established in the Paris Agreement and the 2030 Agenda for Sustainable Development Goals.

Department for Transport (DfT) statistics from 2019 (the last normal year prior to the pandemic that affected human mobility globally) show that 84% of passenger mileages were travelled in by cars, vans and taxis, and produced 91% of domestic transport's total emissions. Most trips are relatively short, where 24% of them were under one mile, 43% under two miles and 68% under five miles (DfT, 2022c). In England, 88% of driven miles were on minor roads (B, C and U roads), while the remaining 12% were driven on major roads (trunk and principal) (DfT, 2020d). Eighty per cent of trips under one mile were on foot, although for longer distances, the car was the most frequent mode (DfT, 2022d). On average, 69% of British people use the car three or more times a week, increasing to 74% using it once or twice per week. Statistically, a citizen travels around 6,500 miles per year (relatively constant value since 2013), where 54 of them are travelled by cycling, in contrast with 3,198 miles as a driver and 1,812 as a car passenger, 158 miles using local buses and 625 by rail (DfT, 2023f). When commuting, 30 minutes on average are required and typically the trip is made by car (68%), with minor differences between regions except in London (27%) (DfT, 2019b).

This global view shows a huge car dependency and its excessive use. As Song et al. (2017) describe, heavy car dependency leads to traffic congestion, pollution and physical inactivity, which impose high direct and indirect costs for society. Shah *et al.* (2021) state that the transportation sector has a significant economic, social and environmental impact on society and its improvement needs to consider all of them to be successful and efficient. Very committed regulations must be applied, as well as the implication for the citizens in their mobility behaviours to achieve the target.

2.2. Measures to reduce GHG transport emissions in the UK

To face this situation, the UK set in 2019 by law that 100% of their emissions must be net zero by 2050 (UK Legistation GOV, 2019), being the first major economy to set legally binding carbon budgets and to legislate to end its contribution to climate change (DfT, 2020a).

In 2020, the "*Decarbonising Transport: Setting the Challenge*" report was published, a document where all existing work and the strategies to be put in place by governments, businesses and society to deliver the significant emissions reduction needed across all modes of transport were put together (DfT, 2020b). Targets and strategic priorities such as accelerating the modal shift to public and active transport, decarbonising road vehicles and how goods are delivered are explained from the current position versus historical data, the current government aims and targets and future work. The document concludes by accepting that more plans and actions will be required if the established legal obligations are to be met, highlighting the vital role of research and innovation in decarbonisation.

In 2021, the "*Decarbonising Transport: a better, greener Britain*" report (DfT, 2020a) was published. This document explains in more detail how strategies defined in the previous report will be achieved based on a series of actions and timings. From all of them, two are specifically related to car use mitigation, and consequently, with GHG car emissions reduction. These are decarbonising road transport and the modal shift to public and active transport.

The first action is focused on removing polluting vehicles from roads. Firstly, the sale of new petrol and diesel vehicles will be phased out by 2030, and all new cars and vans will be fully zero emission at the tailpipe from 2035. Unfortunately, in 2023 this sale measure was delayed and drivers will still be able to buy polluting vehicles until 2035, with the possibility of buying and sell them second-hand after that year, too (MacLellan *et al.*, 2023)). Secondly, the development of a reliable charging infrastructure network. It is expected to see the roll-out of 6,000 ultra-rapid charge points by 2035, including electric vehicle (EV) infrastructure on-street and in public car parks. Thirdly, the implementation of charging schemes to disincentive the use of private motor vehicles in urban areas.

The second action aims to enable citizens to use more sustainable modes. Firstly, a more cohesive, integrated and affordable public transport network, developing a National Bus

Strategy vision and a more efficient and electrified rail network, enabling a better integration between all public modes, walking and cycling would be developed. Secondly, there would be investment of £2 billion to increase the number of people walking and cycling in towns and cities, with an ambitious goal that half of all journeys will be cycled or walked by 2030 (ATE, 2023a), supported by a world class cycling and walking network by 2040.

2.3. Estimated co-benefits from the UK net-zero target

The estimated benefits from these strategies go beyond tackling the climate crisis. From the shift to zero emission private vehicles, it is expected to increase up to £8 billion (gross value added (GVA)) from vehicle manufacture and up to 60,000 jobs in 2050. The CO_2 emission reduction is expected to be between 620 and 850 $MtCO_2$ between 2020 and 2050, which could generate economic savings of up to £8 billion from air quality improvements. Accordingly, there would be noise reductions, which has been classified as the second worst environmental risk factor in Europe (Sørensen *et al.*, 2020), just after air pollution.

From the public transport transformation perspective, savings of between 35 and 37$MtCO_2$ are expected from 2020 to 2050, which could generate economic savings of up to £160 million from air quality improvements. Zero emission buses could contribute up to £1 billion (GVA) in 2050 from zero emission vehicle manufacture and create up to 7,000 jobs. If buses become more popular and allow the shift from private vehicles, road congestion could be reduced as well.

If cycling and walking objectives are achieved, improvements in air quality, health, economy, congestion and noise pollution are expected. Based on estimations given in the report, savings between 1 and 6 $MtCO_2$ emissions from 2020 to 2050 are expected, which could generate savings from £20 to £100 million from air quality improvements. Health benefits are expected in wellbeing due to an increase in physical activity and a risk reduction of developing depression by 31%, which could drastically reduce the global £8.2 billion spent yearly by the National Health Service (NHS). Active travel could contribute between £1 and £4 billion (GVA) in 2050 and create between 40,000 and 100,000 jobs. Congestion will be reduced as walking and cycling require much less urban space than private vehicles. Noise and vehicle toxic tailpipe pollution would be reduced as well, transforming streets and communities into more liveable environments. Lastly, by 2050, future active travel spending is projected to prevent around 50,000–130,000 premature deaths and reduce work absence by around 50–140 million days.

2.4. Scientific research on the net-zero challenge

The previous paragraphs show the current panorama of the English transport sector, as well as the governmental chosen measures to put in place to achieve a sustainable transport environment, estimating extraordinary potential benefits not only for the current climate, but also for other sectors like the economy, health and wellbeing and the environment. Unfortunately, most strategies are nowadays just estimations based on ideal scenarios and/or assumptions (e.g., a full and reliable charging infrastructure network) that require more research and innovation (e.g., electric energy source, the use of hydrogen in road transport).

Scientists and researchers have identified the advantages and disadvantages of each of the previously suggested strategies, grouped in two parts: the decarbonisation of vehicles on the road, and the shift to public and active modes. Their outcomes have been summarised in the following paragraphs.

2.4.1. Decarbonisation of vehicles on the road

The decarbonisation of road vehicles is mainly focused on replacing polluting fossil-fuelled vehicles with zero emission electric vehicles (EVs), which are around three-times as energy efficient as conventional internal combustion engine (ICE) vehicles (International Energy Agency, 2021).

On the one hand, this approach could be beneficial for two of the main environmental issues: air pollution, as they are powered by electricity and do not produce any toxic tailpipe pollution; and noise, as these vehicles do not have the combustion engine and other noise components (e.g., exhaust system) (Pratico *et al.,* 2020). Research studies show that EVs are a promising solution to reduce GHG emissions in the transportation sector (Sadek, 2012; Campello-Vicente *et al.*, 2017; Ahmadi, 2019; Pardo-Ferreira *et al.*, 2020; Agusdinata and Liu, 2023; Desreveaux *et al.*, 2023) and help in tackling the climate change goals previously mentioned.

On the other hand, this strategy has several drawbacks that can make it unsuitable for the short and medium term. The most controversial aspect surrounding EVs is focused on how the DfT estimated predictions (i.e., 91% of GHG emission reduction by 2050 (DfT, 2020a)) will be achieved, when substantial obstacles need to be solved beforehand. Some of them are the following:

- The current vehicle costs (Pratico *et al.*, 2020).
- The current projections of EVs on the roads by 2050 and in the short and medium term (DfT, 2020a; SMMT, 2021).
- The energy source requirements (Sadek, 2012; Vrabie, 2022; Desreveaux *et al.*, 2023).
- The significant ecological impact of battery production (Sadek, 2012; Peters *et al.*, 2017; Marmiroli *et al.*, 2018).
- The potential lack of critical materials (Habib *et al.*, 2020).
- An underdeveloped supporting vehicle charging infrastructure (Chen *et al.*, 2020; Pratico *et al.*, 2020).
- Side effects of their lower noise levels in urban areas for other road users (Pardo-Ferreira *et al.*, 2020).

To all these aspects, the UK Energy Research Centre (UKERC) add concerns about future technology performance, availability, costs, the uptake by consumers and businesses, and the increasing gap between lab and "*real world*" performance of energy use, carbon and air pollution emissions (Brand and Change, 2019). Although EVs sales have increased in recent years (16.6% market share of registrations in 2022 (Mer, 2023)) with the help of subsidies, tax reductions and incentives (Campello-Vicente *et al.*, 2017), only 46% of cars could be zero emissions by 2035, according to the Society of Motor Manufacturers and Traders (SMMT) (SMMT, 2021). When considering the energy source required, Vrabie (2022) states the actual energy suppliers in Europe will not be enough to cover the full shift from ICEs to EVs, and that the actual energy market trends will not be able to support the demand for the next several decades, highlighting that no European national economy can afford the shift today.

In terms of ecology, battery production has a significant impact on the environment (Peters *et al.*, 2017; Desreveaux *et al.*, 2023), due to the growing demand for critical minerals required (Pratico *et al*., 2020; Agusdinata and Liu, 2023). In 2022, Benchmark Mineral Intelligence estimated a requirement for more than 300 new mines to meet the demand for EVs and energy storage batteries (Benchmak Mineral Intelligence, 2022). Additionally, Habib *et al.*, (2020) warned about the potential supply risk of these critical minerals. Besides ecological impacts, the need for these critical minerals could cause conflicts over communities' land, disruptions to livelihoods, access to water, air quality, and health in areas where these minerals could be extracted (Agusdinata and Liu, 2023), as well as social inequalities (Heffron, 2020).

About the vehicle charging infrastructure development, Chen *et al.* (2020) reviewed the state of the required infrastructure in the UK. In their research, it is highlighted that the deployment of EV charging infrastructures would require careful long-term planning and improvement in design, especially considering the relatively fragile infrastructure of electricity distribution not only in locations, but also in converter circuit topology, cost, consumer centric design, reinforcement of electricity distribution networks, and social and environmental factors. Pratico *et al.* (2020) add to the inconvenient list the lack of fast refuelling facilities that make EVs unsuitable for medium and long-distance travel.

Another car-dependence side effect that can remain with EVs is the transport injustice and inequality for those without access to them. NTS statistics from 2019 show that 45% of the poorest households (lowest quantile) do not have access to cars or vans, while the percentage for the richest (highest quintile) is just 14% (DfT, 2023c).

2.4.2. Modal shift to public and active transport strategy

Public modes

The use of public modes is often framed as a key component of building sustainable cities (Lyons and Harman, 2002; Miller *et al.*, 2016; Friman *et al.*, 2020). They can provide energy efficient transportation in an urban setting competing against private vehicles (Schiller and Kenworthy, 2017), minimise GHG emissions and other pollutants, reduce consumption of land, reduce travel time and cost, improve social access, increase economic efficiency and contributions to economic activity (Miller *et al.*, 2016).

Nevertheless, some obstacles make the use of public transport not the ideal option for travelling. According to the UN, only half the world's urban population had convenient access to public transportation in 2019, although this percentage is higher in developed areas of Europe (around 75%)(UN SDGs. Goal 11, 2023). These figures show that there are still areas not fully accessible, especially in deprived and rural zones (Lucas *et al.*, 2008; OSCI, Better Transport and Local Trust, 2021).

The fact of having complex and heterogeneous public transport systems also affects their accessibility. In the UK, the number of private companies providing public transport services is huge in comparison with Germany and the Netherlands, where the public transport sector is integrated within a national framework (Lyons and Harman, 2002). This privatisation has brought complexity to the services, fares and information provided, which adds further layers of inconvenience for users when planning their trips (Lyons and Harman, 2002).

Concerning the GHG emissions, these modes can provide energy efficient transportation in an urban setting competing against private vehicles (Schiller and Kenworthy, 2017), minimising GHG emissions and other pollutants, although the objective of being full zero emissions is far from being achieved. Based on statistics from DfT, in 2020 only 2% of the bus fleet was zero-emission and 84% was diesel engine (excluding hybrids) (DfT, 2022f).

The perception and attitudes towards global public transport modes are also fundamental to incentivise their use; these perceptions are not very positive and encouraging. Public modes are seen as modes only to be used by specific socio-demographic groups (e.g., school children, elderly people, low or middle-class people) (Shah *et al.*, 2021). Other analyses highlight the perception of public modes as inferior to private modes, regarding protection, autonomy and prestige, as well as being perceived as problematic in terms of frequency and reliability (Hiscock *et al.*, 2002; Browne *et al.,* 2011; Shah *et al.*, 2021).

To worsen the attractiveness of public transport modes, it is important to cite the still on-going side effects of the COVID-19 pandemic on the public transport sector. The pandemic impacted it dramatically due to the need for social distancing, the private car being the main winner among transport modes in urban areas (Vega-Gonzalo *et al.*, 2023).

In terms of public transport use, it was observed that frequent public transport users were more likely to have substituted it in favour of private cars than occasional users. Vickerman (2021) analyses the impact of COVID-19 on UK public transport and states that a simple return to the status quo is unlikely as public transport adjusts to a new normal of more home working and fear of crowded spaces. As an example, figures from DfT (DfT, 2023a) show that the number of local bus passenger journeys in England in 2022 (2.8 billion) was still far lower than in 2020, where passenger journeys were 4.1 billion.

Active modes

Cycling and walking are considered the most sustainable forms of personal transport (Song *et al.,* 2017; Brand, *et al.*, 2021) and one of the most promising ways to reduce transport emissions, particularly in short trips (de Nazelle *et al.*, 2010; Frank *et al.*, 2010; Bearman and Singleton, 2014; Scheepers *et al.*, 2014; Keall *et al.*, 2018; Woodcock *et al.*, 2018; Neves and Brand, 2019; Quarmby *et al*., 2019; Brand, Dons *et al.*, 2021). The fact of not generating GHG emissions when walking and cycling (apart from breathing), makes these modes efficient alternatives to reach a net-zero transport sector in urban areas.

Several scientific analyses have demonstrated their benefits in health as well, both physical and mental. In terms of physical improvement, individuals get the habit of exercising to lose weight, reduce obesity, and address a variety of diseases, such as coronary heart disease, obesity and type 2 diabetes (Bray, 2004; Hruby *et al.*, 2016; Department of Health and Social Care, 2019). Just by reducing obesity, it could be possible to reduce the risk of certain types of cancer, high blood pressure and diabetes (PHE, 2017).

From the mental health perspective, Avila-Palencia *et al.*, (2018) developed a two-year longitudinal study in seven European countries where they evaluated the association between the use of different transport modes and their impact on mental health. Their results showed robust evidence that cycling is associated with positive mental health effects (e.g., perceived general health (Scheepers *et al.*, 2015), perceived stress (Avila-Palencia *et al.*, 2017) and mental wellbeing (Martin *et al.*, 2014; Mytton *et al*., 2016)). However, results for walking are inconclusive between different studies that find improvements (Martin *et al*., 2014; St-Louis *et al.*, 2014; Smith, 2017) and others that do not see correlations between walking and better mental health (Richards *et al.*, 2015; Mytton *et al.*, 2016). Positive results were also achieved for both cycling and walking by Singleton (2019).

Despite the important improvements that could be achieved with the increase of people walking and/or cycling, some scenarios could be seen as harmful for them. The first one affects the quality of the inhaled air when sharing the road with cars (McNabola *et al*., 2008), as they would be exposed to harmful toxic pollutants, while the second is the potential increase of injuries or risk of being a victim of a traffic collision (Aldred *et al.*, 2021). Fortunately, and citing PHE *"the evidence is that the health benefits of walking and cycling outweigh any potential health risks and harms"* (Laird *et al.*, 2018).

Unfortunately, there are true barriers that affect the uptake of active travel. The first concerns safety and security. National Travel Attitudes Survey (NTAS) Wave 8 results in 2023 show that 63% of females let other people know their plans as a safety precaution when walking and cycling (DfT, 2023g). Along the same lines, the Cycling Embassy of Great Britain say that the main barrier for cycling is the perception that roads are too dangerous and uncomfortable, especially due to high volumes and high speeds of motor traffic (Cycling Embassy of Great Britain, 2023). In line with this, statistics from the NTS in 2019 show that two-thirds of adults feel that it is too dangerous to cycle on the roads, this value being higher for women than men (71% and 61%, respectively) (Solocombe, 2020). Additionally, Sustrans (2018) analysed the National Cycle Network quality and showed that 42% were very poor, 4% poor, 53% good and only 1% very good.

The second barrier is about weather conditions. Saneinejad *et al.* (2012) explored the relationship between weather and commuting trips in Canada, and results showed that cycling and walking are sensitive to temperatures below 15°C and 5°C, respectively, while in terms of wind speed and precipitation, cyclists are affected twice as much as pedestrians. Another analysis developed by Zhao *et al.* (2019) shows that rainfall events also have significant impacts on walking and cycling even one hour before and two after the rainfall.

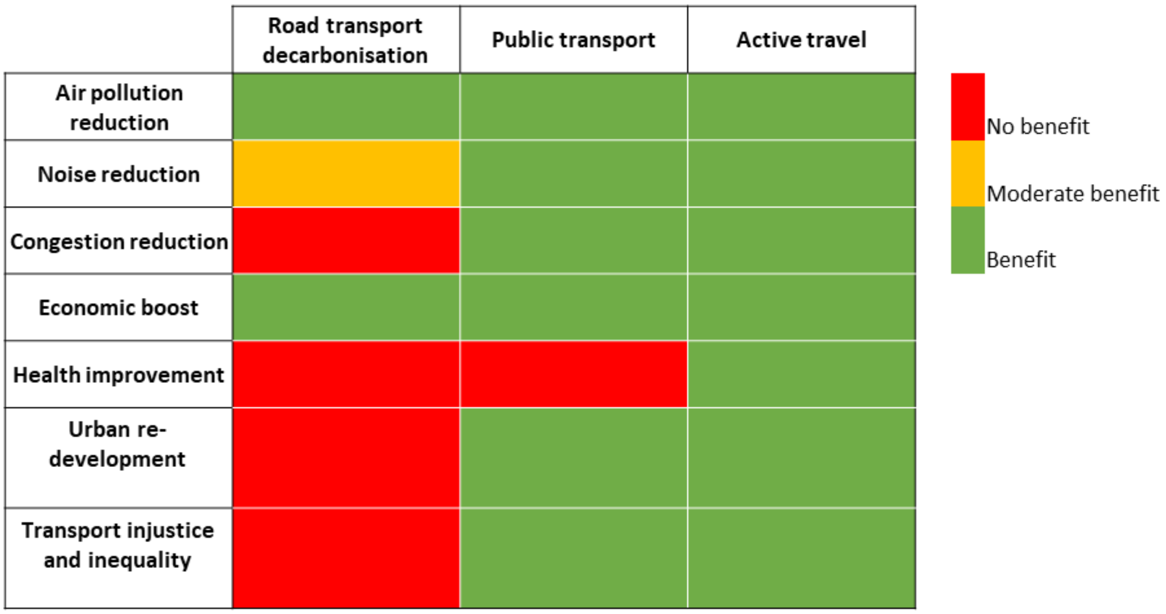
The third barrier is around policy implementation. While projects to improve active travel are announced and approved, not all have been developed or fully implemented. One example is the two-thirds cut (£200m) to promised capital investment in safe walking, wheeling and cycling infrastructure. Entities such as Sustrans consider that this is the consequence of a persistent underfunding by the Government (Sustrans, 2023). Shah *et al.* (2021) suggest why policymakers are not interested in the expansion of active travel modes. In their paper, they suggest that policymakers are afraid to get public acceptance and potential public opposition. Additionally, another reason highlighted by Aldred (2019) about the lack of investments in active travel in low-cycling countries such as the UK, is about another type of fear: the fear of building the required infrastructures and not making any benefit due to cultural barriers.

The fourth barrier is the low willingness of citizens to switch and minimise their car dependency. Although statistics by Ipsos (2022) in 2022 show that almost half of the population (44%) would like to cycle more, a similar proportion (47%) consider they are not the kind of person to use bicycles. Additionally, seven out of ten support actions to increase active travel instead of private cars, but the same proportion considers that they need a car for their lifestyle, showing a strong attachment to car use and ownership. These figures show the differences between what people think would be good for the environment and society, and their personal conviction and/or need to make the move.

2.4.3. Scientific research conclusions

The previous paragraphs summarised the current perspectives about the suggested alternatives to achieve a net-zero transport sector in urban areas. Advantages and disadvantages were identified for each alternative, showing that there is not a unique solution and their combination will be more efficient than if they are applied individually, although the decision to prioritise some of them is key to achieve the final goal. Figure 4 summarises the benefits and potential disadvantages of the three main strategies defined by DfT (2020a), based on scientific research.

Firstly, the strategy that aims to decarbonise vehicles on the roads is mainly focused on replacing polluting fossil-fuelled vehicles with more energy efficient zero emission vehicles, although the global coverage is not assured for the short and medium term due to critical concerns about their current cost, charging infrastructure, energy supply, and environmental and ecological impacts (Heidrich *et al.*, 2022). Questions such as the required amount of en-route charging facilities and chargers to be installed in each location; the potential lack of key components made with critical minerals; the efficiency and reliability of current electrical grid capacity; and its future upgrade to manage the expected demand still needs to be analysed and developed by research and future innovation, respectively. In its favour, three other benefits could be achieved with this measure: cleaner air, better health and noise reduction in urban areas.



	Road transport decarbonisation	Public transport	Active travel
Potential disadvantages	Underdeveloped charging infrastructure Energy source requirements Ecological impact Transport injustice Electric vehicle cost Lack of critical materials	Privatised sector Uneven accessibility Human attitudes and perceptions COVID-19 consequences	Weather conditions Safety and security Policy implementation Low citizen willingness

Figure 4 Potential benefits and disadvantages: comparison between the defined strategies.

Secondly, the modal shift to public and active transport strategy aims to enable people to use more sustainable transport modes instead of private and polluting vehicles. This strategy could be divided in two parts: public and active modes. Public modes have always been considered as a key component for a sustainable transport sector, providing a vital service connecting locations, reducing congestion, noise, GHG emissions and pollutants. Unfortunately, their performance in reducing the number of private cars on roads has not been successful, mainly due to the lack of a reliable access in rural and deprived areas and the poor perceptions and attitudes of the citizens, probably increased by the lack of reliable information from a very segregated service and the current consequences of the Covid-19 pandemic.

Active modes are the cleanest mode of transport that citizens can use, especially for short distances. Consequently, this shift would help to minimise GHG emissions, to improve citizens’ health (both physical and mental), to improve the urban environment with more space for nature and urban activities, and a notable noise reduction, among others. The main challenges are safety and security when walking and cycling, the weather conditions, the implementation of policies and behavioural changes.

Additional to the previous benefits, a potential reduction in transport injustice and inequality, due to the so-called vicious circle of increasing car dependency, could be achieved with both public and active modes. Sustrans (Taylor and Sloman, 2008) highlight the three main measures to apply to achieve transport justice for everyone and two of them are related to these modes of transport: 1) the implementation and definition of decent and accessible public transport routes; and 2) the definition of active travel programmes to incentivise the use of bicycle and walks.

All in all, based on previous scientific research, active travel is the best among the set of options provided by DfT for the short and medium term. Active modes not only have direct benefits on air quality and GHG reduction, but also on health and wellbeing, noise and congestion reductions, as well as in the required infrastructure cost, which is much less expensive and complex than the ones required for EVs and public transport modes. The challenges need to be focused on the different infrastructure interventions required to enable citizens to use more active modes, as well as to understand how human behaviours could change to reduce the use of polluting private vehicles. The investment in active travel has been proved to be a great achievement. Examples of success can be found in Denmark, Germany and the Netherlands (Pucher and Buehler, 2008).

DfT also consider that success will require working in partnership with the public, industry, business, and academia (DfT, 2020a) and this PhD research project aims to bring help and support in the achievement of this goal. This PhD thesis aims to identify different urban mobility policies to enable the citizens to use active travel modes and reduce the use of private and polluting vehicles for a more resilient and less polluted urban environment.

Given that active travel is such an attractive option, we need to find tools to help plan policies and assess their impact. This will be the focus of the next section.

2.5. Transport modelling

The shift to active travel modes is an important and critical challenge nowadays. Its success is critical to achieve net-zero emissions in transport. In England, this challenge has been assigned to ATE, the government's executive agency sponsored by DfT, responsible for making walking, wheeling and cycling the preferred choice for everyone to get around. Their objective is to achieve 50% of trips in towns and cities to be walked, wheeled or cycled by 2030 (ATE, 2023a), regardless of the sex, age, health condition or location of the citizens. Strategies such as the implementation of direct, continuous, physically segregated and safe routes for cycling; the definition of LTN; the increase of cycle parking; and a better connectivity between active and public transport modes, among others, are considered.

These mobility policies need to be tested before they are implemented in the real world with models to understand and estimate (not predict) their success or failure. The following sections explain what transport models are, as well as describing the main types.

Traditionally, transport modelling consists of the development of a model, which has been defined by Bandini *et al.* (2009) as "*an abstract and simplified representation of a given reality, either already existing or just planned to study and explain observed phenomena or to foresee future phenomena".* Translated into the transport sector, it consists of the development of an abstract and simplified representation of the transport sector that defines its characteristics and structure to understand its current situation or test future developments. In transportation, these models are known as travel demand models. Three main models are described below: the four-step model, activity-based model and agent-based model.

2.5.1. The four-step model

The most well-known and used travel demand model is the so-called four-step model (FSM). Originally from 1960s, FSM is the primary tool for forecasting, understanding and assessing future demand and performance of a transportation system, typically defined at a regional or sub-regional scale (McNally, 2007). The main purpose of the model is to be used as a tool for capacity analysis of road networks, analysis of the network development scenarios or analysis of the public transport system (Mladenovic and Trifunovic, 2014).

As McNally (2007), Xintong (2021) and Mladenovic and Trifunovic (2014) explain, these models consist of four different stages: trip generation, trip distribution, mode choice and route choice. Briefly, the first one defines the magnitude of total daily travelled trips (attracted and generated) per zone in the model system at a specific level (e.g., personal, household) for various trip purposes or activities. The second stage consists of recombining trip ends from the previous stage into trips, generating a trip matrix between zones. The result states the magnitude of traffic flows between all Origin-Destination (OD) zones (Ziemke, 2022). Rasouli and Timmermans (2014) describe this stage as an assumption of the laws of thermodynamics applied to social and physical systems, where human behavioural choices are not involved. The third effectively factors the OD table to produce specific trip tables for each of the different transport modes to be analysed. In the last stage, the flows of each transport mode-specific O-D table are loaded on the allowed transport modal network (e.g., roads for cars, rail tracks for trains), usually under the assumption of user equilibrium, where all paths utilised for a given O-D pair have equal impedances. The model output describes the demand for transport as a set of aggregated flows of traffic on the routes of the network and spatially resolved by zones (Scherr *et al.*, 2020; Ziemke, 2022), which are used to analyse policies such as road expansions, introduction of tolls, etc. (Kagho *et al.*, 2020). Due to these models being based on individual trips, they can also be called trip-based models (Ziemke, 2022).

Four-step model limitations

Although these models have been used by transport modellers worldwide and several improvements have made them more efficient and accurate, Mladenovic and Trifunovic (2014) highlight several shortcomings, the most relevant ones being:

- The small number of different trip activities allowed (Johnston, 2004).
- The assumed stability in time of zone's characteristics and relationships.
- The lack of consideration of land use density in trip generation.
- Travel demand considered as independent of the provided transportation system (Vuchic, 2017).
- Neglected levels of road congestion (Johnston, 2004).
- The lack in consideration of new transport systems and facilities.
- The assumption of independence of trips between members from the same household.
- The assumption that average travel times remain constant in future and through the day.
- The gravity concept used during the trip distribution stage tends to overestimate the near trips and underestimate the far ones.
- The modal split stage is mainly focus on three motorised travel modes (car use as a driver, as a passenger and public transport as a passenger) and do not consider active modes (walking and cycling).
- An oversimplification of the modal split due to empirical evidence or socio-economic data (Vuchic, 2017).
- An assumed constant time value for all trip purposes.
- The use of aggregated and static link performance values.
- The estimation of road capacities.
- The assumption that all trips start and end at the centroid of each zone.
- The lack of off-peak models.
- The lack of behavioural considerations.
- The aggregated outcome representing the average behaviour of a group of travellers (which makes it impossible to estimate the behaviour of individual travellers).

Besides them, McNally (2000) added a few more limitations based on McNally and Recker (1986), and the US Department of Transportation (1997) analyses:

- The lack of spatial and temporal interrelationships between trips.
- The lack of the linkages between trips and activities.

- The lack of considering household dynamics, choice complexity and habit formation.

Pinjari and Bhat (2011) state that previously highlighted issues, especially the temporal, spatial and modal linkages between trips, could lead to illogical trip chain estimations.

Based on the previous limitations, and due to fundamental changes in urban environments and human behaviours (McNally, 2000; Franco *et al.*, 2020; Nguyen *et al.*, 2021) that increased concerns regarding traffic congestion and air quality (Pinjari and Bhat, 2011), but also due to the inclusion of new transport modes, travel behaviour is gradually getting more difficult to estimate (Ferreira *et al.*, 2007; Holmberg *et al.*, 2016; DfT, 2019a; Franco *et al.*, 2020). Therefore, other alternatives have been developed and considered to better understand travel behaviours at a microscopic level (Kagho *et al.*, 2020).

2.5.2. Activity-based models

Activity-based models (AcBMs), also known as activity-based travel demand models, analyse travel as daily or multi-day patterns of behaviour, related to and derived from differences in lifestyles and activity participation among the population (McNally, 2000). The motivation of this approach is that individuals' travel decisions are activity-based (McNally, 2000). This means that travel decisions are made by a set of activities and its global context, which cannot be understood individually, where travel is viewed as a demand derived from the need to pursue activities (Bhat and Koppelman, 1999; Davidson *et al.*, 2007; Pinjari and Bhat, 2011). This definition addresses the impossibility of trip-based models to show underlying behaviour and the impossibility of being responsive to evolving policies (McNally, 2000). These models evolve from statistical estimation of aggregated-level (in space, time and travellers (Kagho *et al.*, 2020)) and long-term travel demand used in trip-based models (i.e., FSM), to understand disaggregated-level behavioural response and short-term demand policies, such as congestion pricing and ridesharing, transforming the trip-based perspective to a tour-based (Pinjari and Bhat, 2011).

This new perspective allows the use of disaggregated personal-level information (both in time and space (Rasouli and Timmermans, 2014)). Data contains detailed travel information of each individual (e.g., duration of trips, location, frequency, sequence) (Zhong *et al.*, 2015), and the use of time as a continuous domain, where individuals choose how to use it among their activities and travel, instead of being a simple factor of cost (Pinjari and Bhat, 2011). To achieve this goal, AcBMs require the use of a synthetic travel demand as input data (Ziemke, 2022), which can be defined as a simplified digital representation of the individuals living in the area of study. From each individual, some of their socio-demographic attributes (e.g., age, sex, income) and a daily activity plan (e.g., a sequence of activities where purpose of trip, starting time, geospatial departure and arrival locations and transport mode used) are known. Modelling, therefore moves from computations on zonal aggregates to decision making of individuals (Horni, 2005; Ziemke, 2022), as well as allowing the analysis of policy impacts in certain subgroups of the population (Kitamura, 1988; Ziemke, 2022), based on similar socio-demographic characteristics, which could provide better forecasts of future travel patterns (Castiglione and Bradley, 2014; Ziemke, 2022). Vovsha and Bradley (2006) add as an improvement the possibility of incorporating explicit modelling of joint travel by members from the same household. Besides, Rasouli and Timmermans (2014) enumerate the four main improvements AcBM could achieve when compared against the former model:

- A higher spatial and temporal resolution.
- Human behavioural decisions inclusion.
- An improvement in the integrity of the model system.
- The interdependence of trips as a tour-trip.

Activity-based model limitations

However, as Zhong *et al.* (2015) describe in their comparison between the traditional FSMs and AcBMs, currently the former remains the most popular modelling approach, mainly because they are simpler and easier to implement. Even when AcBMs are more flexible, can provide richer information analysing travel demand and supply at specific times of the day and can represent better demographic and land use variables in policy analysis, FSMs are usually preferred.

2.5.3. Agent-based models

Agent-based models (AgBMs) are a facet of wider Multi-Agent Systems (MAS) research (Malleson *et al.*, 2022), defined as spatio-temporal computational simulations of individuals interacting with the environment and with other individuals during their daily activities, providing a microscopic representation of the individuals' travel decisions, revealing their behaviours and the implications of their interaction in the transportation system (Kagho *et al.*, 2020). Bonabeau (2002) defines them as a technique for the investigation of relationships between the behaviour of individual entities and their influence in shaping system dynamics (Manley and Cheng, 2018). Other researchers (Bonabeau, 2002; Heard *et al.*, 2015; O'Donoghue, 2021; Ziemke, 2022), define AgBM as *"a system modelled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions based on a set of rules"*. Bandini et al. (2009) add that the global system dynamics are not defined in terms of a global function, but rather the result of individuals' actions and interactions (between them and the environment). Abar *et al.* (2017) define the AgBM philosophy as a model of complex systems adopting a bottom-up approach, where the interactions in space and time between agents and the environment are considered first. These models are unique in the ability to combine heterogeneous and dynamically changing processes of complex systems from autonomous agents, intending to investigate the emergent and collective effects on the system (Moyo Oliveros and Nagel, 2016; Huang *et al.*, 2022). As Malleson *et al.* (2022) state, AgBMs are gaining popularity in urban environments as a valuable method for understanding the low-level interactions that ultimately drive cities, although their use and implementation by stakeholders is low.

Agents are defined as the minimal and basic unit and can represent any type of autonomous entity (Huang *et al.*, 2022) (person, vehicle, facility). In transport AgBMs, agents representing humans are characterised by their socio-demographic attributes (e.g., sex, age, income) and an activity plan, which defines their routines to be performed during the simulation (e.g., travel starting times, purpose of the trips, transport modes and activity locations), similarly to an AcBM. Agents representing vehicles are characterised by their use (public or private), speed limit, maximum occupancy and dimensions (width and length); agents representing facilities are characterised by their use, maximum capacity, opening times, etc. Based on their characteristics, agents are governed by a set of rules that define how they interact among themselves and with the environment (Kagho *et al.*, 2020). The combination of the individual characteristics and rules to follow by each agent allows the agents the possibility of possessing the following features (Bonabeau, 2002; Macal and North, 2005; Roorda *et al.*, 2010; Heppenstall *et al.,* 2016; Huang *et al.*, 2022):

- They are autonomous and they do not need any external intervention.
- They can cooperate with the environment and/or other agents to achieve their goals.
- They can learn from the gained experience and can adapt and respond to changes.

Besides the agents, the environment is essential too, as it influences the behaviours of the agents in terms of perception and allowed actions (Bandini *et. al,* 2009). It is the scenario that allows the agents to move and interact in space and time with other agents, including information about the road transport network (e.g., number of lanes, length, maximum speed, capacity, transport modes allowed), the public transport services (e.g., routes, stops and schedules) (Kagho *et al.*, 2020), and any other relevant information (e.g., road gradient). As a whole, this scenario represents a digital replica of a real location with simplified characteristics.

Both the agents and the environment are combined in a computational software to simulate their interactions in space and time, based on their characteristics, rules, activity plans and environmental conditions. AgBMs enable a more realistic modelling of complex systems, since the dynamics and the interaction between the different agents and their environment can be explicitly expressed, as Franco *et. al* (2020) describe. Bastarianto *et al.* (2023) add the ability of the agents to learn, adapt, and hold different perceptions of an environment as important improvements compared against previous models. Furthermore, Manley *et al.* (2014) argue that AgBMs have the potential to move beyond traditional assumptions of traffic distribution equilibrium, building traffic patterns from individual behaviours upwards, considering their own characteristics, preferences and/or disabilities.

The agents' interactions between them and the environment provide a new perspective in transport modelling that could not be obtained from previous models. The interactions of the agents in space and time allow them to adapt and learn from what others do. Examples were highlighted by Bazzan and Klügl (2014), where they describe that agents' interactions allow their adaptation and learning capacity to simulate realistic and optimised behaviours. The decisions made by an individual agent are derived from their own characteristics (i.e., age, car access), but also from the behaviour of the whole group of agents. If a majority of agents use the car at the same time through the same roads and are stuck in congestion, some of them will learn from the experience and adapt their behaviours by choosing a more efficient transport mode (e.g., public transport modes, cycling), changing the route or adapting their trip starting time. Molin *et al.,* (2008) add that these interactions could allow for knowing social interactions between agents from the same household, with similar characteristics and/or preferences. Agents could choose and adapt their trips, transport modes and activities based on their social relationships with others.

Additionally, agents' interactions with the environment allow for knowing how the built environment could affect their daily routines. Characteristics, such as the road type and slope, and the existence of lighting and cycle paths, could be considered when agents, based as well on their own socio-demographic characteristics, decide how, when and where to go. The decisions made by individuals based on the built environment characteristics are encapsulated within the '*spatial cognition*' concept, which describes the effect of environmental factors on mobility (Manley and Cheng, 2018; Gr *et al.*, 2019; Manley *et al.*, 2021), and therefore the transport mode choice.

Agent-based model limitations

Unfortunately, these models have limitations and face several challenges for implementation. Firstly, such models require the collection, processing, and cleaning of vast amounts of data to generate a heterogeneous synthetic population and transport network, where errors could be introduced due to the lack of required data, the use of incomplete datasets or potential requirements of data transformation (Kagho *et al.*, 2020). Secondly, computational efficiency and cost have been also described as current limitations. They are mainly dependant on complex computer environments due to the amount of required agents to be simulated (Kagho *et al.*, 2020; Huang *et al.*, 2022), especially when different components (e.g., mode choice, route choice, scheduling, land use, ride-sharing scheme, destination choice) are combined (Bastarianto *et al.*, 2023). Thirdly, there are limitations in agents' behaviour, where Huang *et al.* (2022) consider that the human behaviours should also consider intelligent perspectives like preferences and memory. In a similar approach, Manley *et al.* (2014) consider that more research is needed in the route choice, where models are based on traffic equilibrium and individual preferences are not fully considered, which could add behavioural homogeneity into the model. Model calibration and validation have also been considered as shortcomings (Kagho *et al.*, 2020; Huang *et al.*, 2022; Bastarianto *et al.*, 2023). There is a lack of explicit calibration and validation stages. Huang *et al.* (2022) state that these processes should be included within the development of the model to demonstrate their validity and accuracy. Bastarianto *et al.* (2023) urge for unified calibration and validation methods. Transparency is another limitation, due to AgBMs being complex models and the understanding of the numerical details and the mechanical process of how agents interact in space and time is not trivial (Kagho *et al.*, 2020). Reproducibility is also a critical limitation of AgBMs (Kagho *et al.*, 2020), as the possibility of other researchers and/or policy makers replicating results is scant, mainly due to confidential data and tools used, although more open-access datasets, tools and repositories have been generated in the last few years (Bastarianto *et al.*, 2023). Lastly, AgBMs lack standardisation (Kagho *et al.*, 2020). Terminologies, concepts, documentation and expectations should be defined and be stable within the field.

2.5.4. Comparison between the transport planning models for active modes

The previous sections have summarised the three main models available to estimate the impact of transport mobility policies. They allow the identification of the potential success or failure before the policies are implemented in the real world. Figure 5 summarises the advantages and disadvantages of each transport model.

Firstly, the FSMs or trip-based models allow the analysis of the transport demand as a set of aggregated traffic flows between the centroids of the defined zones. These models are still extremely popular and in use due to their simplicity and ease of implementation, although their simplicity makes them hold several assumptions and limitations. The most critical ones are the aggregated outcome (in space, time and individuals); the lack of spatial and temporal interrelationships between trips; and the modal split stage is mainly focused on motorised travel modes.

	Four-step model	Activity-based model	Agent-based model
Advantages	Easy to develop	Tour-based perspective Disaggregated data (personal, spatial and time) Multi-day patterns Human behaviour Diversity of transport modes Useful for short-term policies Possibility to test policies for specific groups in society	Tour-based perspective Disaggregated data (personal, spatial and time) Multi-day patterns Human behaviour Diversity of transport modes Useful for short-term policies Possibility to test policies for specific groups in society Agents interact in space and time The effect of the built-environment is taken into account Ability of agents to learn based on their simulated experiences
Disadvantages	Simple Trips Travel time is assumed constant No active modes No consideration of potential congestion Use of aggregated and static data All trips start and end in areas' centroid Aggregated outcomes Human behaviours not taken into account	Data constraints (collection, analysis) Computational time Calibration Validation	Data constraints (collection, analysis) Computational time Calibration Validation

Figure 5 Comparison of advantages and disadvantages of the different transport models analysed.

Secondly, AcBMs improve some of the limitations highlighted for the FSMs, through the analysis of travel demand from a disaggregate point of view considering the individual characteristics (e.g., age, income, sex) and their decisions, the interdependency of trips and the consideration of space and time between activities. These characteristics make AcBMs more flexible and can provide richer information of travel demands at different times of the day, as well as representing better demographic variables within the analysis of mobility policies. Unfortunately, these improvements make these models more difficult to implement, and consequently less broadly used by policy makers and transport planners.

Lastly, AgBMs allow the simulation of the interactions, in space and time, of individuals (agents), based on their socio-demographic attributes and activity plans. AgBMs contain all the information from AcBMs and provide the possibility of virtually representing the individuals' travel decisions, their behaviours and their interactions in the transport network, which could not be obtained with any of the other models described before. Heppenstall *et al.,* (2016) suggest that one of the most appealing aspects of AgBMs is their ability to represent human behaviour and, through simulation, understand how these behaviours play out over space and time.

Consequently, the most appropriate models to analyse policies to enable citizens in the shift to active travel modes are AgBMs, as they allow consideration of individual characteristics of the agents, their interactions in a spatio-temporal environment and the possibility of simulating diversity of transport modes simultaneously. Overall, AgBMs provide the possibility of showing more realistic transport human dynamics than previous models. The approaches of statistical models and AgBMs are opposite to each other. While the first is a top-bottom approach (based on aggregated statistical results), the latter is a bottom-up, where heterogeneous mobility decisions made by the agents can be reproduced (Mehdizadeh *et al.,* 2022) and analysed. As Mehdizadeh *et al.* (2022) estate, statistical models cannot reveal the dynamics about the decisions made by individuals when making choices (e.g., route or transport mode), while AgBMs consider them thanks to the interactions in space and time.

The choice to use AgBMs is supported by other researchers. Franco *et al.* (2020) consider that AgBMs enable a more realistic modelling of complex systems, since the dynamics and the interaction between the different entities and their environment can be explicitly expressed. Kagho *et al.* (2020) highlight that the use of AgBMs to model transport behaviour is growing and the future looks bright for it in the midterm, although there are many challenges that need to be overcome. Batty (2001) also identifies AgBMs as a powerful alternative to consider active modes because individual actors (e.g., agents) are taken into account within the models, where the behaviours of each actor are considered as a function of others in the system.

2.6. Transport AgBMs

Once AgBMs where identified as the best method to analyse the efficiency of urban mobility policies for active modes, the following sections explore in this methodology, as well as its applications and available tools.

2.6.1. Transport AgBM publication research

The AgBM environment is wide and diverse. In the last decades, several AgBMs have been used broadly by different researchers and industries in different fields of research (e.g., biology (An *et al.*, 2017), epidemiology (Alvarez Castro and Ford, 2021), social and nature science (Gilbert and Terna, 2000), education (Kirk Harland and Heppenstall, 2012), computing (Tang *et al.*, 2011), logistics (Clausen *et al.*, 2019), urban planning (Chen, 2012), politics (Dacrema and Benati, 2020), finance (Samanidou *et al.*, 2007; Abar *et al.*, 2017). The use of AgBMs has been increased due to the improvement in the technology development, computational resources and data accessibility (Huang *et al.*, 2022). In the field of transportation, AgBMs have also been used for a great variety of topics (Huang *et al.*, 2022): traffic management frameworks (Adler *et al.*, 2005; Ossowski *et al.*, 2005; Wang, 2005; Chen, Cheng and Palen, 2009), congestion management (Logi and Ritchie, 2002), traffic policy (Iordanova, 2003), traffic signal control (Srinivasan *et al.*, 2006; Chen and Cheng, 2010; Xu *et al.*, 2019; Yu *et al.*, 2021), transport logistics (Serrano-Hernandez *et al.*, 2018) and travel behaviour (Xiong *et al*., 2018).

Classification of transport AgBMs

Transport AgBMs can be classified in four categories based on the level of detail (Passos *et al.,* 2011; Lopez *et al.*, 2018; Nguyen *et al.*, 2021): macroscopic, microscopic, mesoscopic and nanoscopic.

- Macroscopic models are used for the analysis of wide areas, where no detailed modelling is required, due to being based on high-level mathematical models.
- Microscopic models consider a high-level of detail, as agents are simulated individually, being used for urban traffic analysis.

- Mesoscopic models are a combination of the previous models, as traffic entities are modelled at a higher level of detail than macroscopic models, although the agents' interactions and behaviours are less detailed.
- Lastly, nanoscopic models are even more detailed than microscopic, where smaller components of the agents (e.g., sensors from a vehicle) are considered, being especially relevant for autonomous driving scenarios.

The macroscopic, microscopic and nanoscopic models have two fundamental components that need to be defined as input data (Nguyen *et al.,* 2021): demand and supply. The first relates to the travel requirements for each agent, where information about the socio-demographic attributes (e.g., age, sex, income), also known as synthetic population, and the activities performed by each agent (e.g., purpose of the trip, starting time, transport mode) are defined, although depending on the level of detail chosen, different data is required. The second is a digital representation of the road network used by the agents to move between activities. It is a graph of links and nodes that represent the intersections and roads, respectively (Nguyen et al., 2021).

Currently, the use of mesoscopic AgBMs to simulate mixed interactions of micro-mobility modes (e.g., walking, bicycles, e-bikes, e-scooters) is in discussion, as spatial interactions that occur at the micro-level (e.g., traffic safety, intersections, road lane changes) between themselves and other vehicles (e.g., cars, buses) could be missed. Tzouras et al. (2023) highlight this aspect focusing on the simulation of e-scooters, where a dilemma between modelling their behaviours and interactions at a link level and predicting long-term travel behaviour using microscopic models is identified. The former could simplify the interactions, while the latter currently does not have the required capacities to model bicycle or pedestrian traffic or is not capable of simulating large-scale networks. Their conclusion considers the development of a hybrid model that could combine the analysis in network and link levels.

Transport AgBMs literature review

Bastarianto *et al.* (2023) reviewed the use of dedicated transport AgBMs in urban transportation from 2006 to 2022 and identified an exponential increase in the number of publications since 2015. The reasons given to explain the increase of AgBMs are two: the significant improvement in computing performance and the use of fully open-source tools. The topics analysed in the papers have been evolving over time, being focused on congestion pricing initially, while emerging transport modes (e.g., ride sharing, demand responsive transport and EVs) appeared later and have become dominant today. The geographical distribution of papers was analysed as well, and it was observed that most of them are focused on transport scenarios of developed countries (Germany, USA, Switzerland and Singapore). Publications found were grouped in nine clusters:

- General transport modelling (Fujii *et al.*, 2017; Manser *et al.*, 2020).
- Travel behaviour (Shirzadi Babakan *et al.*, 2015; Ali *et al*., 2016; Park *et al.*, 2018; Zhu *et al.*, 2018).
- Emerging transport modes (Fagnant and Kockelman, 2014; Boesch *et al.*, 2016; LaMondia *et al.*, 2016; Inturri *et al.*, 2021; Tzouras *et al.*, 2023).
- Transport policy (Zheng *et al.*, 2012; Zheng *et al.*, 2014; Kaddoura *et al*., 2020).
- Urban logistics (Martins-Turner *et al.*, 2020; Sakai *et al.*, 2020).
- Travel demand (Beckman *et al.*, 1996; Ye *et al.*, 2009; Farooq *et al.*, 2013; Mallig *et al.*, 2013; Wu *et al.*, 2019; Franco *et al*., 2020; Hörl and Balac, 2021b; Sallard *et al*., 2021; Prédhumeau and Manley, 2023).
- Parking (Waraich and Axhausen, 2012; Bahrami and Roorda, 2022).
- Public transport (Shen *et al.,* 2018; Gallet *et al.,* 2019; Narayan *et al.*, 2019, 2020; Manser *et al.*, 2020; Rahman *et al*., 2020; Kii *et al.*, 2021; Barbet *et al.*, 2022).
- Shared autonomous taxi (Hörl, 2017; Lokhandwala and Cai, 2018; Kim *et al.*, 2019; Liu *et al*., 2020).

Mehdizadeh *et al.*(2022) did a review of 86 AgBMs in mobility transition between 2006 and 2021, where '*mobility transition*' refers to the shift from traditional mobility patterns to innovative and sustainable mobility options (Köhler *et al.*, 2009; Fagnant and Kockelman, 2015; Docherty *et al*., 2018; Mehdizadeh *et al.*, 2022). In this review, half of the publications were focused on the distribution of EVs to investigate market share penetrations from different perspectives (Querini and Benetto, 2014; Kieckhäfer *et al.*, 2017; Pagani *et al.*, 2019; Rodemann *et al.*, 2019; Klein *et al.*, 2020; Ning *et al.*, 2020; Huang *et al.*, 2021; Lee and Brown, 2021; Zhuge *et al.*, 2021). The remaining half was focused on several topics: automated mobility on demand (Basu *et al.*, 2018; Oh *et al.*, 2020), modal shift to sustainable modes

(Faboya *et al.*, 2020; Maggi and Vallino, 2021), shared mobility services (car-sharing, ridesharing, bike sharing, carpooling) (Fagnant and Kockelman, 2014; Inturri *et al.*, 2019), and alternative fuel vehicles (hydrogen or natural gas) (Vliet *et al.*, 2010; Sopha *et al.*, 2017).

Transport AgBMs and active modes

Within these two publication reviews, it is possible to identify clusters where modal shift and/or the use of active travel modes are analysed (e.g., transport policy in Bastarianto *et al.* (2023) and modal shift to sustainable modes in Mehdizadeh *et al.* (2022)). This is the case in Zheng *et al.* (2012), where a dynamic cordon pricing scheme is simulated in Zurich (Switzerland). Results show that the applied congestion pricing reduced the travel times, congestion within the area was eased and the effects on leisure activities were stronger than when commuting, although references to the use of active modes are not specified. Zheng *et al.* (2014) analyse the impact of a time-dependent pricing scheme in Sioux Falls (USA), considering the level of congestion in time and the user's adaptation to the toll cost, with the goal of incentivising the use of public transport modes, although active modes were not considered in this publication either. Results show effective congestion reductions in the area of study and a modal shift to public transport modes due to accessibility improvements and money rewards. Kaddoura, Leich and Nagel (2020) analyse different concepts for demand responsive transit in Greater Berlin (Germany), although the possibility of including scenarios for active modes was not considered. Results show that small zones of influence and very low prices could make pedestrians and cyclist move to Demand Response Transit (DRT), while this unwanted consequence was reduced when tariffs were more expensive, and larger DRT areas could shift car drivers to DRT. Maggi and Vallino (2021) research the potential impact of price-based and preference-based policies on commuter's mode choice in urban areas. This scenario considers the agent's characteristics, mode preferences, commuting price and pollution emission estimation when choosing the mode used. Within the mode option, cycling was considered, and results show that agents prefer a shift from car to bicycle than to public modes when the use of cars is disincentivised, although the consideration of physical effort or slopes for cyclists was not cited. Park *et al.* (2018) simulated active modes in New York City (US) to support investment decisions and evaluate the impact of infrastructure changes on walking and cycling. Their results show that improving sidewalk and cycle path conditions could positively increase the number of people using them, although limited characteristics of the built environment (e.g., sidewalk width, bike lane type) were considered, and road gradient was not included.

Besides previous research publications, it is possible to find others analysing active travel modes and modal shifts for a sustainable transport system that were not included within the two previous reviews, mainly due to the models used being generic or self-developed transport AgBM tools, and that were published after these two reviews. Some examples are described below.

Kaziyeva *et al.* (2021) developed an AgBM to simulate transport mobility in Salzburg (Austria) and focused on cycling traffic flows, as a response to the emerging phenomenon for individual mobility, using GAMA (Taillandier *et al.*, 2018). The model simulates mobility patterns of a synthetic population of 186,000 agents in a one-minute time resolution, considering six transportation modes (bicycle, walk, car, car-passenger, public transport and other), while the model was only validated using bicycle counts. Later, Kaziyeva *et al.* (2023) improved the model to be focused on the two active modes, in response to the little attention that cycling and walking have had in transport simulations. This model allows simulation of different traffic conditions with altered travel behaviours and the built environment. Similarly, Leao *et al.* (2017), developed another AgBM using GAMA focused on understanding the patterns and behaviours of cyclists, in the city of Sydney (Australia), although only cycling modes where simulated and gradients of the roads were not considered. The model was validated against data obtained from a mobile phone app that collects information about cyclists in the area of study.

Thompson *et al.* (2017) self-developed an AgBM tool to explore the potential effects in safety when introducing different levels of segregated cycle paths, where drivers are considered to have behavioural adaptations in response to cyclists' exposure. The main conclusion obtained was that soft implementation of cycle paths (i.e., painted lanes) are not enough to keep cyclists safe when a behavioural adaptation is assumed among drivers. Thompson *et al.* (2019) simulated and analysed the effects of cycling density and collisions between cycling and motorists at road intersections, using a self-developed AgBM tool. They conclude that potential collisions could be reduced when the number of cyclists passing through the intersection is increased, making car drivers more aware of the presence of cyclists on the road. Jafari (2022) provides a new AgBM tool (AToM), based on MATSim (Horni *et al.*, 2016), to analyse cycling in the region of Greater Melbourne (Australia). Different built environmental interventions affecting diverse groups of society were tested (e.g., the implementation of cycle lanes and the impact of traffic signals on cycling), considering different subgroups of the population. The conclusions obtained for the former were that older cyclists and middle-aged female groups would increase the use of the bicycle if new cycle lanes were implemented, due to improvement in safety and security, although interactions between cyclists and car drivers were not considered as only bicycle trips were simulated. For the latter, it was concluded that traffic signals are the most important factor that affects cyclists' speed. The model was validated against traffic speed sensors.

Jafari and Both (2021) have also analysed the use of active transport modes within Melbourne. They developed a MATSim model to test different scenarios for sustainable modes. Within them, they analysed the current cycling infrastructures, the existence of gaps in the network and the potential health improvements when enabling people to use active modes. Schlenther *et al.* (2022) investigate scenarios to reduce the number of motorised vehicles on the road in Hamburg (Germany), using MATSim. They analysed the impact of implementing economic penalties to those agents using motor vehicles, the implementation of segregated cycle paths to incentivise the use of bicycles, the possibility of using ride-sharing, the inclusion of shuttle payable services to and from public transport stops, the upgrade of public transport schedules, the implementation of parking limitations and speed limit and road capacity reductions in urban areas. Results achieved showed that the attractiveness improvement of public transport modes are not enough to achieve a great shift from the use of polluting vehicles to sustainable modes (around a 3%-point decrease), although more significant reductions are achieved with policies that penalise the use of private vehicles (8%-points). In terms of cycling, the implementation of safe infrastructures could increase the number of cyclists by 8%-points, although the model did not consider the characteristics of the built environment, so the choice of cycling is not affected by road characteristics (e.g., gradient and road type), which limit the accuracy of the results achieved. Lastly, Hitge and Joubert (2023), developed a model to estimate a potential cycling demand in Cape Town (South Africa). Their model showed that 32% of agents would benefit from cycling, although the percentage was reduced by 8% when socio-demographic characteristics (e.g., age, gender, household income, household composition and dwelling type) were considered. Spatially, their results showed that almost half of those agents that could benefit from using bicycles were concentrated in a small area of the whole area of study, which could help policymakers in prioritising the implementation of new cycle paths.

In terms of walking, Badland *et al.* (2013) self-developed an open-source simple AgBM tool focused on walking to test scenarios to improve walkability in neighbourhoods, where roads were used instead of sidewalks due to lack of access to the required dataset. Yang *et al.* (2011) developed a new AgBM tool to simulate the behaviour of people walking, considering attributes like age, sex, walking ability, and attitudes towards walking. The latter characteristic evolves over time as a function of previous experiences and attitudes toward walking of the other individuals within their social network, among others. Their model is applied to a non-real city, so validation of a specific region in the world is not possible.

Reasons for the lack of AgBMs focused on active modes

As can be observed, the number of publications concerning AgBMs that focus on active modes for a sustainable and less polluting transport sector is modest. Only ten publications focused on cycling (Shimizu *et al*., 2014; Leao *et al.*, 2017; Thompson *et al.*, 2017, 2019; Lu *et al.*, 2018; Kaziyeva *et al.*, 2021; Maggi and Vallino, 2021; Jafari, 2022; Schlenther *et al.*, 2022; Hitge and Joubert, 2023), two on walking (Yang *et al.*, 2011; Badland *et al.*, 2013) and another three on both (Park *et al.*, 2018; Jafari *et al.,* 2021; Kaziyeva *et al.*, 2023) were identified.

Batty (2001) highlights that the main reason why walking is usually discarded from the analyses (although the concept could be extrapolated to all active modes) is due to transport models originally being focused on vehicle expansion, as a response to the increase in the private vehicle demand. Even nowadays, Batty's perspective can still be considered valid. Additionally, although active modes are a fundamental component to achieve a net-zero transport future, most efforts seem to be focused on the electrification of vehicles. This converges with the number of publications combining AgBMs and EVs, as was observed by Bastarianto *et al.* (2023) and Mehdizadeh *et al.* (2022). Batty (2001) also highlights the lack of available granulated data to analyse pedestrian movements (and other active modes). Kaziyeva *et al.* (2023) also agree with the lack of validation data, while Jafari (2022) adds the heterogeneous nature of active travel behaviours. The lack of available data should be reduced due to new datasets and ways to quantify and define active travel patterns (e.g., bicycle counts, walking counts, mobile phone data); while the heterogeneous nature of active travel behaviours is researched by fields of transport psychology and transport behaviours, among others.

Transport AgBMs and active modes within the industry

Fortunately, the analysis of active modes combined with AgBMs is gaining momentum within the industry. One example is the case of the City Modelling Lab (CML), an Arup department focused on the simulation of transport scenarios using AgBMs to achieve a net-zero transport future. Within their expertise, they develop scenarios where active modes are the core. Nick Bec, CML leader, explains in an interview that they break down modal silos and show all the benefits active travel can create for their clients (ZAG Daily, 2023). They consider active modes as a main component of their work and expect that active modes will have a more significant role in transport policy, infrastructure and investment. In line with this approach, they have developed scenarios where socio-demographic attributes as well as conditions of the built environment (e.g., slope and road conditions) are considered when choosing and using bicycles (e.g., maximum speed reached based on the socio-demographic attributes and the road conditions) (Kozlowska, 2023). They also agree that active travel is overlooked in decision making due to the difficulty of quantifying its impact and benefits when compared to other transport modes (Intercharge, 2023).

2.6.2. Transport AgBM tools

Since AgBMs have been used as transport models, several tools have been developed and used for a wide variety of transport modelling purposes. Nguyen *et al.* (2021) developed a very detailed list of more than 35 AgBM tools, with some of the most well-known being: MATSim (Horni *et al*., 2023), POLARIS (Auld *et al.*, 2016), the integration of SUMO (Krajzewicz, 2010) and JADE (Bellifemine *et al.*, 2005), AgentPolis (Jakob *et al.*, 2012), ITSUMO (Bazzan *et al.*, 2010) and SimMobility (Adnan *et al.*, 2016).

MATSim (Multi-Agent Transport Simulation) is an open-source mesoscopic tool written in Java, firstly developed by ETH Zurich in 2006 and now contributed to and developed by researchers worldwide. This tool simulates large-scale (Nguyen *et al.*, 2021), mesoscopic (Franco *et al*., 2020), multi-modal (Bösch and Ciari, 2015; Poletti, 2017) traffic and congestion patterns considering individualised information of the agents (Horni *et al.,* 2023), and vehicular traffic flow (Auld *et al.*, 2016), in a queue-based paradigm (Bazzan *et al.*, 2010), through a road and transport network supply. The agents interact in space and time and compete for transport resources (infrastructure and available modes), following a stochastic (Horni et al., 2016) co-evolutionary algorithm (Ziemke, 2022) that allows the agents to learn and improve their performance based on their interactions until an equilibrium is reached.

POLARIS is an open-source large-scale mesoscopic model written in C++. It was published in 2013 (Nguyen *et al.*, 2021) and was the first to integrate the activity-based demand model estimation, network simulation and intelligent transportation system operation components within the simulation, although it is not a tool specifically designed for transport modelling, but general purposes (Auld *et al.*, 2016).

The SUMO (Simulation of Urban MObility) and JADE (Java Agent Development Framework) integration is a combination of two open-source tools. The first is a microscopic traffic simulation framework written in C++ that simulates the mobility of vehicles (Krajzewicz, 2010), whilst the latter is a framework to develop AgBMs and allows the interaction of agents (individuals) in the environment with the vehicles (Bellifemine *et al.*, 2005), considering traffic control systems (e.g., traffic lights). This combination, developed by Soares and Kokkinogenis (2014) allows JADE agents (drivers) to be linked to SUMO agents (vehicles) (Nguyen *et al.*, 2021). It simulates a population of drivers (with information of their activities as individual trips, flows or routes) within two road networks. The first is a nanoscopic network where drivers make decisions about their movements considering the traffic control system, while the second is a microscopic network where vehicles interact (Soares and Kokkinogenis, 2014). It was developed as a response to the current and future urban congestion due to the increase of population in urban areas, as well as to the complexity and uncertainty of the transportation system.

AgentPolis, developed by the Artificial Intelligence Centre at Czech Technical University in Prague (Franco *et al.*, 2020), is a tool written in Java that allows the modelling of multi-modal transport systems, providing to each agent asynchronous and free interactions between the environment and other agents. This allows them to adjust their plans at any time based on their observations of the environment and/or communication with other agents (Jakob *et al.*, 2012). However, Čertický *et al.* (2014) critique the tool because most of the software architecture is hidden and does not allow for fine tuning of some variables (Inturri *et al.*, 2019).

ITSUMO (Intelligent Transportation System for Urban Mobility) is an open-source microscopic traffic simulator written in C++ and Java (Nguyen *et al.*, 2021). It allows the modelling of different traffic actors (e.g., drivers, intelligent transportation system and autonomous vehicles) as autonomous agents, considering the control of traffic lights and en-route re-planning, applying a combination of AgBM and AI techniques, its focus and main goal being to simulate traffic control scenarios (Bazzan *et al.*, 2010). This tool simulates traffic movements in a very simple approach, by applying cellular automata (CA) techniques in discrete steps (not continuous) (Bazzan *et al.*, 2010).

Lastly, SimMobility is an open-source microscopic tool written in C++ (Nguyen *et al.*, 2021), where land-use, transportation and communication interactions are considered between different types of agents, its main focus being on intelligent transportation systems, transportation networks and vehicle emissions simulations. This tool allows the simulation of scenarios where the time steps are fractions of a second (e.g., changes of road lane, braking, mobile phone communications between agents), seconds to minutes or days (e.g., activity plans of the agents) and days to months or years (e.g., long-term choices such as house and job relocation) (Adnan *et al.*, 2016).

Between all of them, MATSim is the most popular and the most frequently used transport AgBM (Bastarianto *et al.*, 2023) and possesses the largest user community (Nguyen *et al.*, 2021). Besides its popularity, MATSim has been identified as the tool that best suits the required conditions to simulate urban mobility policies to enable citizens to use active travel modes. Tzouras *et al.* (2023) conducted a qualitative assessment about the use of different transport AgBM tools based on the following ten criteria:

- Is open-source and allows the development or integration of multiple extensions
- Has been used to simulate shared mobility

- Has been used to perform large scale transport networks
- Can describe spatiotemporal variation of demand
- Can simulate bicycle traffic in cycle lanes
- Can simulate pedestrians on sidewalks
- Can simulate mixed traffic
- Considers socio-demographic characteristics
- Can integrate new choice models
- Can simulate multimodal trips

Within the compared tools, MATSim and SimMobility were the ones that achieved the best results (nine out of ten criteria in both cases). MATSim lacks a proper simulation of pedestrians on sidewalks, although it is possible to consider them as part of the simulation using a dedicated network. SimMobility lacks the simulation of bicycle traffic in cycle lanes, which implies that bicycles share the roads with other vehicles at all times.

Comparison of the previous two tools, based on their previously explained characteristics, makes MATSim the preferred tool. Firstly, MATSim simulates a normal working day, while SimMobility simulates three different and combined time steps (i.e., from fractions of a second up to years), which could overcomplicate and oversize the goal of this project. Secondly, MATSim uses a mesoscopic road network with detailed information, while the SimMobility tools use very detailed nanoscopic networks that are not required for the purpose of this project either, as their main purpose is traffic management. Lastly, MATSim is a mature transport AgBM tool being in use for more than 15 years, and although it is not perfect nor fully validated, possesses the required capacities and qualities requested to simulate transport mobility scenarios.

2.6.3. MATSim models

MATSim has been used for different and diverse approaches. One of the main ones is to model transport scenarios of cities, regions, or countries. Examples are the transport simulation models developed for Singapore (Erath *et al*., 2012), Santiago de Chile (Kickhöfer *et al.*, 2016), Berlin (Ziemke *et al.*, 2019), Basel (Becker *et al.*, 2018), London (Serras *et al.*, 2016), Switzerland (Horni and Balmer, 2016), Zurich (Rieser-Schüssler, 2016), Munich

(Kickhöfer, 2016), Barcelona (Picornell and Lenormand, 2016), Caracas (Walter *et al.*, 2016), Dublin (Cudden, 2014), Germany (Illenberger, 2016), Hamburg (Klüpfel and Lämmel, 2016), New York city (Dobler, 2016) and Toronto (Weiss *et al.*, 2016), among others. In these scenarios, the outcomes show the transport mobility in space and time of the simulated areas.

These scenarios could be then used for a great variety of simulated purposes: firstly, to analyse current transport situations; secondly, to test the potential implementations of infrastructure interventions (e.g., new road network developments, tolls); thirdly, to test changes in human behaviours (e.g., transport modes use based on personal characteristics, new transport modes); and lastly, to test the consequences and impact of natural hazards (e.g., floods). From the first group, it is possible to find publications using MATSim to estimate public transport congestion in UK urban areas (Raimbault and Batty, 2021) and to optimise taxi services (Maciejewski and Nagel, 2013). Publications within the second group are related to replanning strategies for congested traffic (Tchervenkov *et al.*, 2020), to testing efficient truck bans in urban areas (Joubert, 2019), the implementation of infrastructures for electro-mobility (Rojano-Padrón *et al.*, 2023) and the implementation of a cordon toll policy in urban areas at various times of the day (Bassolas *et al.*, 2019). The third group analyses the human behaviours when using different transport modes based on their sociodemographic attributes (Müller *et al.*, 2022), the adoption of shared micro-mobility modes (Diallo *et al*., 2023), the implementation of car-sharing schemes (Ciari *et al.*, 2016), ride-sharing mobility services (Franco *et al.*, 2020), car-pooling and car-sharing services (Ayed *et al.*, 2015), shared autonomous vehicles (Müller *et al.*, 2020) and autonomous taxi services (Hörl, 2016). The last group contains publications analysing the evacuation of cities due to a tsunami (Muhammad *et al.*, 2017), the response of the agents affected by extreme weather conditions (Heyndrickx *et al.*, 2015), the alternative road traffic routes due to natural disasters (Yaneza, 2016) and the impact of river floods (Saadi *et al.*, 2016).

There are MATSim scenarios focused on cycling, developed by Afshin *et al.*, (2021); Jafari (2022); and Hitge and Joubert (2023), as previously cited. Apart from developing scenarios for active modes, there are also publications expanding the capacities of MATSim when simulating these modes. This is the case of the bicycle contribution developed by Ziemke et al. (2019), who developed an extension to model bicycle traffic more realistically, considering characteristics of the built environment (i.e., type of the road, the road surface type, the existence of cycle paths and gradient). These characteristics are considered by cyclists when choosing their routes, providing more realistic results of bicycle traffic and cyclists' behaviours.

In addition to being a popular tool among academic researchers, MATSim is gaining momentum in the industry. Projects developed by Arup CML were described before, while Catapult Connected Places have been developing MATSim models for the analysis of Mobility as a Service (Catapult Connected Places, 2018), assessing sustainable transport solutions for rural mobility (Connected Places Catapult, 2020), and the introduction of new mobility services in urban areas (Franco *et al.*, 2020; Catapult Connected Places, 2021). Government transport departments are also interested in the use of MATSim for their transport simulation and analysis. New Zealand, in partnership with Arup, is developing a MATSim model to simulate the behaviour of New Zealand's transport system and test road pricing scenarios (Ministry of Transport, New Zealand, 2022). The Swiss Federal Railways (SBB) developed a MATSim model to simulate the entire population of the country and support real decisions in terms of service and infrastructure (Scherr *et al.*, 2020). Germany is also developing MATSim models. The Institute of Transport Research (DLR in German) is building a MATSim model jointly with the Technical University of Berlin (TUB). Their goal is to develop a model for a successful transport sector and investigate innovative transport services for passengers and goods (German Center for Aviation and Space Flight (DLR), 2024). Additionally, Technical University of Dresden (TUD), Technical University of Berlin (TUB) and the city of Leipzig are building another model of the city to simulate autonomous vehicle scenarios (TU Dresden, 2023).

2.7. Limitations of current methods

This literature review has shown the current climate crisis we face and the need to reduce GHG emissions, particularly from the transport sector. Consequently, a detailed description of the DfT strategies to tackle the transport decarbonisation challenge, as well as the different transport models available to test mobility policies were provided. The outcome was that active modes are the best option to decarbonise transport in the short and medium term, while transport AgBMs are the best approach to simulate transport policy scenarios to enable the use of walking and cycling.

Research publications on the topic are scarce. Several limitations that prevent a detailed representation of both the population and the built environment characteristics for active modes were identified. Therefore, the need for this thesis is based on the following limitations of current methods:

- The need to generate a very detailed synthetic population: current methods have a very limited amount of socio-demographic attributes that define each synthetic individual (e.g., SPENSER, Eqasim) (see section 3.3). This thesis develops a new, very detailed and open-source synthetic population framework to generate synthetic population with 12 socio-demographic attributes (see section 3.3.4). Attributes related to individual characteristics (e.g., age, sex), familiar relationships (e.g., marital status, children dependency), spending power (e.g., economic activity, occupation, annual gross income) and mobility access (e.g., driving license, car access, bicycle access) are provided per synthetic individual. A more detailed synthetic population will allow the allocation of specific trip patterns and travel behaviours to population sub groups. The possibility of discrimination in terms of mobility against small communities is, therefore reduced.
- The need to consider built-environmental characteristics to simulate cycling. In the vast majority of the publications reviewed, a lack of link between bicycle simulation and the characteristics of the built environment was identified. Only very few number of publications take into account a limited amount of attributes (e.g., the type of road and surface, the slope and cycle paths), which could be insufficient to simulate cycling realistically. This thesis proposes the use of an open-access attribute (i.e., *quietness*) developed by Cyclestreet (2022a) that ranks roads for cycling depending on a great variety of built environment characteristics (see section 3.4.4). Consequently, the MATSim bicycle contribution developed by Ziemke *et al.* (2017) was updated with his help to consider the *quietness* attribute by cyclists when choosing routes (see section 3.6).

The combination of these two identified research gaps allows simulating more detailed mobility scenarios (see section 3.8). A more heterogeneous synthetic population and a cycling-focused network allow for the possibility of simulating more realistic behaviours, as more diverse mobility patterns are considered and cycling agents have a better understanding of the built environment when choosing their routes.

Chapter 3 will explain in more detail the steps followed to develop a validated MATSim model, representing a regular working day in space and time of the study area (Tyne and Wear region). Additionally, several urban mobility policies are described with the objective of reducing the number of private and polluting vehicles on the roads.

Chapter 3. Methodology

The limits of my language mean the limits of my world. Ludwig Wittgenstein

Following the literature review from the previous chapter, Chapter 3 defines the methodology adopted by this study including the setup of a MATSim model and the later simulation of several urban mobility policy scenarios.

3.1. High-level overview of methodology

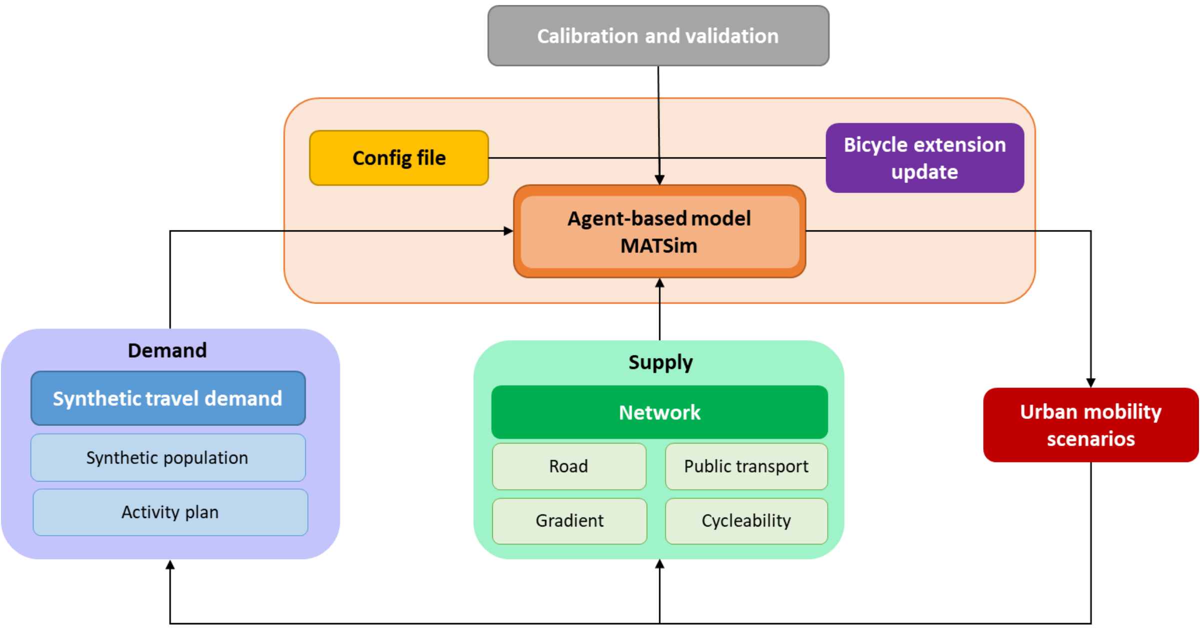


Figure 6 Developed methodology to define a MATSim model and apply urban mobility policies.

MATSim (orange box) is the chosen transport AgBM tool to simulate the normal urban mobility of the study area first, and then the different urban mobility policies for a more sustainable and decarbonised transport sector. It follows a co-evolutionary framework (see section 3.2) that allows the agents to compete and interact between themselves and the built environment in space and time. This tool requires the development of two main components:

a synthetic travel demand or *demand* (blue box) (see section 3.3), and the network or *supply* (green box) (see section 3.4). Figure 6 summarises all the described steps.

The synthetic travel demand is a simplified digital representation of the real population, with individual socio-demographic characteristics (see section 3.3.1) and an activity plan that represents the activities performed on a normal working weekday by each individual (see section 3.3.4). This is a key input to most agent-based simulations (Borysov *et al.*, 2019), so its accuracy is crucial for a realistic representation of the population and their urban mobility interactions. The network consists of a digital geospatial representation of the road and transport networks in the study area, where characteristics of the roads are considered (see section 3.4). It is used by the synthetic individuals to move between activities by different transport modes.

These two components, besides a config file (yellow box) (see section 3.5), are imported into the MATSim model (orange box), where an updated bicycle extension (purple box) (see section 3.6) is enabled to simulate cycling routes considering characteristics of the built environment. The initial baseline scenario is calibrated and validated (grey box) (see section 3.7.1) until results reflect a business-as-usual case in the area of study (see section 3.7.2). After the baseline scenario is validated, different urban mobility policy scenarios are applied (red box) (see section 3.8). Their objectives are to modify the demand and/or supply inputs to estimate their effectiveness in reducing the number of polluting vehicles on the road, and, therefore, lower GHG emissions.

Although the proposed methodology is the standard procedure, the process and data flow used in each stage have been generated following a self-developed framework. Each stage is defined in the following sections with a great level of detail, with special emphasis on the four novel contributions developed within this doctoral thesis (i.e., open access, open-source and transferrable synthetic population, the addition of a cycleability rating (or *quietness*) within the network, the update of the MATSim bicycle extension, and the simulation of tailored policy scenarios in the study area).

In all cases, open-source datasets and tools were used, when possible, and all developed tools and datasets generated have been defined as open access, when data restrictions allowed it.

This will allow other researchers to replicate and reuse them in any other region within England, as they are accessible through several GitHub repositories.

3.2. MATSim framework

Several AgBM tools were analysed and compared in the literature review chapter (see section 2.6.2), where MATSim was identified as the most convenient tool to simulate urban mobility policies focused on reducing the use of private motor vehicles and enabling the use of active modes.

MATSim is an attractive and a convenient tool for transport simulations due to its framework composition. It consists of a co-evolutionary framework that allows the agents to compete in space and time for the transport resources (vehicles and infrastructures) to achieve their goal in an efficient manner. The framework consists of five stages (Horni *et al.*, 2023),with stages 2, 3 and 4 being part of an iterative loop, following the concept of the co-evolutionary algorithm (Ziemke, 2022). The stages are as follows: initial demand, execution, scoring, replanning and analysis (figure 7).

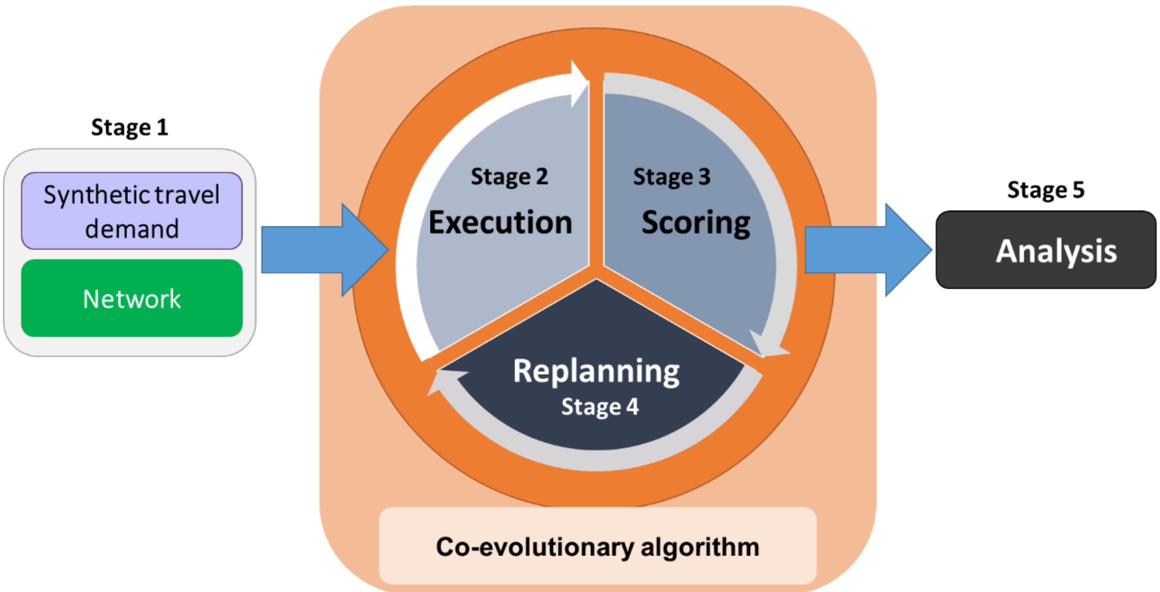


Figure 7 MATSim framework.

3.2.1. Stage 1: Initial demand

The first stage consists of the definition of the main input datasets: the synthetic travel demand and the network. The development of the first is typically created using external dedicated tools (see section 3.3.3), while the second can be generated using tools designed within MATSim, although in this thesis an alternative procedure was followed (see section 3.4).

3.2.2. Stage 2: Execution

The iterative loop starts with the second stage, which simulates the interactions of all the agents (or a sample of them) in space and time based on their individual activity plans and the network characteristics. The default physical simulation of the agents is a queue model (Gawron, 1999; Ziemke, 2022; Horni *et al.*, 2023), where every section of the network (link) allows the mobility of the agents based on its own characteristics and the number of agents using it at the same time. Each agent stays in a link for at least a minimum amount of time, depending on the length of the link, storage capacity, flow capacity and the transport mode used. The characteristics of length and allowed transport modes provide the minimum time required by the agent to stay in the link when free flow is possible (i.e., no congestion), based on the distance and the maximum speeds allowed for both the link and the vehicle type. To consider congestion, the flow capacity parameter restricts the rate of agents that can leave the link in a period of time (normally per hour), and the storage capacity parameter restricts the total number of vehicles that can be located at the same link and at the same time. Consequently, if a link is considered full based on its characteristics, a new agent cannot enter it until another agent leaves it, based on the queue system.

3.2.3. Stage 3: Scoring

The third stage computes the satisfaction (i.e., utility maximisation) of each agent's plan when interacting in space and time with other agents and the environment. It is calculated using the Charypar-Nagel utility function and it is computed as (Charypar and Nagel, 2005; Nagel *et al.*, 2016) (equation 1):

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)}$$

Equation 1 MATSim scoring function.

Where $S_{act,q}$ is the utility (satisfaction) that the agent obtains when performing activity q (normally positive), while $S_{trav,mode(q)}$ is the (dis)utility that the agent obtains when travelling between activities (normally negative). N is the total number of activities performed by the agent.

The utility of an activity ($S_{act,q}$) is defined as (Charypar and Nagel, 2005; Horni *et al.*, 2023) (equation 2):

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{late\ ar,q} + S_{early\ dp,q} + S_{short\ dur,q}$$

Equation 2 MATSim utility function.

Where:

- $S_{dur,q}$ is the utility of performing activity q;
- $S_{wait,q}$denotes waiting times (i.e., when the activity location is not open and the agent has to wait until the facility can be used);
- $S_{late\ ar,q}$ is the applied penalty in case the agent arrives late to the activity;
- $S_{early\ dp,q}$ is the penalty applied when the agent leave the activity earlier than expected; and
- $S_{short\ dur,q}$ is the penalty for a 'too short' activity (normally set to zero).

Travel (dis)utility for a leg q ($S_{trav,mode(q)}$) is defined as (Horni *et al.*, 2016) (equation 3):

$$S_{trav,q} = C_{mode(q)} + \beta_{trv,mode(q)} * t_{trav,q} + \beta_m * \Delta_{m_q} + \left(\beta_{d,mode(q)} + \beta_m * \gamma_{d,mode(q)}\right) * d_{trav,q} + \beta_{transfer} * x_{transfer,q}$$

Equation 3 MATSim travel disutility function.

Where:

- $C_{mode(q)}$ is a transport mode-specific constant;
- $\beta_{trv,mode(q)}$ is the marginal utility of time spent travelling by mode(q);
- $t_{trav,q}$ is the travel time between consecutive activities;

- β_m is the marginal utility of money;
- Δ_{m_q} is the change in monetary budget caused by fares;
- $\beta_{d,mode(q)}$ is the marginal utility of distance when travelling by mode(q);
- $\gamma_{d,mode(q)}$ is the mode-specific monetary distance rate of mode(q);
- $d_{trav,q}$ is the distance travelled between consecutive activity locations;
- $\beta_{transfer}$ are public transport transfer penalties; and
- $x_{transfer,q}$ is a 0/1 variable indicating if a public transport transfer occurred between the previous and current leg.

3.2.4. Stage 4: Replanning

The fourth stage allows a percentage of the agents to modify their plans based on a strategic criteria (e.g., change transport mode (Grether *et al.*, 2009), choose an alternative route, leave an activity earlier/later (Balmer *et al.*, 2005), change activity location (Horni *et al.*, 2012)), as defined by the modeller. Each agent has a memory containing a fixed amount of day plans (normally five), containing information of the daily activity chain and the obtained score value (Horni *et al.*, 2012). Agents that are allowed to modify their plan generate a new plan in their memories, while the agents that are not allowed choose one from their memory (in case they have more than one), based on a probability distribution function (Nagel and Flötteröd, 2009), considering the previous obtained scoring values. When the maximum number of plans in their memories is reached and a new iteration is finished, the worst plan is removed, keeping only the best. This is how agents learn, based on their experiences with other agents in the environment.

Once the replanning stage is finished, the loop of Stages 2, 3 and 4 is iterated as many times as the modeller defines (i.e., until the model reaches an equilibrium in the average scoring value of all agents and the mode shares keep relatively constant). Through each iteration, agents learn from their interactions in space and time and adapt their behaviours to achieve their goals, maximising their scoring value. It is a frequent practice to disable the strategy criteria within the replanning stage after a certain number of iterations (80% in this study) to allow them to choose between their best plans without any new modification. Since then, agents are only allowed to choose between the plans stored in their memories, based on the probability distribution function defined by (Nagel and Flötteröd, 2009).

3.2.5. Stage 5: Analysis

The fifth stage is reached once the iterative loop is finished and outputs are generated. Different datasets containing the interactions of the agents in space and time are generated and different geospatial, socio-demographic and transportation analysis could be generated, depending on the purpose and the simulation goals with external tools (i.e., QGIS (QGIS Development Team, 2023), Simunto Via (Senozon AG, 2018)).

3.3. Synthetic travel demand

Two types of information form a synthetic travel demand: the representation of individuals in the study region with socio-demographic attributes (e.g., age, sex, income, driving license); and their daily activity plans that define their activities and trips (e.g., purpose of trip, departure time, transport mode used) (figure 8). The first is called synthetic population, while the second is the activity plan.

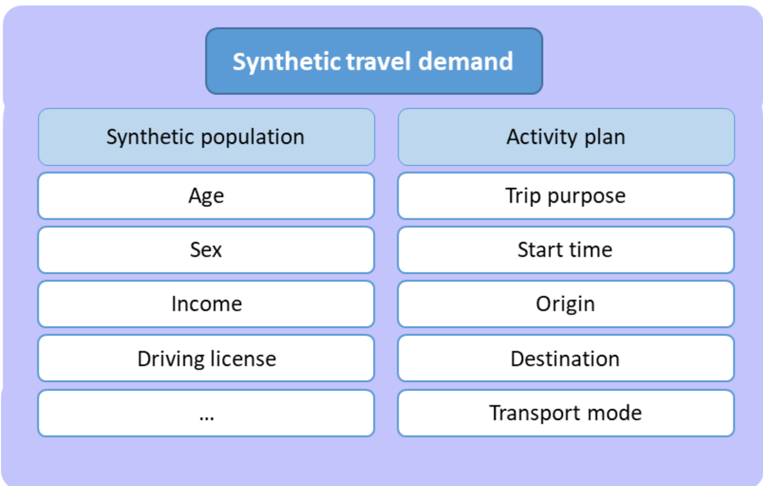


Figure 8 Synthetic travel demand composition. Synthetic population with several socio-demographic attributes of the individuals and activity plan with information defining each trip.

3.3.1. Synthetic population

The concept of a synthetic population refers to a simplified and realistic microscopic representation of individuals (Moeckel *et al*., 2003; Gearda *et al.*, 2013; Yaméogo *et al.*, 2020), with distinct characteristics and exhibiting distinct behaviours (Wu *et al.*, 2022; Zhou *et al.*, 2022) between them (Gearda *et al.*, 2013). The goal of a synthetic population is to generate a population which is statistically close to the real one (Moeckel *et al.*, 2003; Barthelemy and Cornelis, 2012), derived from available data (Yaméogo *et al.*, 2020), such as census, mobile phone (Franco *et al.*, 2020) or survey datasets, among others. Some of the benefits of generating a synthetic population are to estimate and/or project current and/or future populations to make informed decisions of current and/or future needs and demands (Lomax *et al.*, 2022).

Unfortunately, very detailed information on socio-demographic attributes for all individuals at a small geographical scale does not exist or is not accessible for the general public (Lomax *et al.*, 2022; Wu *et al.*, 2022) due to privacy reasons (Garrido *et al.*, 2020). Only the characteristics of a sample and aggregated socio-demographic statistical variables of the actual population are known (Moeckel *et al.*, 2003; Yaméogo *et al.*, 2020). This renders it infeasible to generate a perfect population that represents each individual as in reality. Consequently, the development of synthetic populations follows different methods based on the available data (Felbermair *et al.*, 2020), size of the population to synthesise and the final application purpose (Barthelemy and Cornelis, 2012)

Population synthesis is an important stage in the modelling process because it generates the basis for any demand investigation (Garrido *et al.*, 2020). The inhabitants of a specific region, their activities and behaviours, as well as their current and future needs and demands can be described with a great level of detail (Gearda *et al.*, 2013; Lomax *et al.*, 2022). The accuracy of synthetic populations is particularly important and depends on the quality and detail of the data used (Zhu and Ferreira, 2014). The extent to which a synthetic population can represent the ‘real’ population in the aggregated values and get as close as possible at individual level has a significant impact on the credibility of the simulation that relies on it (Garrido *et al.*, 2020; Zhou *et al.*, 2022).

The field of synthetic population development has received increasing attention in recent years due to an increased focus on AgBMs in the transportation arena (Bowman and Ben-Akiva, 2001; Moeckel *et al.*, 2003; Zaid and Pat, 2005; Bradley *et al.*, 2010; Wegener, 2014; Zhu and Ferreira, 2014; Blainey and Preston, 2019; Borysov *et al.*, 2019; Briem *et al.*, 2019; Balac and Horl, 2021). Furthermore, synthetic populations have also been used in a great and diverse variety of other research fields: demographic sector (Gearda *et al.*, 2013; Wu *et al.*, 2018; Alonso-Betanzos *et al.*, 2021); future construction plans (Clark and Lomax, 2018; Alonso-Betanzos *et al.*, 2021); health (Xu *et al.*, 2017; Krauland *et al.*, 2020; Alvarez Castro and Ford, 2021; QUB Planning School, 2021; Spooner *et al.*, 2021; Wu *et al.*, 2022); energy (Zaid and Pat, 2005; Druckman and Jackson, 2008; Panos and Margelou, 2019); and water (Willis *et al.*, 2013; Rees *et al.*, 2020).

Despite of the previous synthetic populations examples, the use of existing models is not always possible due to constraints in data availability (Zhu and Ferreira, 2014), knowledge of the programming language used, scalability (Tanton, 2013) and inconsistencies in the format and accessibility of datasets (Lomax *et al.*, 2022). These drawbacks especially affect AgBMs, as the number of attributes required is greater than for other applications, as a higher heterogeneity is required between the agents to represent their behaviours in space and time.

3.3.2. Synthetic populations tools for a UK context

For the UK context, two existing models were analysed with the goal of identifying the best of them to generate a synthetic population to simulate transport mobility behaviours with AgBMs. Firstly, SPENSER (Lomax *et al.*, 2022) is a model for the UK. Secondly, Eqasim (Balac and Horl, 2021), is a model applied for several regions around the world but not in the UK, focused on developing synthetic travel demands for transport scenarios using AgBMs. With them, we consider two different possibilities: a dedicated model for the UK, and the possibility of adapting a model to the UK, respectively.

SPENSER (Synthetic Population Estimation and Scenario Projection Model) (Lomax *et al.*, 2022) is an open-source spatial and dynamic microsimulation model developed by the University of Leeds. It allows the development of synthetic populations and projections of people and households at fine spatial scale, from OA level (Output Area) (i.e., geographical areas where the resident population is between 100 and 635 persons (ONS, 2023a)) upwards, across the whole of Great Britain (Lomax, 2023). This model consists of six stages that allow definition of future infrastructure planning scenarios, although the development and projection of a synthetic population comprises only the first three (Lomax *et al.*, 2022):

- Stage 1: Data downloading and cleaning from official UK institutions from the latest census (2011 when writing this thesis) and projection data. *UKCensusAPI* tool extracts data from the different sources depending on the study area (i.e., the ONS for England and Wales, the National Records for Scotland (NRS), Statistics Wales and the Northern Ireland Statistics and Research Agency (NISRA)) and converts it into a common format. *UKPopulation* tool extracts household estimate data (disaggregated by household type), and projection data to the desired year (2019 in this thesis), taking into account future constraints (e.g., new housing developments) at local authority (LA) level.
- Stage 2: The development of the baseline synthetic individual population and household datasets. *Household microsynthesis* tool creates synthetic households from census data, considering occupied private households, communal residences, and unoccupied dwellings. The output is consistent with census aggregate values at different geographical levels (e.g., OA). *Humanleague* tool creates the synthetic individuals, following several microsimulation methods, at MSOA level (i.e., Middle layer Super Output Areas) level (ONS, 2023a). The output is adjusted at LA level.
- Stage 3: Projection of the baseline synthetic population from previous stage to the desired year. The projection stage handles households and individuals separately, projecting households in time (yearly) following a survival probability and considering new housing developments based on LA level household constraints collected in stage 1 (i.e., using *UKPopulation* tool). Individuals are grouped into households using the *assignment* tool. Consequently, every individual is associated with a household and *vice versa*. The order in which households and individuals are matched is the following:
  - Matching HRP attributes (e.g., age, sex and ethnicity group) between both household and individual, so their relationships are preserved.
  - Partners of HRPs already assigned to a household.
  - Multi-person households.

- Communal households.

Once a household is complete, no more individuals can be assigned to it. If there are still individuals unassigned to a household, they are associated to those households that are not yet complete.

The output is a set of files containing information of each household and individual per LA level. Households are defined by 12 attributes: ID, OA area, type of accommodation, building and tenure, number of occupants, rooms, and bedrooms, type of central heating, household HRP domestic situation, HRP socio-economic class, HRP ethnicity and number of cars. Individuals are defined by six attributes: ID, household ID, age, sex, ethnicity group and MSOA area level (geographical areas where the resident population is between 5,000 and 15,000 persons).

Examples of research using SPENSER are Spooner *et al.* (2021), modelling epidemic scenarios between humans, and Wu *et al.* (2022) for small area health and socio-economic outcomes in Great Britain.

Eqasim (Balac and Horl, 2021) is an open-source model used to develop synthetic travel demands to be applied to transport AgBMs, such as MATSim (Horni *et al.,* 2023). It proposes a general pipeline that can be applied to many regions using open-access datasets (based on availability access to required datasets).

The pipeline to develop a synthetic population is based on a multi-level spatial zoning system (Hörl and Balac, 2021c), where the greatest area (i.e., city) is sub-divided in smaller zones (i.e., boroughs, census zones). It uses micro-sample census data of the population (individuals and households) from the area of study, besides other institutional sources to get income information. The pipeline starts cleaning and transforming the input data, then socio-demographic and economic attributes and household locations are generated, based on direct sampling from the micro-sample census data (Hörl and Balac, 2021c). The income is assigned per household based on a uniform distribution, considering the centile of the respective sub-level from the area of study.

The output from the synthetic population development is a list of households and individuals with their socio-demographic and economic attributes (household size, income and number of cars for households; and age, sex, employed, ongoing education and socio-professional category for individuals).

The tool has been used for scenarios in Paris (Hörl and Balac, 2021c, 2021a; Eqasim, 2023b), California (Hörl and Balac, 2021d) and Sao Paulo (Eqasim, 2023a).

Both models are open-source and allow generation of synthetic populations using open datasets for the UK (SPENSER) or for several areas in the world (Eqasim). Unfortunately, none of them is the ideal tool for the development of very detailed synthetic populations, as the number of attributes provided for each individual is scarce in both cases. SPENSER provides information for three attributes (age, sex and ethnicity group), Eqasim five (age, sex, employed, ongoing education, socio-professional category). The advantage of using AgBMs in transport is that individuals interact in space and time, and the more heterogeneity of agents in the model, the richer and more accurate the results that can be achieved, avoiding the risk of having many similar and 'standard' agents with very similar attributes and behaviours, which would not represent the real population faithfully.

Based on this comparison, the approach was the use of SPENSER with the development of the desired attributes applying a self-developed tool using census and statistical data of the area of study (see section 3.3.3). Consequently, the use of Eqasim was discounted as the entire UK census and statistical input datasets would need to be adapted to the tool and extra attributes would also need to be generated.

The following section explains how a very detailed synthetic population for any region in the England can be generated, using SPENSER and the synthPopEng tool developed in this thesis. The output is a synthetic population with 12 different attributes for each individual in the study area.

3.3.3. Synthetic population methodology

The methodology proposed to develop a very detailed synthetic population for any region in the UK consists of the combination of two main tools: SPENSER and synthPopEng (Alvarez Castro, 2022) (figure 9). The former creates the basic synthetic population, consisting of household and individual characteristics. The latter was developed as part of this PhD by the author to implement eight additional attributes based on the results obtained from the first. The inclusion of more socio-demographic and economic attributes is important to make the synthetic population more heterogeneous and diverse, closer to reality to replicate their behaviours more accurately. Lucas *et al.* (2016) model the travel behaviour of socially disadvantaged population segments in the UK and identify major differences in travel behaviour between individuals based on their household income, the presence of children and the possession of a driving licence, concluding that the inclusion of additional socioeconomic variables is useful for identifying significant differences in the trip patterns.

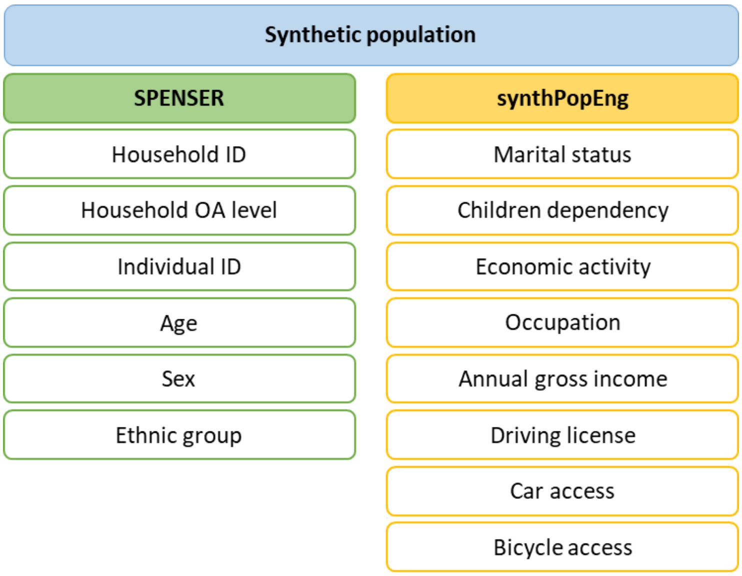


Figure 9 Synthetic population. Attributes generated with SPENSER and synthPopEng.

SPENSER (see section 3.3.23.3.2. Synthetic populations tools for a UK context for a detailed description) can be used directly through a Docker image (NISMOD, 2020), which allows using a Docker container in the command line and running the scripts, where the area of study (at LA level) and the year to project the base synthetic population are required. In this thesis, a synthetic population of the NE of England was developed, consisting of eight LAs (Durham, Northumberland, Newcastle upon Tyne, Sunderland, Gateshead, South Tyneside, North Tyneside and Darlington) for the year 2019.

The following steps were followed to generate the synthetic population:

1. Download the image: Sudo docker pull spenser:1.5
2. Run the image: Sudo docker run –it spenser:1.5
3. Generate the baseline synthetic individual population and household for the specific local authorities (LAs) (e.g., EXXXXXXX1) and at OA scale level: Python scripts/run_microsynth.py EXXXXXXXX OA
4. Project the households and individuals to the desired year using a specific config file for a specific LA: Python scripts/run_ssm.py -c config/configFile.json EXXXXXXXX
5. Group individuals into households by matching common characteristics between them and the household reference person (HRP), for a specific LA: Python scripts/run_assignment.py –c config/ssm_default.json EXXXXXXXX

The output for each LA consists of two files containing information about each household and individual, with the attributes highlighted in section 3.3.2. For more detailed information about how to use SPENSER, see Lomax et al (2022) (Lomax *et al.*, 2022) and the Docker image (NISMOD, 2020).

SynthPopEng is a set of Python Jupyter notebooks developed as part of these thesis that allows implementation of eight more socio-demographic attributes, incrementally assigned to the population, based on the relationships between the attributes (see Figures 10 - 20), SPENSER outputs, 2011 UK census, DfT and ONS datasets. Figure 10 shows the classification of these new attributes in three categories: family dependencies (green), spending power (blue) and mobility access (orange), besides the inter-dependencies among them.

An open-access GitHub repository (Alvarez Castro, 2022) is available with all codes and detailed documentation explaining where to find the required dataset, data cleaning process, code dependencies, requirements and usage.

The methodology followed for each attribute, as well as the datasets used, are described below.

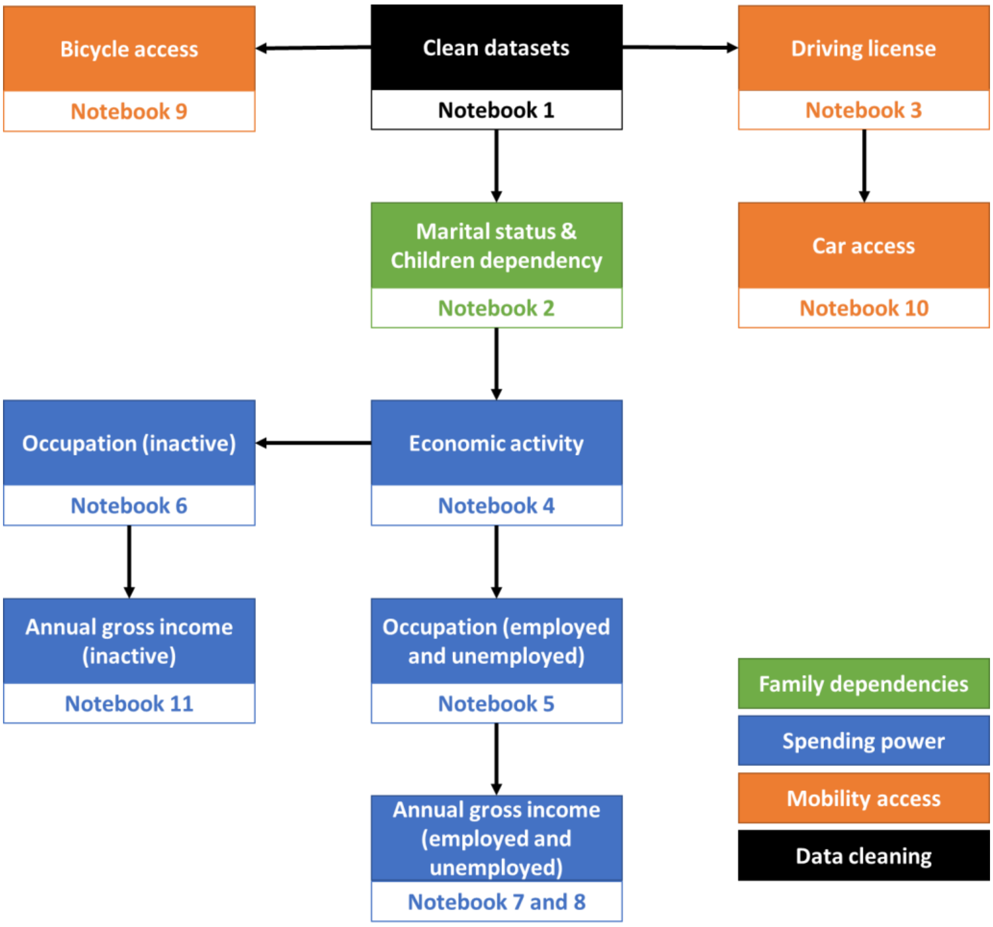


Figure 10 Structure of the Python notebooks developed within the synthPopEng tool.

Family dependencies

Family dependencies are a critical component in human lives. Human behaviours are deeply linked to their family circumstances, such as being married or having children. Research studies have found that single individuals spend more time in leisure time (Lee and Bhargava, 2004) and their physical activity is greater (Puciato and Rozpara, 2021) than their married counterparts. The presence of children in the family makes changes in the use of time, work situation and composition and size of social networks (Davy *et al.,* 2007), encourages the use of the car (McCarthy *et al.*, 2017) and affects more women's travel patterns than men's (McGuckin and Nakamoto, 2005; Ng and Acker, 2018).

Marital status

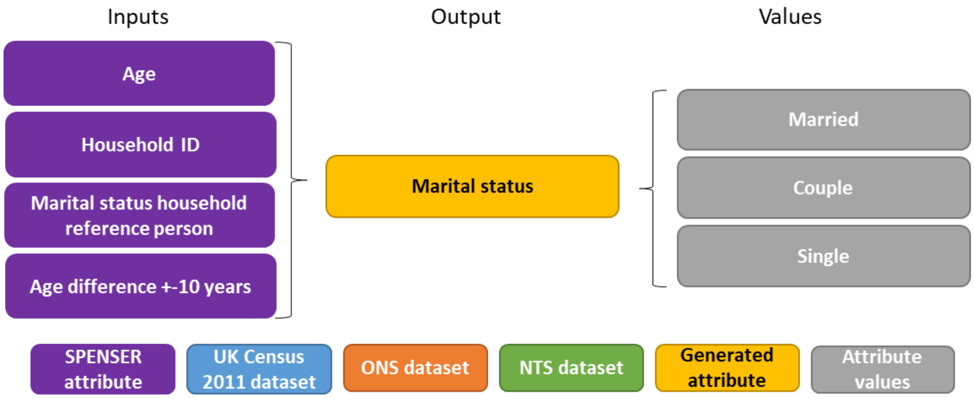


Figure 11 Marital status attribute. Description of required inputs and expected output values.

Marital status classifies individuals in two categories: married or single. To determine the value for each individual, characteristics such as the domestic situation of the HRP and the age of each individual sharing the household are considered. In the case that the domestic situation of the HRP is "*married, same-sex civil partnership couple or cohabiting couple household*", the individual is older than 18 years and there is another adult with a similar age (+/-10 years), then both individuals are considered married. In case there is more than one option, the closest in age to the HRP is selected. In the remaining cases, the individual is considered as single. Figure 11 shows the attributes used to generate the attribute and the different values assigned.

Children dependency

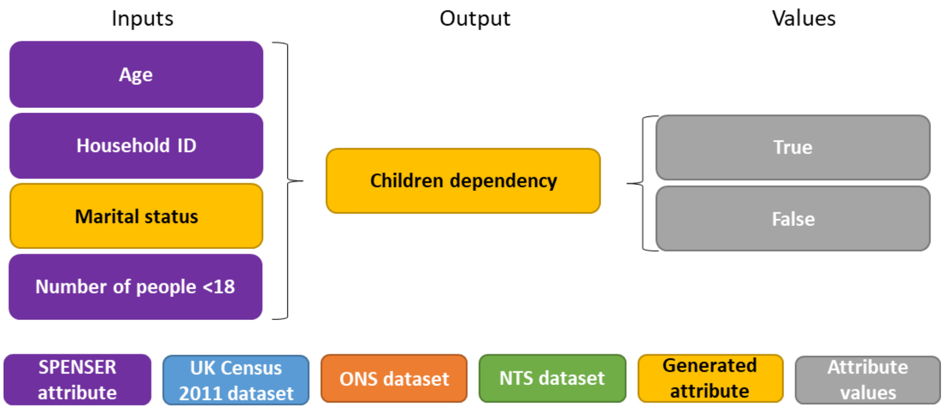


Figure 12 Children dependency attribute. Description of required inputs and expected output values.

This attribute identifies individuals with dependent children at home (Boolean value). Based on ONS definitions, dependent children are those aged under 16 years living with at least one parent or aged 16 to 18 in years in full-time education, excluding all children who have a spouse, partner or child living in the household (ONS, 2019). In this methodology, individuals are assigned children dependencies if their marital status is married or the domestic situation of the HRP is 'lone parent household', the individual is older than 18 years and there is at least one child in the household (aged up to 16). In any other cases, the individual does not have any children dependencies. Figure 12 shows the attributes considered.

Spending power

Economic power is another factor that influences the behaviour of individuals, which is derived from their economic activity and occupation type. Close and Jundi (2020) conducted a survey in 2019 of adults living in the Tyne and Wear region (UK) to identify their willingness towards shared and emerging mobility services. Outcomes show that only specific groups in society are more attracted to those modes, principally younger residents aged under 40 and those with household incomes of over £60,000. Additionally, those with higher levels of education think more actively about environmental concerns and use more diverse transport modes than other groups in society, especially the youngest. In 2019, the UK Government released a report about inequalities in mobility and access in the transport system, showing that lower income households travel less overall in the UK, making nearly 20% fewer trips and travelling 40% less distances than the average household (Lucas *et al.*, 2019).

Economic activity

Economic activity attribute classifies individuals in three categories (i.e., employed, unemployed and inactive), based on their age and sex attributes and external datasets from the 2011 UK Census (ONS, 2011c) and ONS (ONS, 2023c). The first contains detailed information of the three different economic activity categories, by sex, range of age and OA area in 2011, while the second contains regional annual statistical information of economic activities by sex and range of age from 2019. Figure 13 shows the attributes used to define the economic activity for each synthetic individual.

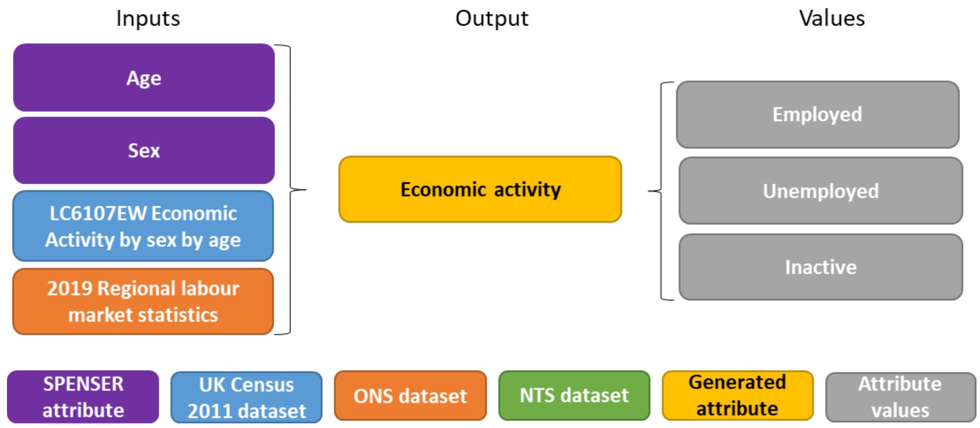


Figure 13 Economic activity attribute. Description of required inputs and expected output values.

To transform the 2011 UK census data into a 2019 projected census data, two scale factors are required: one to project the changes of the total number of individuals per type of economic activity (employed/unemployed/inactive) from 2011 to 2019 (equation 4), and another to update population changes between 2011 and 2019 (equation 5). The first is calculated by comparing the total number of individuals per type of economic activity in 2019 and those in 2011 using the ONS dataset (ONS, 2023c). This factor allows identification of the trend of individuals in each economic activity category in the area of study in the range of years. The second scale factor is calculated by comparing the total population per range of age, sex and OA area from the 2019 synthetic population created with SPENSER and the one from the 2011 UK census. This factor allows determination of whether the population has increased or decreased in the eight-year gap considering the previous three attributes.

$$\text{Scale factor economic activity x} = \frac{\text{ONS number of individuals per sex and range of age in economic activity x 2019}}{\text{ONS number of individuals per sex and range of age in economic activity x 2011}}$$

Equation 4 Scale factor used to project economic activity values to 2019.

$$\text{Scale factor population per OA area} = (\text{population in 2019 per OA area, range of age and sex}) / (\text{population in 2011 per OA area, range of age and sex})$$

Equation 5 Scale factor for the population per OA area.

The combination of both scales projects the number of individuals per type of economic activity from 2011 to 2019 per OA area, considering five range of ages ((16, 24), (25, 34), (35, 49), (50, 64), (65, 120)) and two types of sex (male, female).

Once the 2011 census data is projected to 2019, individuals from the 2019 synthetic population are categorised as one of the three economic activity options considering their location (household's OA area), range of age and sex. Additionally, the inactive category was assigned an extra constraint to select those individuals whose household socio-economic class is student (NSSEC = 9), as this category is considered as inactive. Similarly, those individuals whose household socio-economic class is "*Never worked and long-term unemployed*" (NSSEC = 8) were assigned to the '*Unemployed'* class.

Occupation

Occupation attribute was defined in two ways, depending on the economic activity of the individuals. In case individuals were classified as employed or unemployed, the occupation attribute classifies them in nine types.

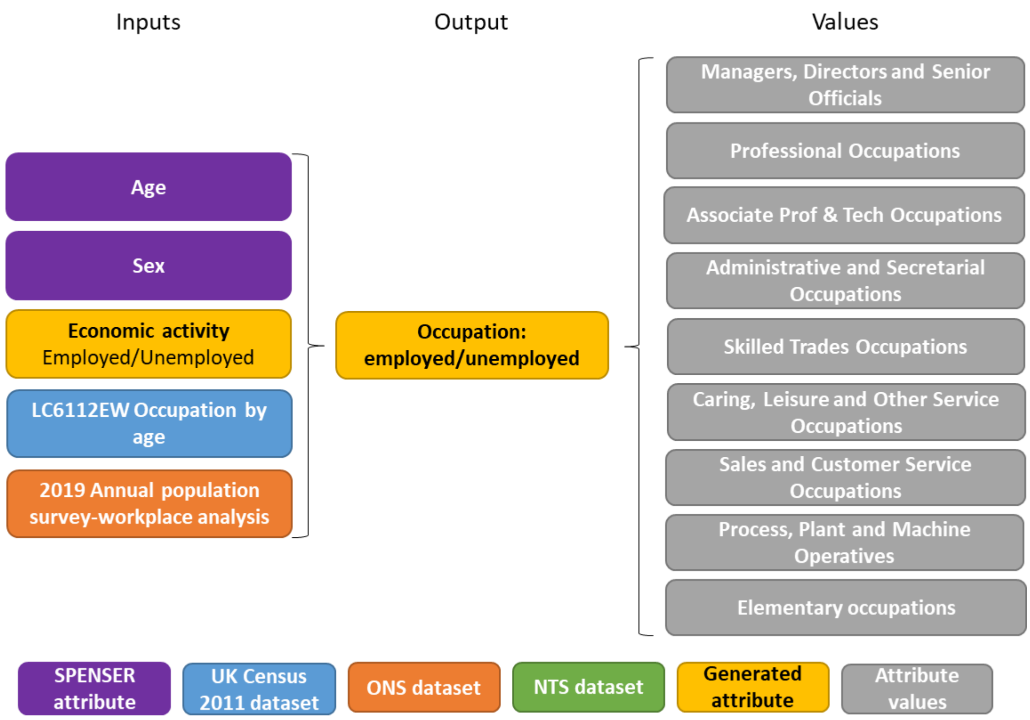


Figure 14 Occupation attribute for employed or unemployed agents. Description of required inputs and expected output values.

The classification is based on their sex, age and economic activity attributes, the first two being generated with SPENSER, the last with the syntheticPopEng methodology developed in this thesis, showing the incremental assignment procedure followed to build a more heterogeneous and detailed synthetic population. Additionally, external datasets from the 2011 UK Census (ONS, 2011d) and 2019 ONS (ONS, 2022a) are used. The first identifies the number of individuals of each category per OA area and range of age in 2011, while the second contains regional annual statistical information of occupations per LA and sex. Figure 14 summarises the inputs used and outputs obtained.

Similar to the economic activity attribute, two scalar factors for each category were required: one to project the total amount of individuals for each category, and another to quantify the increase or decrease of the total population per OA area in the eight-year gap, which is the same for each occupation category. Both scale factors were obtained in the same manner as in the previous attribute (equations 4 and 5).

Once the 2011 census data is projected to 2019, individuals from the 2019 synthetic population are categorised as one of the nine occupation options, based on their location (household's OA area), range of age and sex. In this case, the percentage of individuals per sex are not projected per OA area, as this value is not known from the 2011 census. Consequently, the occupation type sex-proportion is based on global data from 2019 ONS only (ONS, 2022a). Additionally, the order in which the occupation categories were assigned per sex differ, as those occupation where more individuals of a specific sex are allocated in real life were prioritised, based on ONS data (ONS, 2022a).

Five different categories (student, looking after family or home, sick, retired, and other) were assigned to those individuals classified as inactive in the previous economic activity attribute. This classification is based on the same already generated attributes (i.e., age, sex and economic activity), besides external datasets from the 2011 UK Census (ONS, 2011b) and 2019 ONS data (ONS, 2023c) (figure 15). The first quantifies the number of inactive people in each inactive category in 2011 per OA area, while the second quantifies the annual percentage of inactive individuals per category and sex.

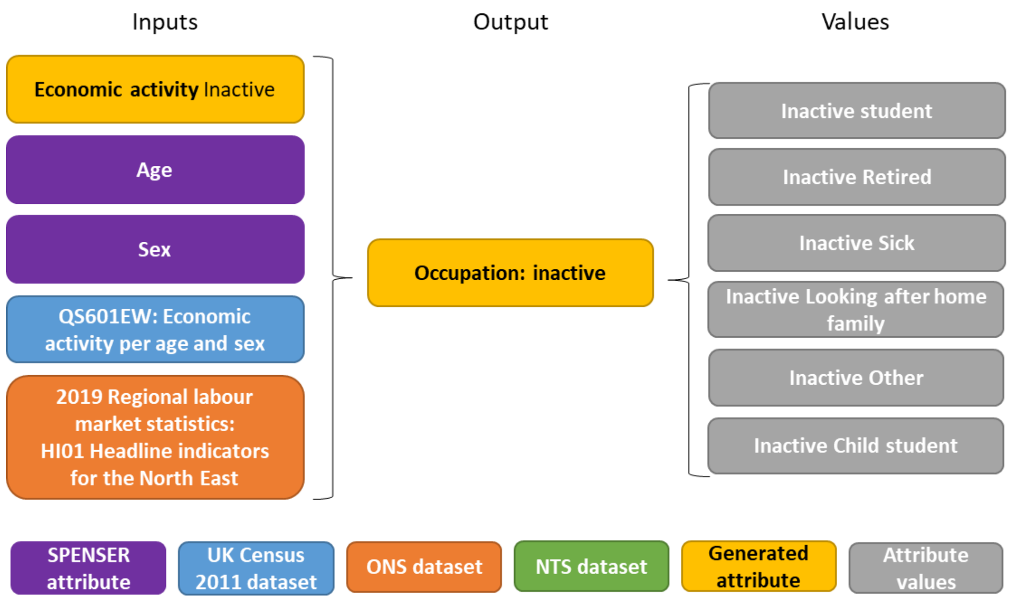


Figure 15 Occupation attribute for inactive agents. Description of required Inputs and expected output values.

Similarly, two scale factors per inactive category to project the data to 2019 were required. These factors were calculated in the same manner as in the previous attributes (equations 4 and 5). The way that individuals were categorised in each type of inactivity depends on the inactive category:

Synthetic individuals are categorised as '*students'* if they meet one or more of the following requirements in descending order:

- The household where they are allocated belongs to education (QS420_CELL = 26).
- Their HRP socio-economic class is student (NSSEC == 9).
- The household is considered a multi-person household (LC4408_C_AHTHUK11 = 5) and their age is between 16 and 35 years.
- The household is considered as a one-person household, married, cohabitating couple (LC4408_C_AHTHUK11 = 1, 2, OR 3) and their age is between 16 and 35 years.

In the case that more individuals need to be categorised as students per OA area, individuals are chosen based on their age, assuming young individuals have more chances to be considered as students.

Individuals are classified as '*looking after family or home*' when they meet one or more of the following requirements, in descending order:

- Their marital status is married and have children dependencies.
- Their marital status is married, do not have children dependencies and are considered the oldest in the OA area.

It was assumed that families with children are more likely to keep one member at home (especially women based on (ONS, 2023c)) and that within older marriages the presence of one member at home is more likely than other family compositions. In the case that more individuals need to be included in this category per OA area, individuals are chosen based on their age, assuming older individuals have more chances to be considered in this category.

'*Retired'* individuals were identified based on their age only:

- First those between 60 and 64 years old.
- Secondly those between 55 and 59.
- Thirdly those between 50 and 54.
- Finally, anyone below 50.

Additionally, any inactive individual aged 65 or more was considered as retired, due to lack of information for individuals older than 64 years within the ONS dataset (ONS, 2023c).

'*Sick'* individuals were classified based on their age as well, choosing first those aged between 50 and 64 and secondly (if necessary) those below 50, assuming older people are more likely to be considered sick than younger generations.

Category '*other*' was assigned to those remaining individuals that were not categorised in any of the previous options.

In each of the previous categories (occupations for employed, unemployed and inactive), obtained results were compared against 2019 ONS statistical data (ONS, 2023c). If the percentage differences between all individuals of a category were greater than 1%, the first scale factor was updated to increase or decrease the number of required individuals in each category. Lastly, all individuals aged below 16 were considered as '*inactive children students'*.

Annual gross income

Annual gross income was defined in two ways, depending on the economic activity of the individuals. The annual gross income for those employed or unemployed individuals is based on their sex and age, occupation and external datasets from ONS (ONS, 2022d, 2022c, 2022b) (figure 16), following an incremental procedure as in the occupation attribute. The first ONS dataset contains statistical information of minimum and maximum annual gross income per occupation type and year at region scale, the second quantifies the gender pay gap per UK region and year, and the latter quantifies statistical values for the annual gross income per range of age in England.

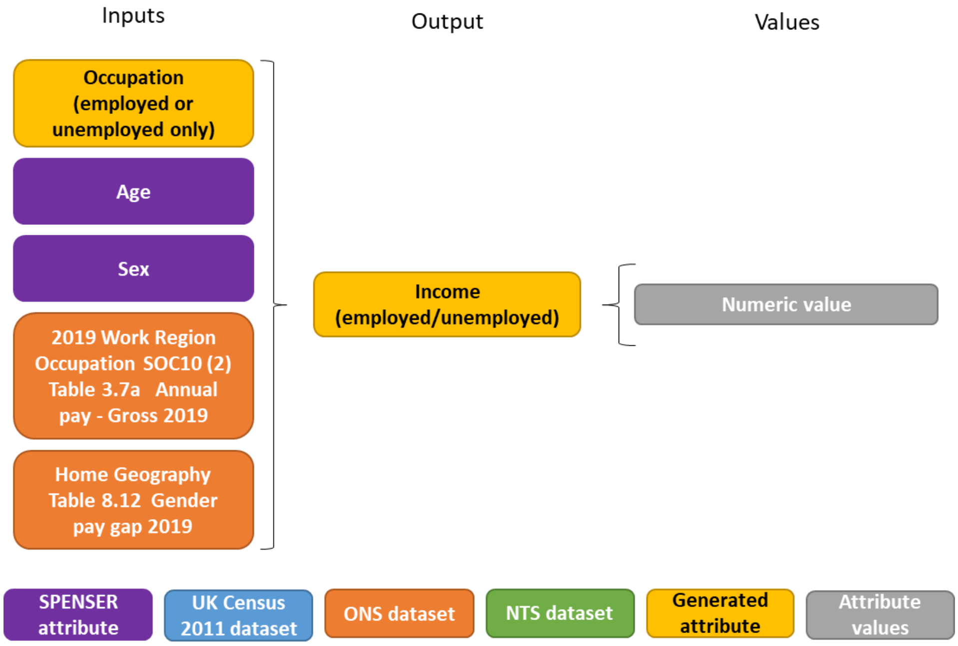


Figure 16 Annual gross income attribute for employed or unemployed agents. Description of required inputs and expected output values.

For each occupation, an iterative process is followed until statistical values obtained (minimum, maximum, mean and median) are relatively similar to those from ONS (2022d), (i.e., the relative error threshold is below 0.1 in absolute value (equation 6)).

$$Error\ threshold = \frac{Observed - Calcualted}{Observed}$$

Equation 6 Error threshold used to estimate the accuracy of the minimum, maximum, mean and median value for each occupation type.

Firstly, the maximum and minimum annual gross income values for a specific occupation are estimated, based on ONS (2022d). Depending on the age of the individual, a minimum and maximum value are defined within the previous global minimum and maximum values based on statistical values from ONS (2022b), where the annual gross income per range of age is defined. Mean values from 2019 show that the range of age earning the lowest is between 16 and 17, followed by 18-21, 22-29, 60+, 30-39, 40-49 and finally 50-59. These values are manually adjusted proportionally to the global minimum and maximum values that can be earned for the occupation. Values per range of age are not disaggregated per occupation type but are global values for the whole UK. It is assumed that the order in which the different age range is allocated are applicable for all the different occupation types. Once the minimum and maximum values are estimated for the specific occupation and range of age, a random value is chosen between the ranged values and the gender pay gap per occupation type is applied. If the individual is a female, the annual gross income assigned before is reduced by half of the gender pay cap value obtained from ONS (2022b). In the case that the individual is a male, the annual gross income assigned before is increased by half of the gender gap value.

Once the annual gross income is assigned to all individuals from the same occupation type, statistical values (min, max, median and percentiles) are compared against those from ONS (2022d). If results are not close enough to those expected, then it is necessary to modify the estimated global minimum and maximum values, as well as those estimated for the range of ages. This procedure is iterated as many times as required until results obtained are significantly close to those from ONS (2022d) (i.e., the relative error threshold is below 0.1 in absolute value (equation 6)).

At this stage, the annual gross income values obtained are statistically similar to those in reality, although the earnings based on range of ages could not be correct, since the values were heavily dependent on estimations. To achieve better results about the median income per range of ages, income values from agents earning less than expected were exchanged with those earning more than expected, assuming more heterogeneity of incomes between the individuals of different occupations in the same range of ages. This iterative process needs to be run as many times as required, until calculated median gross income value for the people in each range of age is within suitable limits to the data provided by the ONS (2022c).

It is important to highlight that ONS values refer to the whole UK and the synthetic population developed is for a specific region, so differences are expected.

For those individuals categorised as inactive, the annual gross income attribute is assigned based on different attributes and statistical values, depending on the inactivity type (Figure 17):

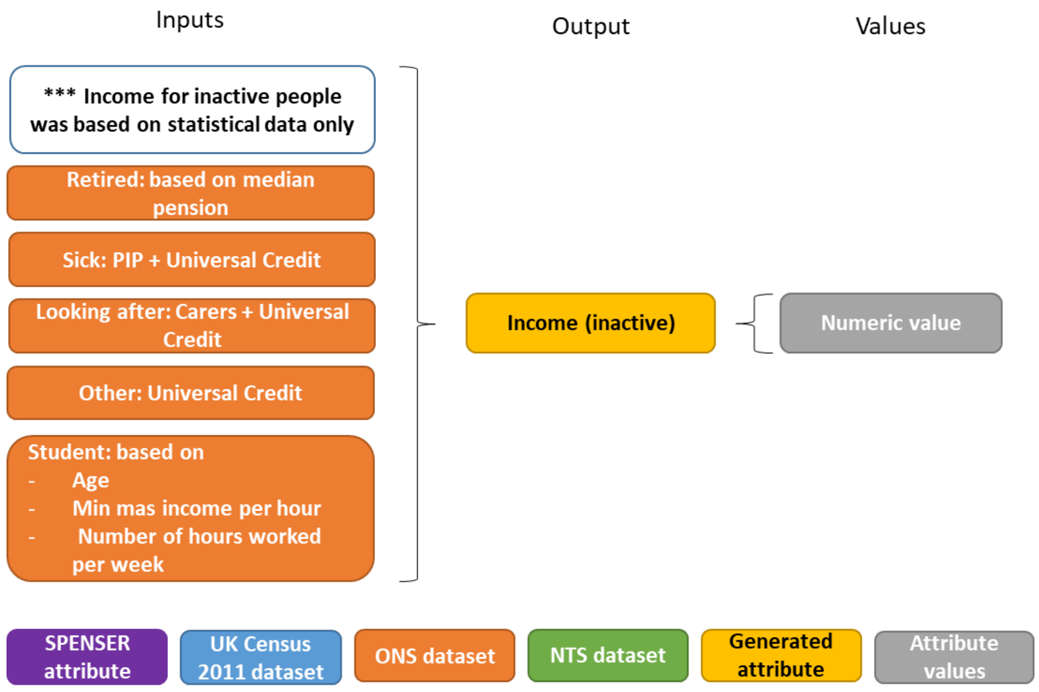


Figure 17 Annual gross income for inactive agents. Description of required inputs and expected output values.

- *'Retired'* individuals were assigned the annual gross income value depending on their marital status, applying data from the UK Government (Department for Work and Pensions UK, 2020), where median annual gross incomes per year are defined per marital status.
- *'Sick'* individuals get the annual gross income values based on the PIP (Personal Independence Payment) (UK Government, 2023e) and Universal Credit (UK Government, 2023f). The first are some benefits individuals can get when suffering a long-term physical or mental health condition or disability, or difficulty doing certain everyday tasks or getting around. The second is a payment to help with living costs. The final value assigned depends on their age and children dependencies.

- Those individuals '*looking after home or family*' are assigned an annual gross income based on the carers allowance (UK Government, 2023a) and Universal Credit (UK Government, 2023f) , considering their age and children dependencies as well.
- Those classified as inactive '*other'* were assigned their annual gross income based on Universal Credit only (UK Government, 2023f) and depending on their marital status, age and children dependencies.
- Lastly, '*students'* get their annual gross income based on their age and a random number of hours worked per week (from five to 20), being the payment per hour dependent on the age of the individual, where the minimum refers to the national minimum wage per age (UK Government, 2023d) and the maximum an estimated value. It was assumed that all students earn an income, regardless of whether it is obtained from work or any other alternative (e.g., family)

Mobility access

The access to different transport modes also defines and conditions human travel behaviours when carrying out their daily routines. The possibility of accessing a car brings the possibility of going anywhere whenever, while its lack conditions movements and possibilities if other transport modes are not an alternative. This could generate barriers to employment, education and healthcare, besides producing social isolation (Lucas *et al.*, 2019). Socio-demographic attributes also affect the use of cars, as highlighted by Tiikkaja and Liimatainen (2021), where it is stated that women have less access to the household car than men. Linked to the use of a car is the possession of a driving licence, which depends on socio-demographic attributes such as age and sex, among others (DfT, 2023b; NTS, 2023e). Møller and Jensen (2022) identify in Denmark that the existence of several cars in a high-income household, with no historic records of accidents, increases the likelihood of licencing at young ages. An alternative mode of transport is the use of bicycles. Based on NTS (2023 a), the ownership of a bicycle differs on age, with young individuals (aged 5 to 10) being more likely to have access to bicycles (83%) than any other individuals in different range of ages, although a peak between those aged 40 to 49 is observed (50%).

Driving license

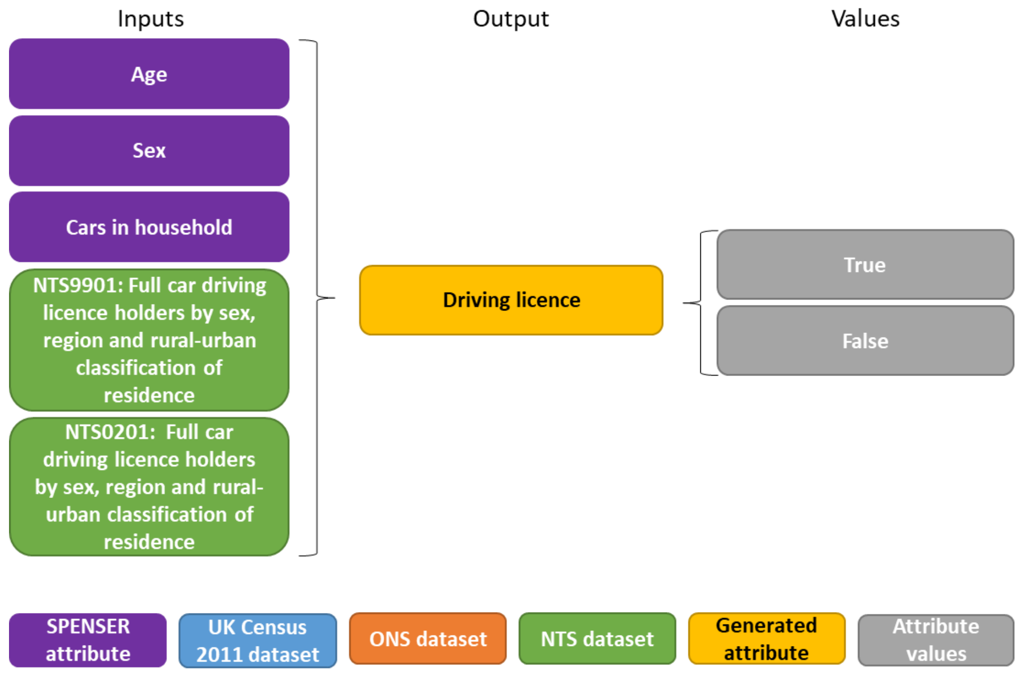


Figure 18 Driving license attribute. Description of required inputs and expected output values.

Driving license attribute identifies driving license holders (Boolean attribute) based on their attributes and external datasets from NTS (DfT, 2023b; NTS, 2023e) (Figure 18). The first provides information of percentages of driving licence holders per range of age and sex in England and the second the percentages of driving licence holders per sex only in different regions of England. In this case, the NTS information does not provide any detailed spatial definition (e.g., OA or MSOA area), only percentage values related to England (DfT, 2023b) or a specific English region (NTS, 2023e). Consequently, only the range of ages, sex and the number of cars in household attributes were considered.

When comparing both NTS datasets, it is possible to estimate the percentage of males and females by range of age that hold a driving licence per year in the area of study. In the 2019 case, the percentage of males with a driving licence in the NE is 79%, while the total percentage of men in England with driving licence is 80%. Because these two values are very similar, it was assumed that the mean value of driving licences in England per range of ages could be applied to the NE males. In the case of females, the values were weighted for each range of age (equation 7), as differences were more significant (63% in the NE and 71% in England).

$$\text{females(aged x, y)NE} = \frac{\text{\% females(aged x, y) in England}}{\text{total \% females England / total \% females NE}}$$

Equation 7 Weighted value for each female group of age.

At that stage, the percentage of individuals holding a driving license per range of age and sex in the NE region was estimated.

When assigning the driving licenses to the agents, the number of cars in the household are also considered. As Tiikkaja and Liimatainen (2021) state, the existence of cars in a household does not mean that every adult in the household can use it. To identify those with a driving license, it was firstly assumed that at least one adult in a household with at least one-car holds a driving licence. This constraint avoids having households with vehicles and no one being able to use them. Secondly, it is also known that the possession of a driving licence does not imply the necessity of having a car. Therefore, it was assumed that individuals living in households with more than one car have a higher probability to hold a driving licence than those living in a household with one car, and even more than those without a car in the household. Initially, the probability values for each category were assigned randomly and were adjusted after a few iterations. The best results were obtained when these values were 0.2, 0.3 and 0.5 for households without a car, with one car and with more than one, respectively.

Car access

The car access attribute identifies those individuals who can use a car from the household (Boolean value). The individuals are allowed to have access to a car if two conditions are satisfied: they hold a driving licence, and the household has at least one car. In any other cases, individuals are not allowed to have access to a car from the household. Figure 19 shows the attributes considered when assigning synthetic individuals the possibility of access to a car in the household.

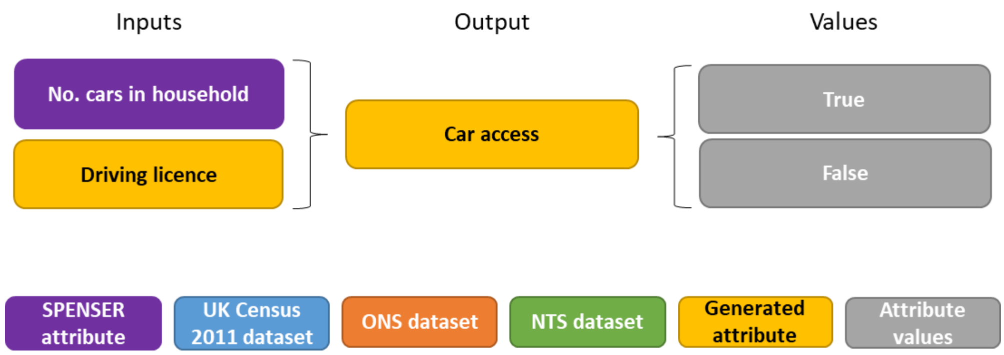


Figure 19 Car access attribute. Description of required Inputs and expected output values.

Bicycle access

This attribute identifies those individuals who have access to a bicycle in the household (Boolean value), using statistical data from the NTS (NTS, 2023a), where information about bicycle ownership by age in England is provided. Due to the scarcity and lack of detail of information on bicycle ownership, the individuals with bicycle access were randomly selected based on their age only. No spatial characteristics were considered, as spatial data related to the number of people owning bicycles were not found. Figure 20 shows the attributes considered when assigning synthetic individuals to access bicycles.

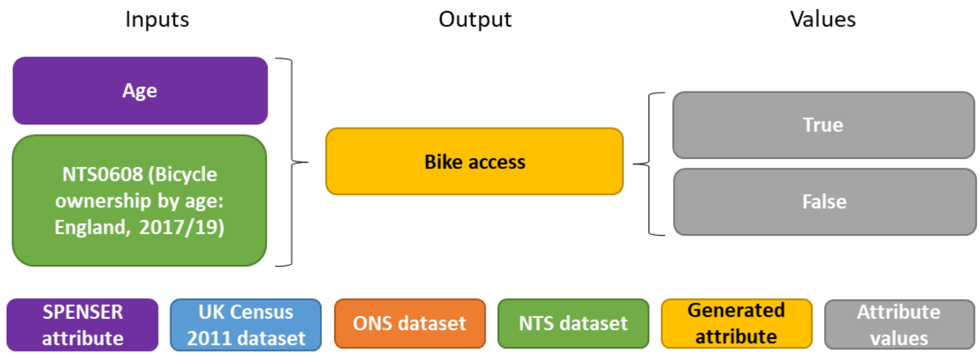


Figure 20 Bicycle access attribute. Description of required inputs and expected output values.

3.3.4. Synthetic population outcome, reproducibility and limitations

The outcome of all the steps followed in section 3.3.3 provides a very detailed synthetic population, which overcomes the limitations of the existing methods described in section 3.3.2 to generate a heterogeneous synthetic population. This achievement allows the possibility of taking into account minority groups within society that would be ignored in the case of a minor amount of attributes, showing a more realistic view of the world. Table 1 summarises the attributes generated for each agent in the synthetic population.

Individual		
Column	**Comment**	**Values**
Individual ID	Individual unique ID	Unique NTS Individual ID
Household ID	Household unique ID	NTS Household ID
Age	Numerical age value	0-85
Sex	Gender - 2 categories	1 (males),2 (females)
Marital status	Marital status - 2 categories	Married, single
Children dependency	Children dependency	Boolean
Economic activity	Type of economic activity - 3 categories	Employed, unemployed, inactive
Occupation	Type of occupation - grouped in 14 categories	Managers, directors and senior officials Professional occupations Associate professional and technical occupations Administrative and secretarial occupations Skilled trades occupations Caring, leisure and other service occupations Sales and customer service occupations Process, plant and machine operatives Elementary occupations Student Retire Sick Looking after home /family Other
Income	Income value grouped in deciles	Numeric value starting at 1
Driving licence	Driving licence holder - 2 categories	Boolean
Car access	Access to car in household- 2 categories	Boolean
Bike access	Access to bicycle in household- 2 categories	Boolean

Table 1 Description of the attributes generated for the synthetic population. A definition of the attribute name (first column), a short description of their meaning (second column) and expected values (third column) are provided.

Reproducibility and time requirements

This self-developed methodology is easily transferable to any other region in England, simply by adjusting the parameter values related to the region of interest for each of the desired socio-demographic attributes.

The computational time varies depending on the attribute calculated and the amount of synthetic individuals processed. In the case of the NE of England (circa 2.6 million synthetic individuals) the estimated times varied between one hour (e.g., marital status, children dependency, bicycle access, car access) and a day (e.g., economic activity, occupation, annual gross income, driving license).

Limitations

The proposed methodology described above is based on incremental attribute assignment. It initially starts with only consideration of attributes obtained from SPENSER (as in the case of marital status and children dependency), and gradually includes some of the attributes developed within the methodology, supported by statistical datasets from the UK census 2011, ONS and NTS. Figures 11 –20 show the dependencies of each new attribute with the previous generated ones. This incremental procedure can result in uncertainties and propagate inaccuracies to attributes generated subsequently that could produce an unrealistic representation of the population from the study area. Consequently, the annual gross income attribute could be less accurate than the economic activity, as the first is calculated after generating the economic activity and occupations attributes, while the second is directly derived from SPENSER attributes and official datasets only. Figure 10 shows the order, and therefore their dependencies, in which attributes are generated.

Additionally, the population projection from 2011 UK census data to 2019 (based on ONS statistics) follows a purely linear projection, based on statistical data without considering any changes in employment, new construction developments or transport infrastructures at specific locations in the study area. This limitation assumes that the proportion of individuals with certain characteristics increase or decrease proportionally in each area based on the relationship between 2019 and 2011 statistical values, as described in equations 4 and 5.

In order to minimise these uncertainties, several validation procedures were applied to the new attributes. Aggregated results considering several socio-demographic attributes at once (e.g., age and sex) but also their geospatial distribution at MSOA level were compared against statistical and spatial data from ONS and NTS, conditioned by the available resources (see section 4.1.1). This validation stage provides a measure of the level of confidence that can be achieved and quantify the accuracy and precision obtained. Sections 5.2.1 discusses the validated results. Despite the validation procedures followed, the results obtained cannot be considered as the ground truth. A more exhaustive validation method is required where more than two attributes are compared together (e.g., age, sex, income and marital status) to link the interconnections of the selected attributes and obtain a more realistic representation of society. This area of improvement has been highlighted as future work in section 5.4.1 to achieve more precise and accurate results.

3.3.5. Activity plans

Activity plans are the other main component required to generate a synthetic travel demand, complementing the synthetic population described above. They define the activities performed by each individual during a normal working day, containing information about their purpose of trips, starting-ending times, origin-destination locations and transport modes used, among others.

This information is sensitive, and the level of granularity provided depends on the purpose and scope of the project. The acquisition of this data is not open to the public at a very detailed spatial resolution, due to privacy reasons, as this information could help identifying patterns of specific individuals. Currently, two main data sources store this information: travel diaries and mobile phone data.

Travel diaries are household surveys that contain information of the trips generated by individuals in a specific area and time. This information, combined with their socio-demographic attributes, allows the analysis of the daily mobility behaviours and patterns at the individual and aggregated level of detail. These surveys have some shortcomings, mainly due to trip omissions when individuals are surveyed (Wolf *et al.*, 2003; Forrest and Pearson, 2005). Additionally, the lack of accuracy provided by the citizens when estimating the trip times, distances, locations and routes followed (Stopher and Greaves, 2007; Stopher *et al.*, 2007) can affect the analysis and understanding of human mobility.

In the UK, the National Travel Survey (NTS) is the source of up-to-date and regular information about personal travel patterns by residents of England within Great Britain and monitoring trends in travel behaviour (Cornick *et al.*, 2020). The annual surveys collect information on how, why, when and where people travel as well as factors affecting travel (DfT, 2023i), besides their socio-demographic attributes. In 2019, 6,162 households participated, including people in all age groups and children (DfT, 2020c). Within the NTS, different datasets can be accessed: NTS (DfT, 2022b), NTS special licence access (DfT, 2022a) and NTS secure access (DfT, 2023h). The three datasets contain the same information (i.e., socio-demographics and travel diaries) from 2002 to 2021, although their spatial resolutions and requirements to get access to the data differ between them.

Due to the limitations in the collection of travel diaries highlighted before, the use of mobile phone data has been considered as an alternative. The most widely applied type of mobile phone data in travel behaviour research are cellular network-based data (Wang *et al.*, 2018; Wu *et al.*, 2019), although GPS, Wi-Fi and Bluetooth positioning systems could be used (Wang, *et al.,* 2018). This data has been widely used for travel recognitions (Yang *et al.*, 2016; Gong et al. 2018; Wang et al. 2018; Marra *et al.*, 2019; Guo *et al.*, 2022, 2023), which proof its usefulness for AcBMs (Cui et al. 2021; Hafezi *et al.*, 2021; Guo *et al.*, 2023) and AgBMs.

The use of mobile phone data has some advantages when compared against traditional travel diaries. Firstly, the sample is not affected by unconscious bias introduced by the individuals in surveys, but recorded data show what individuals do (Franco *et al.*, 2020). Secondly, other potential biases are reduced as a larger geographic area is covered (Wang *et al.,* 2018; Wu *et al.*, 2019), although it depends on the market penetration of the telecom company collecting the data (Wang *et al.,* 2018). Franco *et al.* (2020) achieved a 30% penetration in their analysis, which is greater than the average percentage of individuals surveyed in travel diaries. This population sample increase helps in reducing the gaps when new dwellings and regenerated areas are not covered by traditional methods (Franco *et al.*, 2020). Lastly, this data is rich in spatio-temporal information (Wang *et al.*, 2018).

Despite their advantages, mobile phone data also have some disadvantages. The first is the lack of socio-demographic attributes of the individuals (Wang *et al.*, 2018) due to privacy reasons (Chen *et al.*, 2016; Guo *et al.*, 2023), although some attributes could be provided (e.g., age and gender (Franco *et al.*, 2020)). Secondly, this information can only be obtained directly from telecom companies based on specific licences and agreements to keep clients' privacy secured (Wang *et al.,* 2018). Thirdly, and linked to the previous, the data provided by telecom companies are spatially and temporally aggregated and anonymised (Chen *et al.*, 2016; Franco *et al.*, 2020). Fourthly, due to spatial aggregations, short trips can be underestimated since several trips can be done within the same aggregated area, being impossible to be identified (Franco *et al.,* 2020). Fifthly, secondary activity types (e.g., shopping, medical appointment) are difficult to recognise (Guo *et al.*, 2023), as well as the transport modes used (Franco *et al.,* 2020), although both can be inferred based on assumptions and dedicated algorithms.

3.3.6. Activity plans assignment

The methodology explained in this section covers the identification of the most relevant activity plan data source from the options listed in the previous sections and an Exploratory Data Analysis (EDA) of the dataset chosen to identify only those activity plans to be used, based on spatial and temporal patterns (figure 21).

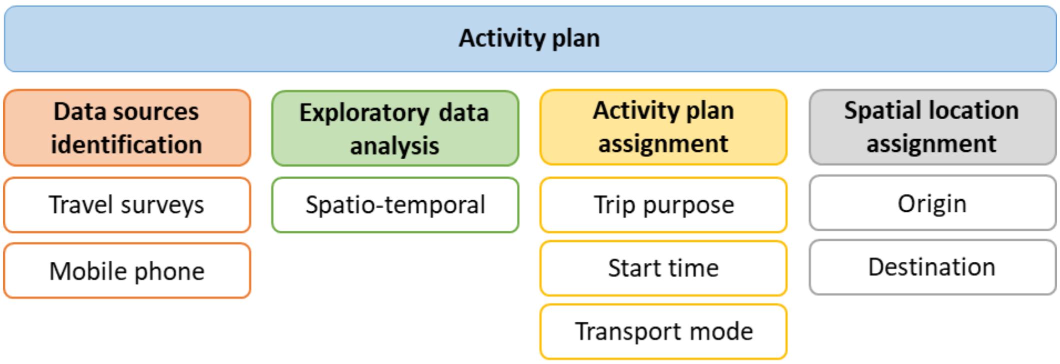


Figure 21 Activity plan. Methodology followed to assign activity plans to the synthetic individuals.

Once the data is identified, cleaned and processed, the method to assign daily activities to each agent in the 2019 synthetic population is explained, considering common socio-demographic attributes between both datasets and travel relationships between individuals living in the same household. Finally, it is explained how activity locations are assigned to each individual, depending on the trip purpose.

The potential benefits of each available and identified data source for agents' activity plans were analysed to assess the potential benefits of each one, allowing the selection and use of the most appropriate sources for this project. The use of mobile phone data was discarded based on the following reasons:

- Although an open license was obtained from a telecom company (O2 Telefónica) to use 2016 data from the area of study, the data was temporally (hourly) and spatially (MSOA area) aggregated as OD matrices, due to privacy reasons.
- The anonymised data did not contain any socio-demographic attributes.
- The activity types provided in the data were very scarce (e.g., home based work, home based other, none home base).
- Only two transport modes were identified (i.e., road, rail).
- The possibility of underestimating short trips due to spatial aggregation could lead to the absence of many of these trips in the data, which are fundamental in the project, as they are the main type of trips that can be walked and cycled.

Consequently, NTS travel diaries are regarded as the best option, although biases in trip omissions and poor trip characteristic estimations could affect the quality of the data. The three national survey datasets cited before have the required data to develop a very detailed synthetic travel demand. They contain a wide variety of socio-demographic attributes (with nine attributes matching those developed for the 2019 synthetic population), as well as very detailed seven-day travel diary plans from each individual surveyed (23 activity purposes, starting and ending times in minutes, 28 travel modes). Additionally, travel diaries range from 2002 to 2021, which will allow a larger sample size to be used, as the number of surveyed households per year is low, varying from 2,822 (year 2020) to 9,453 (year 2004). Within them, the NTS special licence dataset (DfT, 2022a) was chosen for the following reasons:

- The spatial granularity is at LA level, enabling the use travel diaries from the whole of England with similar patterns to those in the area of study and discard outliers (e.g., London). This will allow for increasing the number of travel diaries that could be used, instead of being constrained to those travel surveys within the study area. The other alternative datasets have spatial granularities at rural/urban (DfT, 2022b) or OA area scale (DfT, 2023h), which are non-detailed or very detailed for the purpose of this thesis, respectively.

- The acquisition of the dataset requires a simple (although it is a long process over time) approval from the data owner. The other two alternatives require either minimum (DfT, 2022b) or very concise and specific (DfT, 2023h) approval processes.

As previously highlighted, an extremely low number of households are surveyed per year, which implies that only a small representation of the population is considered. To increase the number of travel diaries and therefore, their heterogeneity, travel diaries from several years and areas of England need to be used, instead of only those from 2019 and the Tyne and Wear region. Consequently, the spatio-temporal framework was analysed via an EDA to identify individuals with similar activity plans in space and time to those in the area of study in 2019 and discard any outliers.

Results show very similar mobility patterns in every region in England except London. Figures 22 and 23 show similar trip purposes and transport modes respectively, between all regions except in London (red line), where quite different values are obtained (London is a region where the use of cars is lower than any other, while the use of public modes is the opposite). Within similar regions, differences are minimum. Some minor discrepancies can be observed in sport, holiday and other trip purposes (figure 22), and the use of other local buses (figure 23), which indicate that people in those regions have similar mobility patterns.

Travel mobility patterns were also analysed based on the evolution of the average number of trips by day of week (figure 24) and month (figure 25) between 2002 and 2019. Results show that from 2002 until 2011, less trips were made every year, decreasing linearly. Since 2011, the trends are stabilised, although differences between weekdays and weekends are observed, especially on Sundays, where around a 40% fewer trips are made when compared to weekdays (figure 24). In the case of months (figure 25), similar patterns from 2011/2015 to 2015/2019 are shown, indicating that people tend to do fewer trips now than before. Differences can be observed between months as well, with February and August differing the most when compared to the others, but following the similar trend, although fewer clear patterns can be identified.

Besides the previous analysis, the trips in progress by time of day of week and trip purpose by trip start time from 2006 to 2019 (figures 26 and 27) were also compared. Results show that patterns are stable in time, with minimum differences for weekdays (between morning and afternoon peaks), although more variability can be observed during weekend days (figure 16). In the case of the activity purposes (figure 27), very small differences can be observed in the 13-year analysis period, indicating that travel patterns are kept relatively constant in time during weekdays, experiencing the morning and afternoon peaks at the same time.

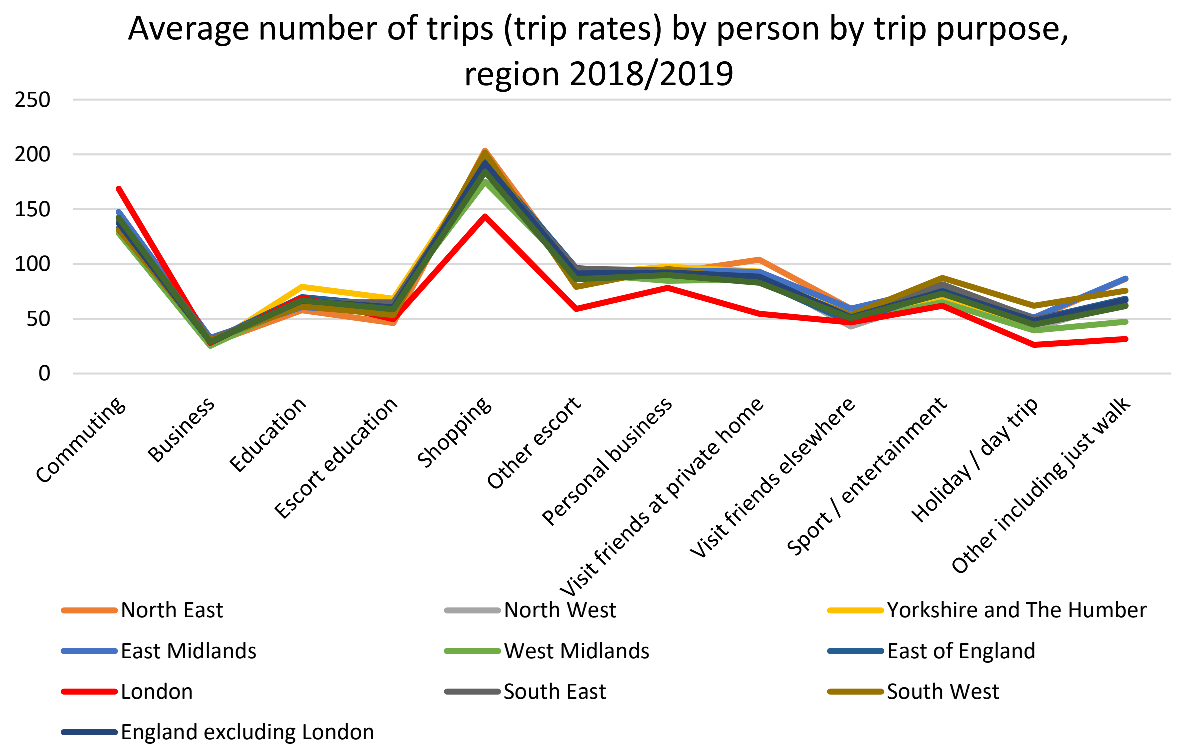


Figure 22 Average number of trips by person, trip purpose and region 2018/2019.

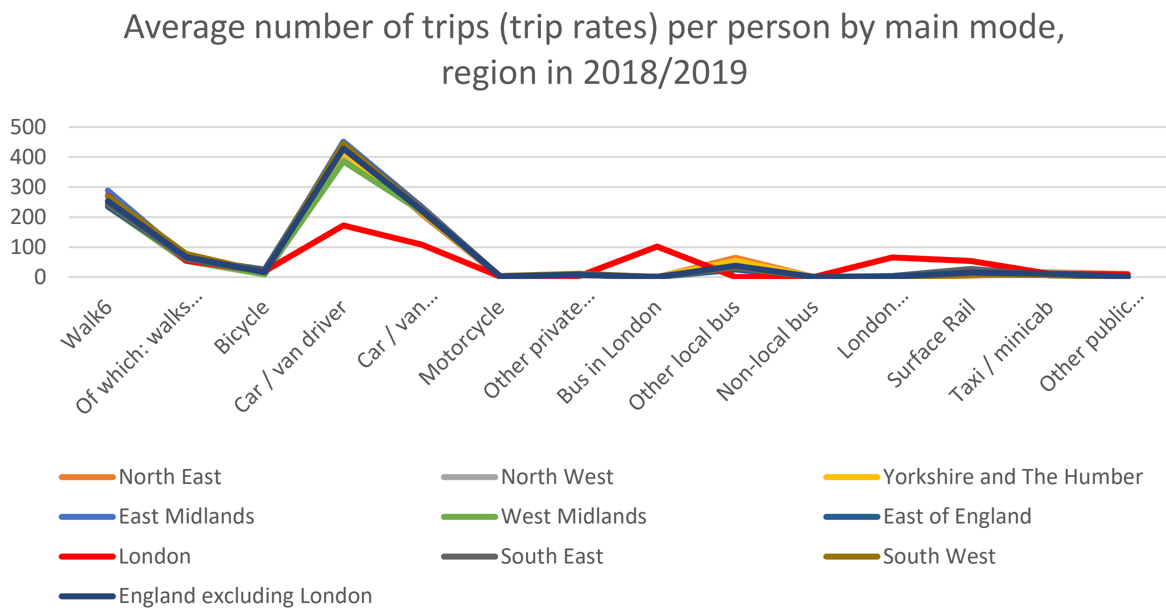


Figure 23 Average number of trips (trip rates) per person by main mode, region in 2018/2019.

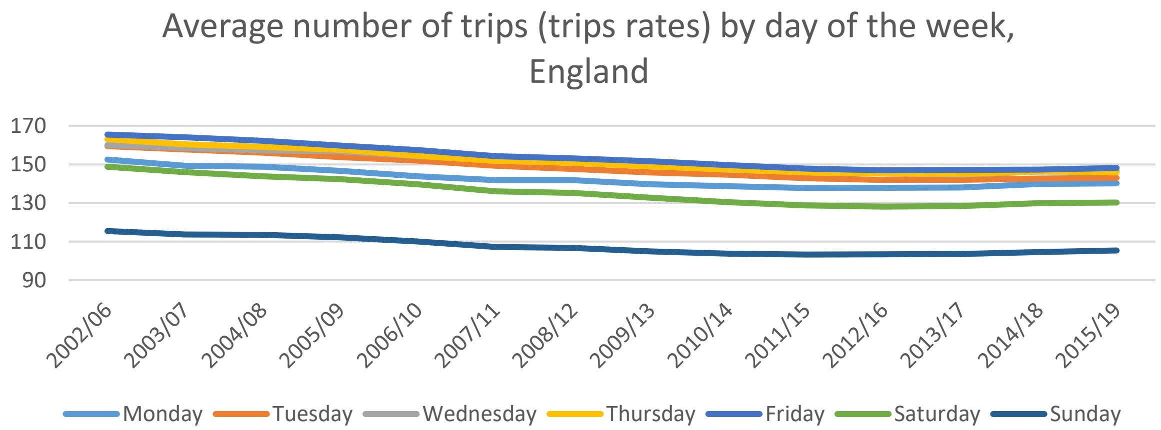


Figure 24 Average number of trips by day of the week in England (2002-2019).

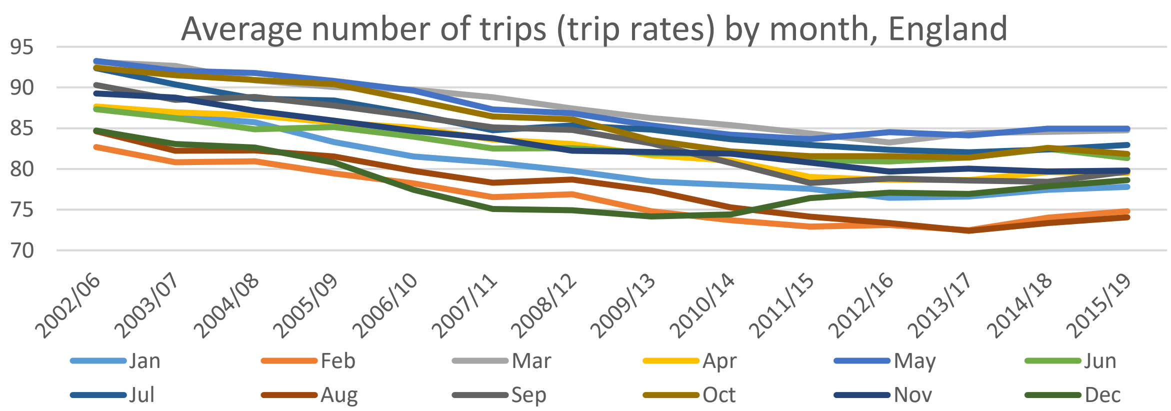


Figure 25 Average number of trips (trip rates) by month, England.

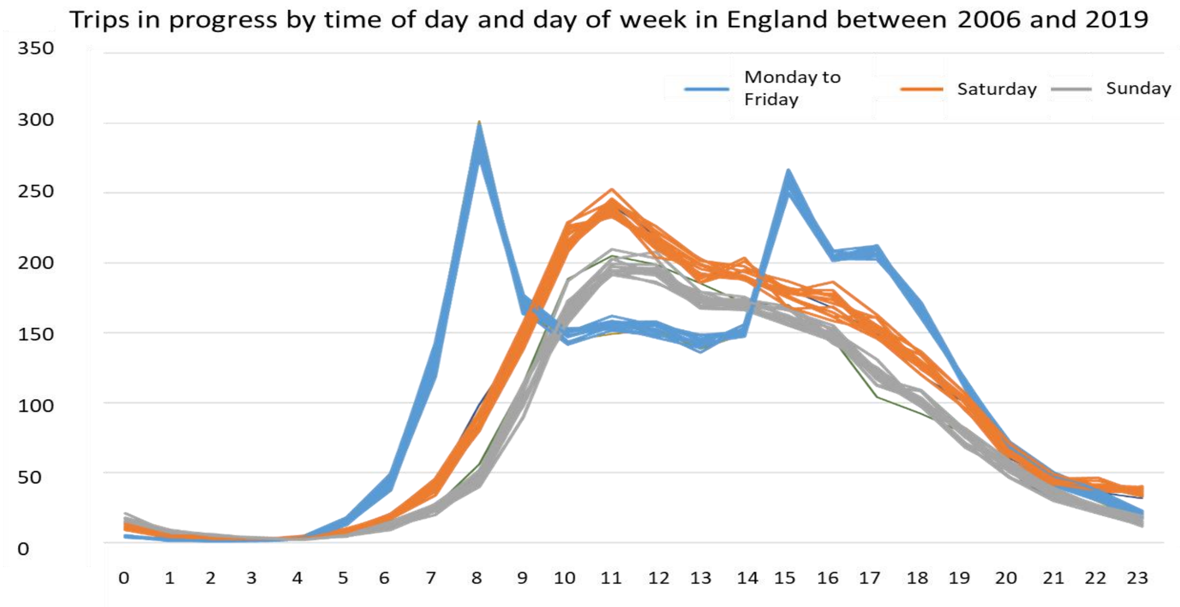


Figure 26 Trips in progress by time of day and day of week in England between 2006 and 2019.

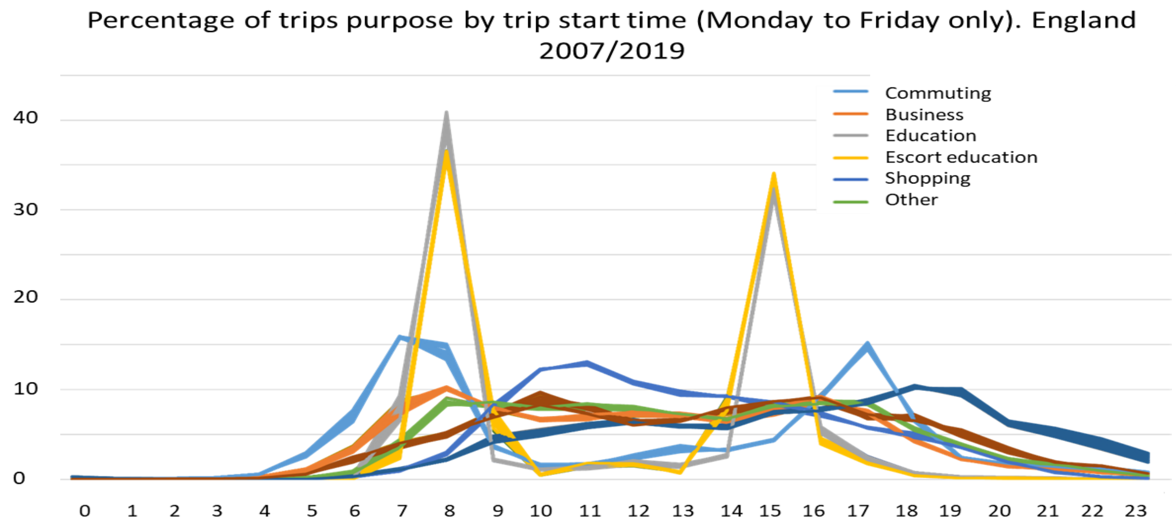


Figure 27 Percentage of trip purpose by trip start time (Monday to Friday only), England 2007/2019.

Consequently, the conclusion made regarding the spatial and temporal extension of travel diaries to use in the research project was clear. All regions except London were considered as similar in travel mobility patterns, as well as those travel diaries surveyed between 2011 and 2019. Additionally, to make the simulations reflect a normal working day, only weekdays when children have educational activities were selected. This last constraint considers two premises: to avoid the effect of weekends and the effect of different activity patterns in children and their parents. Every weekend, bank holiday, summer, Easter and Christmas holidays were discarded.

Attribute	Value
Age	0-5
	6-10
	11-15
	16-19
	20-29
	30-39
	40-49
	50-59
	60-64
	65-75
	>75
Sex	1 (male)
	2 (female)
Marital status	Married or couple
	Single
Children dependency	True
	False
Economic activity	Employed
	Unemployed
	Inactive student
	Inactive retired
	Inactive looking after home/family
	Inactive sick
	Inactive other
	Inactive child student
Income	Decile 20
	Decile 40
	Decile 60
	Decile 80
	Decile 100
Driving license	True
	False
Car access	True
	False
Bicycle access	True
	False

Table 2 Common socio-demographic attributes and values between NTS and synthetic individuals generated in the synthetic population.

In total 1,038,736 unique trips from 336,008 different days and 90,578 unique individuals were considered. Individuals were grouped in households based on common 'household ID' attribute, with the same 12 socio-demographic attributes and values as those individuals from the 2019 synthetic population developed in section 3.3.3 (see table 2). Trips were defined by

11 attributes, providing information about the purpose (14 categories), starting and ending time, main mode of transport (seven categories), journey sequence in the day, and distance.

Once the activity plans were identified, it was necessary to develop a methodology to transfer them to the individuals generated in the 2019 synthetic population and obtain the complete synthetic travel demand required.

This procedure considers the socio-demographic attributes of the agents from both datasets. The assumption made was that individuals with similar socio-demographic attributes behave and act in an analogous manner. Scientific examples in favour of this assumption were given in section 3.3.3, where the development of new attributes for the 2019 synthetic population (i.e., family dependencies, spending power and mobility access) were considered as crucial to differentiate travel behaviours between individuals with different characteristics. Additionally, it was observed that the NTS dataset includes the possibility of accompanying another member of the household to work, school, home or other activity (escort activities). This implies that the NTS dataset keeps those interactions between members of the same household (when provided by the surveyed individuals only), which are key factors to be considered when a realistic synthetic travel demand is generated.

The methodology developed to match individuals from both datasets was applied with the Activity_plans_dev tool (Alvarez Castro, 2023), a set of open-source Python Jupyter notebooks developed by the author as part of this study. This tool allows the identification of individuals from the 2019 synthetic populations with both similar personal and family characteristics to those individuals from the NTS dataset. The similar personal characteristics and values considered are their nine common socio-demographic attributes, while the similar family characteristics depend on the family dependency attributes only (marital status and children dependency).

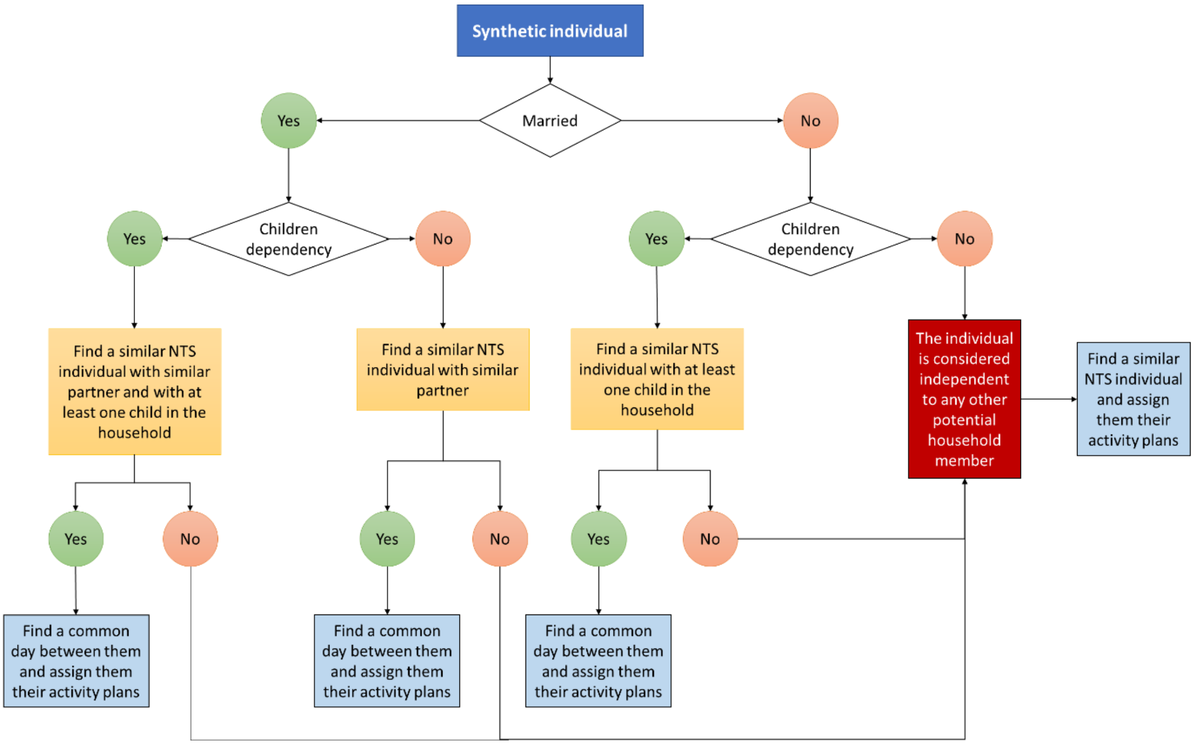


Figure 28 Workflow diagram showing the methodology followed to transfer NTS travel diaries to the synthetic individuals based on their socio-demographic attributes.

The chosen methodology works as follows (figure 28). A single individual from the 2019 synthetic population is selected randomly and their socio-demographic attributes are analysed. In a case where the individual has family dependencies, similar household members are selected from the NTS dataset.

- If family dependencies refer to a married or couple individual, similar individuals with the same socio-demographic attributes are selected from NTS. Among them, their partners are compared against the 2019 synthetic population individuals' partner considering only their range of age, economic activity, income, driving licence, car access and bike access attributes. If the selection has more than one option, the choice is made randomly. In cases where there is no match, a second selection for the partner is made considering only their age, economic activity, driving licence, car access and bike access attributes. If the selection in this second case has more than one option, the choice is made randomly.
- In a case where the family dependencies refer to a married or couple individual with dependent children (i.e., below 16 years old), the same procedure described before is

followed. In this case, the number of children is not considered, only the existence of them in the household.

- If family dependencies refer to a single individual with children dependencies, similar individuals with the same socio-demographic attributes from NTS are selected. Similarly to the previous case, only the existence of children in the household is considered.

At this stage, members from both datasets with similar socio-demographic attributes and family dependencies are matched. The next step is to find a common day between them and transfer their daily trips from the NTS dataset to the 2019 synthetic population, individually. For children, the transferred daily trips are those belonging to the NTS children closest in age.

In the case that previous matches were not successful, or the individuals do not have any family dependencies (e.g., single and no children dependency), they are considered as independent individuals from any other member of the household and will not keep any relationship with other members when doing their daily activities. For these individuals, the daily trips are transferred from NTS dataset considering only common socio-demographic attributes. Firstly, all nine common attributes between synthetic agents and NTS dataset were compared, matching 78.8% of the cases. Secondly, those that were not matched in the previous iteration were compared again but considering only seven attributes (sex, range of age, marital status, children dependency, car access, bike access, economic activity), matching 68.2% of the remainder. Thirdly, only six attributes were considered (sex, range of age, marital status, children dependency, car access, economic activity), achieving a match of 86% of the remaining individuals. Fourthly, only four attributes (sex, range of age, marital status, children dependency), with a 47% match. Fifthly, three attributes (sex, range of age, children dependency), with a 25% match. Finally, the remaining 0.06% of synthetic individuals who were not matched because no similar individual was found in the NTS dataset, were assigned a random activity plan. Table 3 summarises the results obtained.

	Matching with household interactions	No household interactions					
		9 attributes	7 attributes	6 attributes	4 attributes	3 attributes	Random match
Total percentage matched	84.0	12.6	2.3	0.9	0.07	0.02	0.06
Relative percentage matched	84.0	78.8	68.2	86.1	46.7	25.0	100.0
Number of synthetic individuals matched	2222234	333336	61376	24603	1852	529	1587

Table 3 Summary of the total and relative percentage of activity plans transferred to the individuals based on the followed methodology.

Some updates were required to fix some inconsistences in the assigned activity plans, such as children driving cars (i.e., their transport mode was updated to car passenger) and incorrect trip times. Additionally, all activity plans were forced to start and end at households, which is a constraint required by MATSim to run the simulations.

Individual ID	Purpose	Transport mode	Starting time	Ending time	Location (x,y)	Distance
5554_E02041682	work	car	370	405		15 miles
5554_E02041682	shop	walk	750	765		0.7 miles
5554_E02041682	work	walk	780	930		0.7 miles
5554_E02041682	home	car	1000	1055		15 miles

Figure 29 Example of an activity plan assigned to a synthetic individual following the previously developed methodology.

At this phase, all individuals from the 2019 synthetic population were assigned an activity plan based on their socio-demographic attributes, with some of them also keeping interactions with other members of the same household during their activities. All activity plans transferred contain information of the starting and ending time, purpose (23), transport mode used (7) and distance travelled for each trip, as shown in figure 29. The only missing and required information is the location of each activity. Although the NTS dataset used provides information at LA level only, this information is not valid, as activity plans from other regions beyond the area of study with similar patterns were used to expand the sample size provided. Therefore, specific locations need to be assigned to each activity.

The spatial allocation of activities (figure 30) was assigned using a process developed as part of the MISTRAL project (Pregnolato *et al.*, 2017) and activity_location_dev (Alvarez Castro, 2023) tools. The first is a tool developed by Newcastle University to match real households with households from synthetic populations, based on common characteristics. The second is a set of open-access Python Jupyter notebooks as part of this research that assigns locations to the activities, depending on the activity type and distances between consecutive activities.

Figure 30 Identified spatial location for the activities undertaken by the individuals (OSM basemap).

The activity locations were assigned in the following order:

- Household location for each one.
- Workplace location for those with a work activity.
- Educational location for those with an educational activity.
- Rest of activities except escort (i.e., accompanying) activities.
- Escort (i.e., accompanying) activities.

These locations were assigned as described below:

Households

The MISTRAL model identifies the spatial location of the households where individuals from the 2019 synthetic population were allocated. This tool classifies each residential dwelling in four categories (detached, semi-detached, terraced, and apartment), based on their spatial characteristics and the relationship between adjacent households, using the AddressBase dataset (Ordnance Survey, 2021). Once all real buildings are classified, they are matched with households from the 2019 synthetic population per LA and OA area. In a case where a synthetic household in a specific OA area is not assigned a real building based on its type, a different type is tried. In a case where a synthetic household cannot be assigned in its OA area due to all real buildings being occupied, it is matched with a similar building in an adjacent OA area. Household locations are assigned which are known as the starting point for each individual, as this location is considered fundamental for the definition of the remaining activities. More information about the MISTRAL tool can be obtained in (Pregnolato *et al.*, 2017).

Workplaces

Workplace locations were assigned to those agents with a work activity in their activity plans, using 2011 UK census origin-destination (OD) matrices by transport mode (the same seven options as those in the activity plans) and MSOA areas (ONS, 2011a). These matrices provide estimates of the usual number of residents in the area of study aged 16 and over in employment, travelling between MSOA areas. These values were linearly projected to 2019, calculating a ratio between the number of employed individuals in the 2019 synthetic population and the number of them in 2011, per MSOA area.

These estimated flows of workers per MSOA area quantify the number of individuals travelling between areas, while the activity plans assigned to the synthetic individuals identify the distances travelled to work from the previous activity. To identify the MSOA zones to which a synthetic working individual has to be assigned, it is necessary to calculate the distances between MSOA zones. Distances were calculated between their centroids, considering the Open Street Map (OSM) road network (Geofabrik, 2023), instead of Euclidean distances. This approach provides a more realistic representation, as constraints such as bridges and tunnels are considered when calculating distances between locations that are divided by natural elements (e.g., rivers and mountains), which is the case in some urban zones in the area of study.

Then, synthetic working individuals were assigned a working MSOA zone based on the distance travelled and the transport mode used from the activity plan and the total number of individuals allowed to travel between MSOA zones from the OD matrices. In a case where any synthetic working individual is not assigned a working MSOA zone due to the maximum capacity of workers to all potential destination levels from their origin being reached, it is considered that the individual works outside the area of study and will not be assigned any activity plan.

The knowledge of the MSOA zones where the synthetic individuals work is not enough when the synthetic activity demand dataset is used in AgBMs. It is required to identify a specific building within the area with a working purpose (e.g., offices, factories) for more realistic and detailed results. OSM buildings (Geofabrik, 2023) were identified as workplaces using OSMOX (Arup, 2023), a tool developed by Arup CML that classifies buildings in different categories based on their tags (e.g., commercial, industrial, office, government, hospital, school, university and amenity). Complementary to this tool, a method that considers only those workplaces with a floor area greater than 15 square meters was developed within the thesis. Those buildings were assigned a maximum capacity attribute, which estimates the maximum number of employees depending on the floor area, number of floors and the density of workers per workplace type. The first two components are obtained or derived directly from the OSM buildings, while the third is obtained from the UK Employment Density Guide (UK Homes and Community Agency, 2015), where the employment density per square meter depending on the workplace purpose is estimated. This maximum capacity attribute allows synthetic employees to be assigned to buildings in the same MSOA zone randomly until the maximum capacity of a building is reached. In that case, that building is not considered for the remaining synthetic agents, which are forced to be allocated to any other building with capacity. The result is an uneven and realistic workplaces distribution, according only to the buildings' characteristics and spatial location.

Educational places

Educational facilities are those attended by synthetic students with educational activities in their daily plans. Depending on their age, the students are allowed to attend specific types of education facilities. Consequently, a methodological distinction was made in the way these locations were assigned, due to data limitations. Two different groups were considered: those below 16 years and those equal or above.

Educational facilities in the area of study for those individuals aged 15 or below were identified using an open-access dataset provided by the UK Government (UK Government, 2023b), where information about their status (open, closed), capacity and location (projected coordinates) are shown.

The procedure to identify the educational facility for each synthetic individual was similar to the one followed before for the synthetic workers: calculating the road network distances between centroid areas (in this case using OA areas, smaller areas that can provide more accurate results). Within them, the school with the highest capacity is chosen, as those facilities are prioritised, considering them more important than smaller ones, due to the fact only a proportion of the individuals will be simulated in the AgBM. Once an educational facility reaches the maximum capacity, it is considered full and not available for the remaining students to be assigned an educational facility. In the case a student is not assigned any educational facility because there is none or all possible facilities are complete in its assigned area, the distance is iteratively increased until at least one facility is available. This procedure was also applied in Spooner *et al.* (2021).

The remaining students are assigned only to college or university facilities, when aged up to 17 or above 17, respectively. The followed procedure is a combination of the previous two. Firstly, educational facilities related to colleges or universities are identified applying OSMOX (Arup, 2023). Secondly, a maximum capacity attribute is calculated based on the same attributes as those considered for workplaces. Thirdly, road network distances between OA centroids are used to identify those potential facilities reached from their households. Similarly, as it was assumed for the youngest synthetic students, those facilities with the highest capacity value were chosen first. The procedure finishes when all students are assigned a location for their educational activity.

Remaining activities other than escorting (i.e., accompanying someone else)

The locations for the remaining activities were firstly identified applying OSMOX (Arup, 2023) to OSM buildings (Geofabrik, 2023) and adding the supermarket locations from Geolytix (Geolytix, 2023). The classification of buildings in the activity categories was similar to that previously explained for workplaces and educational facilities for students older than 15 years. The result was a set of buildings classified in one or more activities, depending on their characteristics (e.g., a shopping centre can be classified as 'shop', 'leisure' and 'eat').

The location assignment to the synthetic individuals, based on their activity plans, was carried out applying concepts derived from spatial interaction modelling (SIM) techniques. This technique enables one to evaluate the demand of flows and movements (e.g., people, goods) between two locations in space (O'Kelly, 2019; Travel Forecasting Resources, 2023), which has been an important concept in the social sciences, specifically in geography, economics and sociology (Wilson, 1971). SIMs are usually the first two steps in the FSMs described previously in the literature, as spatial generation and trip distributions are estimated (Travel Forecasting Resources, 2023; Rodrigue, 2024). The assumptions made in the model to estimate the interactions (T) between an origin (i) and a destination (j) are a function of the attributes of the origin (V_i), the attributes of the destination (W_j) and a fraction of distance between the origin and destination (S_{ij}) (Rodrigue, 2024) (equation 8).

$$T_{ij} = f(V_i, W_j, S_{ij})$$

Equation 8 Definition of the Spatial Interaction Modelling technique (Rodrigue, 2024).

This assumption can be defined as the demand from the origin (i.e., the characteristics of the origin), the attractiveness of the destination (i.e., how attractive each area is for a specific activity), the competitiveness of the destination (i.e., how good the destination area is when compared against others), and the cost of travelling or accessibility between origin and destinations (i.e., the distance) (Wilson, 1971; Newing, 2018) (equation 9).

$$T_{ij} = Demand_i * \ Attractiveness_j * Competitiviness_j * \frac{1}{Accesibility_{ij}}$$

Equation 9 Spatial Interaction Modelling technique applying the demand, attractiveness, competitiveness and accessibility factors (Newing, 2018).

Some of these concepts were used to estimate the likelihood of individuals' movements between areas when doing their activities. The translation of previous concepts to the developed methodology is as follows:

The whole area of study was divided into zones: OA zones when distance travelled between consecutive activities is below 10 kilometres; and MSOA zones in the remaining cases. These zones identify the origin (the area where the individual is located during their previous activity) and potential destinations that the synthetic individual can reach within the distance provided by the activity plan (accessibility factor) for their next activity. For each potential destination zone, their attractiveness (i.e., the number of total facilities in the zone dedicated to the activity the synthetic individual has to do (e.g., food shop)) and the competitiveness (i.e., the total number of facilities in the zone) are calculated. Additionally, an extra accessibility component is included which considers the distance between the potential destination zone and the zone where the household of the synthetic individual is located. This last component is added to avoid the synthetic individuals choosing areas far from where they live, incentivising activities to happen close to their households. Each potential destination zone is assigned a selector factor (Tij) that identifies its likelihood of being selected. One of them is selected randomly based on their probability values (equation 10).

$$T_{ij} = Attractiveness_i * \ Competitiviness_j * \frac{1}{Accesibility_{ij}} * \frac{1}{Accesibility_{household\,j}}$$

Equation 10 Spatial Interaction Modelling technique applied in the methodology.

Once a destination zone is selected, it is necessary to identify a specific building within it dedicated to the activity that the synthetic individual is undertaking (e.g., food shop). In this case, the specific facility is chosen based only on the competitiveness factor, considering the floor area of the amenity and the total number of amenities within 100 meters. These components try to identify those amenities that could attract more individuals based on their size and the possibility of doing more activities in the surrounding area. When all potential destination buildings where the activity can be done (food shop in the example) are identified, one is chosen randomly based on a probability value that considers the size and number of other facilities in the surrounding area. Figure 31 shows the procedure visually. The origin (blue dot), the household location (pink) and the potential destinations (yellow) are highlighted (left); the chosen MSOA zone is identified (middle); the facility (red dot) within the MSOA zone is assigned (right).

Figure 31 Visual representation of the SMI technique to identify the location of the next activity (OSM basemap).

This procedure is followed for each activity in the activity plan that is not for work, education and escort, similarly as it was done by Spooner *et al.* (2021).

Escorting (i.e., accompanying someone else)

Escort activities refer to those activities that a synthetic individual does accompanying someone else from the same household (e.g., to work, to school, for shopping). In these cases, these individuals were assigned the same location as those individuals doing the complementary activity (e.g., work, education, shop). In the case that a synthetic individual with an escort activity is not associated with any other member of the household doing a complementary activity (due to a lack of trip sharing at household level in the activity plan), the individual is assigned another activity (e.g., leisure) that will be done alone.

Table 4 summarises the characteristics of each trip in the activity plan of each agent within the synthetic population.

Trip		
Column	**Comment**	**Values**
Trip ID	ID given to the trip	Unique ID
Day ID	ID given to all trips made by an individual on a given travel day	Day ID
Individual ID	Individual unique ID	NTS Individual ID
Household ID	Household unique ID	NTS Household ID
Journey Sequence	Journey number on a given travel day	Numeric value starting at 1

Number of Stages	Number of stages - actual number	Numeric value starting at 1
Main Mode	Main mode of travel - grouped in 7 categories	walk bike car car_passenger bus metro train
Trip Purp To	Trip purpose - grouped in 14 categories	work education food_shop shop medical eat other lesiure_act lesiure_sport home escort_home escort_work escort_education escort_other
Trip Start	Trip start time - minutes past midnight	0-1439
Trip End	Trip end time - minutes past midnight	0-1439
Trip Dist	Trip distance in miles	Numeric value stating from 0
Trip Total Time	Total trip time - minutes	0-1439

Table 4 Description of the attribute names (first column), description (second) and expected values (third) of the activity plans assigned to the synthetic individuals.

Once the activity plans of each synthetic individual contain all required information (i.e., starting time, purpose of trip, origin location, destination location and transport mode), it is required to identify only those synthetic individuals that interact at least once during their activity plans with the main urban area of the study area: the Tyne and Wear region. A selection of those individuals undertaking at least one activity within this area or passing through it was made. The reason for only considering these synthetic individuals is mainly because the project is focused on simulating mobility policies in the main urban areas within the area of study. The reduction of synthetic individuals in the simulation will allow simulating faster scenarios and with a larger sample.

After those synthetic individuals are identified, it is required to convert the file into a format that MATSim can use. This procedure was done using PAM (Arup, 2020), another open-source Python library developed by Arup CML that allows reading of synthetic travel demands and transforming them into new formats, validating and visualising the activity plans. Figure 32 shows the representation of the activity plan assigned to a synthetic individual, while figure 33 shows its geospatial representation.

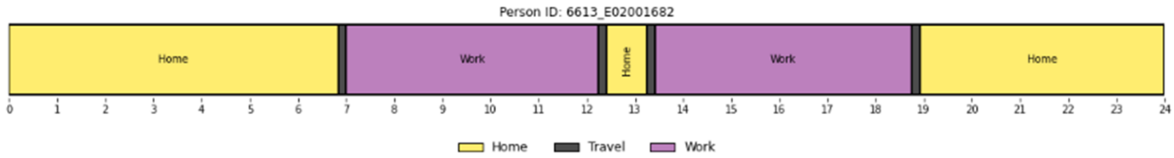


Figure 32 Visual representation of an activity plan assigned to a synthetic individual, using PAM.

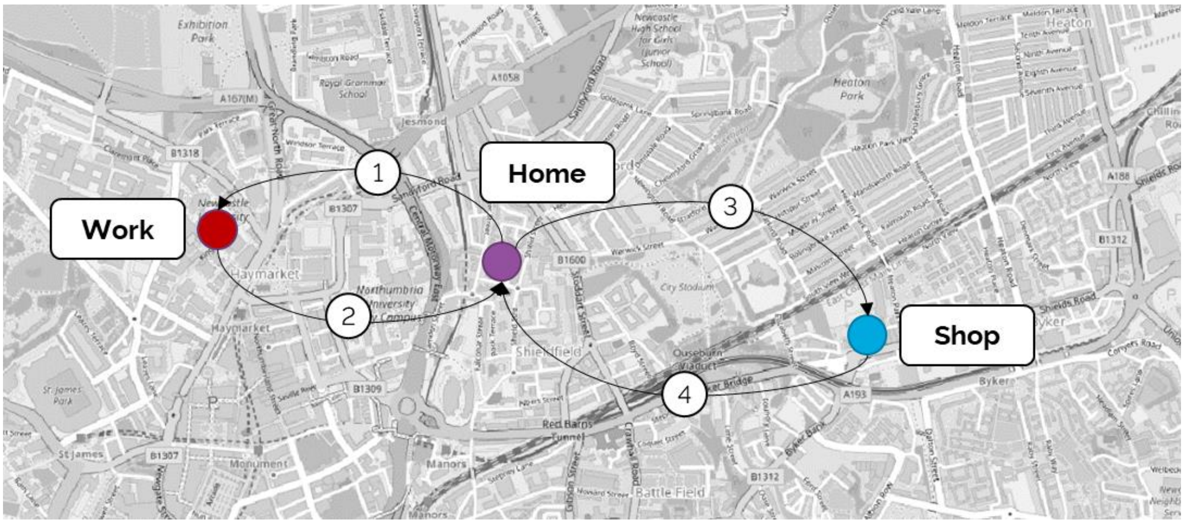


Figure 33 Geospatial representation of the activity plan assigned to a synthetic individual (OSM basemap).

The output generated is an xml file (figure 34) containing all socio-demographic attributes and activity plans, divided in activities and legs, for each synthetic individual, structured and defined based on MATSim requirements.

```xml
<?xml version="1.0" encoding="UTF-8"?><!DOCTYPE population SYSTEM "http://matsim.org/files/dtd/population_v6.dtd"><population>
  <!--Created 2022-07-19 13:47:32.668175-->
  <person id="5542_E02001682">
    <attributes>
      <attribute class="java.lang.String" name="subpopulation">high_income</attribute>
      <attribute class="java.lang.String" name="gender">2</attribute>
      <attribute class="java.lang.String" name="age">34</attribute>
      <attribute class="java.lang.String" name="marital_status">Married or couple</attribute>
      <attribute class="java.lang.String" name="children_dependency">False</attribute>
      <attribute class="java.lang.String" name="economic_activity">Employed</attribute>
      <attribute class="java.lang.String" name="occupation">2.0</attribute>
      <attribute class="java.lang.String" name="income">group_5</attribute>
      <attribute class="java.lang.String" name="driving_license">True</attribute>
      <attribute class="java.lang.String" name="car_access">True</attribute>
      <attribute class="java.lang.String" name="bike_access">False</attribute>
      <attribute class="java.lang.String" name="household_OA_level">E00041814</attribute>
      <attribute class="java.lang.String" name="hid">27364_E00041814</attribute>
    </attributes>
    <plan selected="yes">
      <activity type="home" x="415898.0" y="563944.0" end_time="06:00:00"/>
      <leg mode="car" trav_time="00:41:00"/>
      <activity type="work" x="426955.0" y="560496.0" end_time="17:50:00"/>
      <leg mode="car" trav_time="01:10:00"/>
      <activity type="home" x="415898.0" y="563944.0"/>
    </plan>
  </person>
```


Figure 34 Example of the synthetic travel demand of a specific synthetic individual in XML format.

After applying the previously described methodology, the synthetic travel demand is ready for further processing in detail in MATSim.

The effort put in to developing the code to transfer travel diaries to synthetic individuals based on common socio-demographic attributes makes it easy to apply it to other regions, in England or any other area with similar socio-demographic attributes. The main requirement to use the code is to get access to the travel diaries.

Computational times, as described before for the synthetic population, vary depending on the number of synthetic individuals to be processed. In the case for the NE region, the assignment of activity plans took around a day. Then the identification of the activity locations took around 10 hours per activity type.

3.4. Network

Once the synthetic travel demand input dataset was generated, the other main component required to run transport AgBM simulations is the network, which can be defined as a digital geospatial representation of the road and public transport network used by the agents.

The goal of this input data is to provide the agents with a built environment that allows them to move between activities. Its geospatial representation, combined with transport mobility characteristics (e.g., allowed modes, maximum speed), the existence of public transport facilities (e.g., stops, routes and schedules) and other important characteristics of the environment (e.g., gradient), defines and constrains the routes followed by the agents when trying to reach their destination, following their activity plans.

The methodology to generate a network is diverse and depends on the purpose of the model, although a minimum geospatial representation of the roads is required. In this specific case, the project aims to explore policies to reduce the use of private motor vehicles and incentivise the use of active modes. Consequently, a methodology focused on this last group is fundamental to simulate realistic mobility policies.

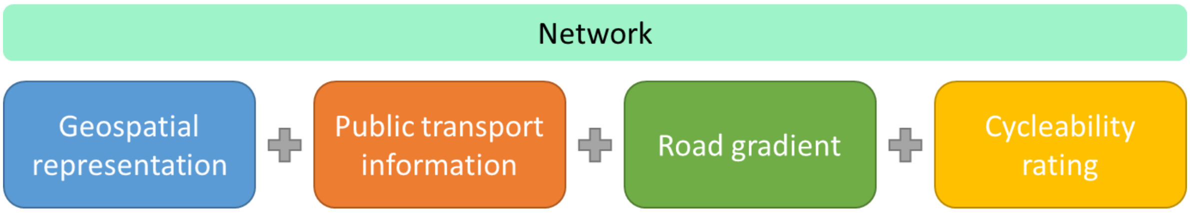


Figure 35 Four main components included in the network.

The network developed in this thesis contains four main components (figure 35): the geospatial representation of the road with an extensive variety of transport mobility characteristics (blue); the public transport information (orange); the road gradient (green); and a road cycling rating value that classifies each road for cycling, depending on its built characteristics (yellow).

3.4.1. Geospatial representation

The first component consists of OSM data, obtained from Geofabrik (2023), a free downloading server that extracts daily updated OSM data (i.e., lines, multilinestrings, multipolygons, points) from any region in the world. A data cleaning process was required to keep only the road and public transport networks within the study area, which is achieved using the Osmium tool (Osmium, 2023), a multipurpose command line tool that enables OSM data manipulation. This tool was used to filter those relevant features (i.e., roads and public networks) and remove all unnecessary information (e.g., buildings, points of interest). This information is relevant to identify transport mobility characteristics of the network, identifying the agents that will be able to use them, as well as the way they are used (e.g., speed), depending on the transport mode used.

The procedure of developing the geospatial network dataset was done in two stages: firstly, creating a dataset containing all roads within the Tyne and Wear region (i.e., the main area of study in this thesis); secondly, creating a second dataset containing only the major roads from the NE region in England (the whole area considered when developing the synthetic travel demand). The reasons for applying this two-step procedure are mainly two. Firstly, although the synthetic travel demand generated in the previous chapter covers the whole NE region, the area of interest in this research is Tyne and Wear, the main urban conurbation within the region. To simulate realistic urban mobility policies within this urban zone, only the agents living within and in the surrounding areas interacting with the Tyne and Wear region were considered, while those agents not interacting at any time with the zone were not considered. Consequently, only main roads connecting Tyne and Wear with the surrounding towns and cities were required. Secondly, the reduction in road network complexity and quantity reduces computational time during the simulation stage.

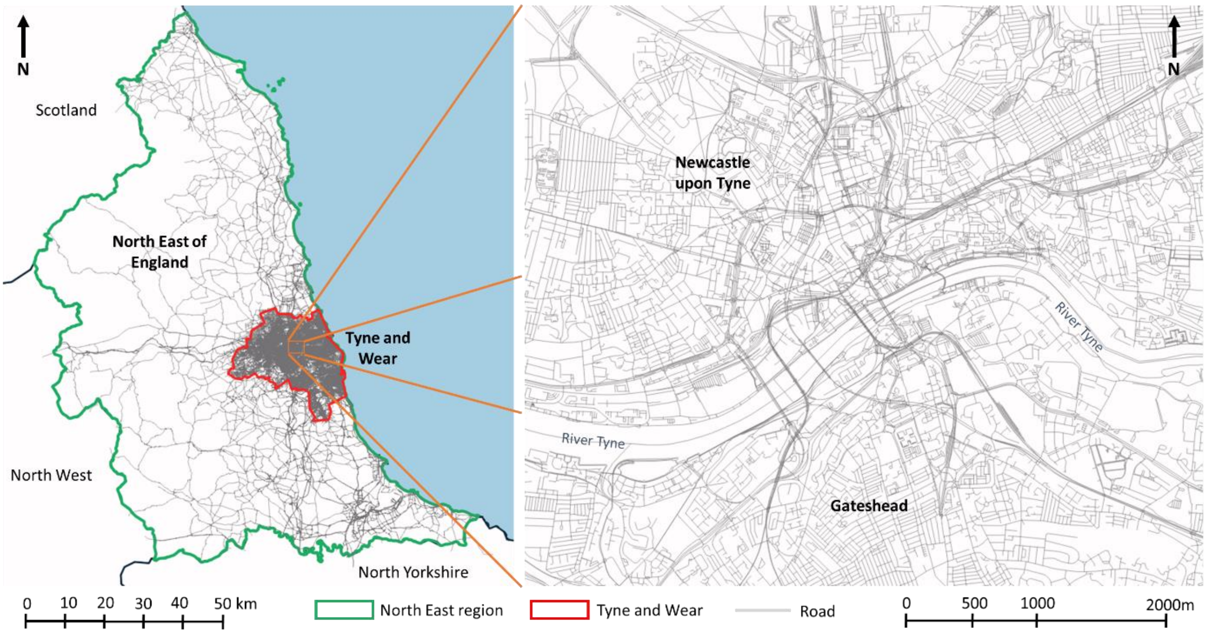


Figure 36 Geospatial representation of the OSM road network in the NE of England (left) and a detailed area of the city centres of Newcastle upon Tyne and Gateshead (right).

Both datasets were merged using Osmium (Osmium, 2023), obtaining a single OSM file covering the whole area of the NE. The result is a set of links (line segments) and nodes (starting and ending points of each link) of the whole study area. Figure 36 shows the geospatial representation of the network developed, showing the whole area (left) of the NE (green) and the Tyne and Wear region (red), and a detailed representation of the urban network at a higher scale (right). In total, 319,845 links defined the study area.

3.4.2. Public transport

The second component, the public transport information, describes the spatio-temporal characteristics (e.g., their routes, stops, calendar and schedules) of the different public modes in the NE (i.e., bus, rail, light rail and ferry).

This information was collected from open-access sources in the General Transit Feed Specification (GTFS) format. Rail data was obtained from the Rail Delivery Group (2023), while for the other public modes data came from Traveline (2023). Both GTFS datasets were merged, clipped to the area of study and cleaned of errors, using UK2GTFS (University of Leeds, 2022), an R package to convert and work with public transport data. The result was a set of text files containing information about the stop locations, routes, trips, stop times, calendar, calendar dates and agencies, covering the whole NE.

This combined public transport GTFS dataset was merged with the road network created before, using PUMA (Arup, 2022b). The result was a set of XML files that define the road and public transport network (network.xml), the public transport schedules (schedule.xml) and the public transport vehicles' characteristics (vehicles.xml). Despite having a standard and open-access tool to accomplish this goal (e.g., PT2MATSIM (Poletti, 2017)), an alternative and not open-source tool was used (PUMA (Arup, 2022b)), as a result of an established collaboration with Arup CML. Mentoring support and the use of this tool was allowed in this thesis in exchange for feedback.

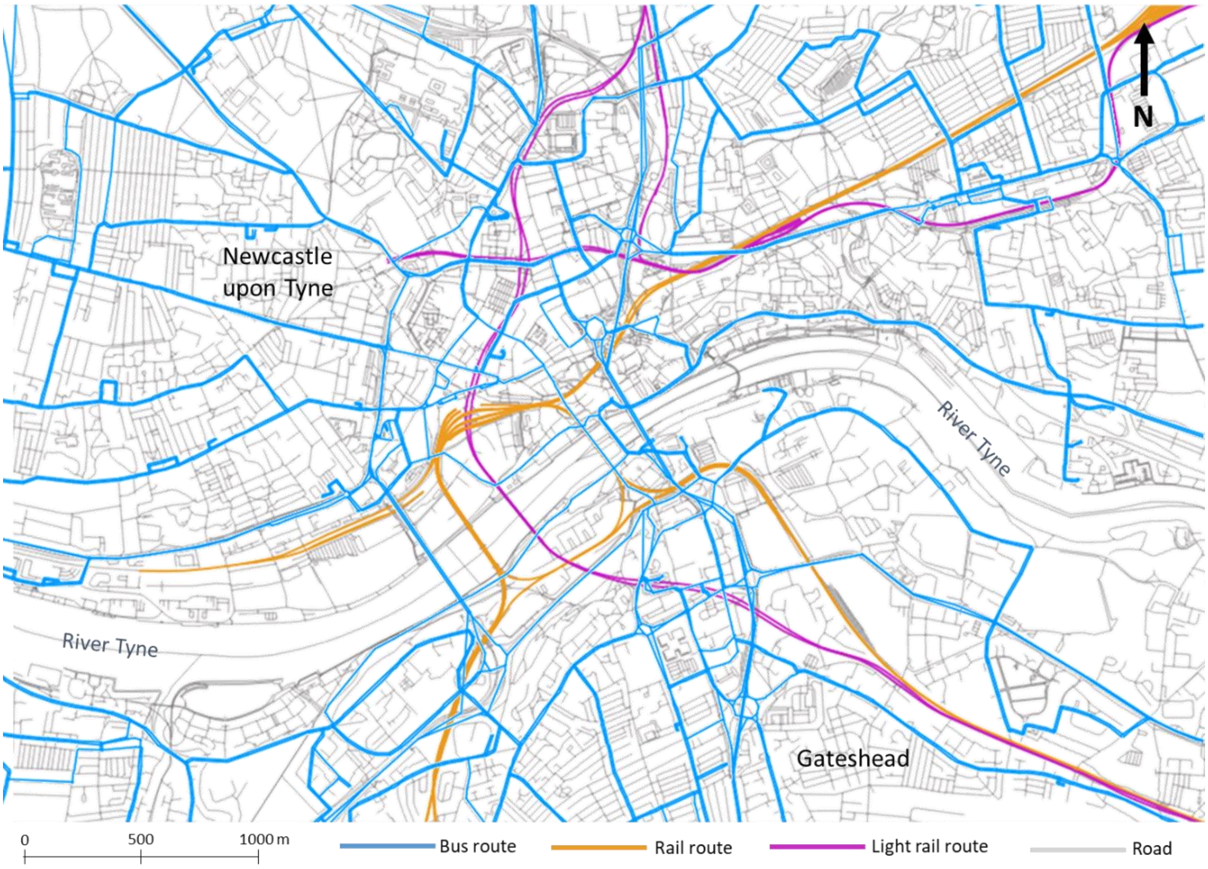


Figure 37 Detailed representation of the public transport routes in urban areas of Newcastle upon Tyne and Gateshead (OSM basemap).

Additionally, the network was simplified by removing unnecessary intermediate nodes using open-source GeNET (Arup, 2022a; Kozlowska *et al.*, 2023), another tool developed by Arup. The network file was used as the unique input data, obtaining a lighter file as output (59% size reduction), allowing faster simulations. Figure 37 shows a detailed representation of some public transport routes (bus (blue), rail (orange) and light rail (purple)) in areas of Newcastle upon Tyne and Gateshead.

3.4.3. Road gradient

Beyond road and public transport networks, additional information is required to understand, simulate and estimate human mobility patterns, especially when active modes are expected to play a fundamental role. One of them is the gradient, which provides information about the steepness along the links. This value is important for active modes, as physical activity is required when walking and cycling. The existence of steep zones could reduce the attractiveness of these modes and its consideration when simulating active travel routes must be a critical factor, especially for cycling. The addition of the gradient allows conversion of a flat network into a 2.5D network.

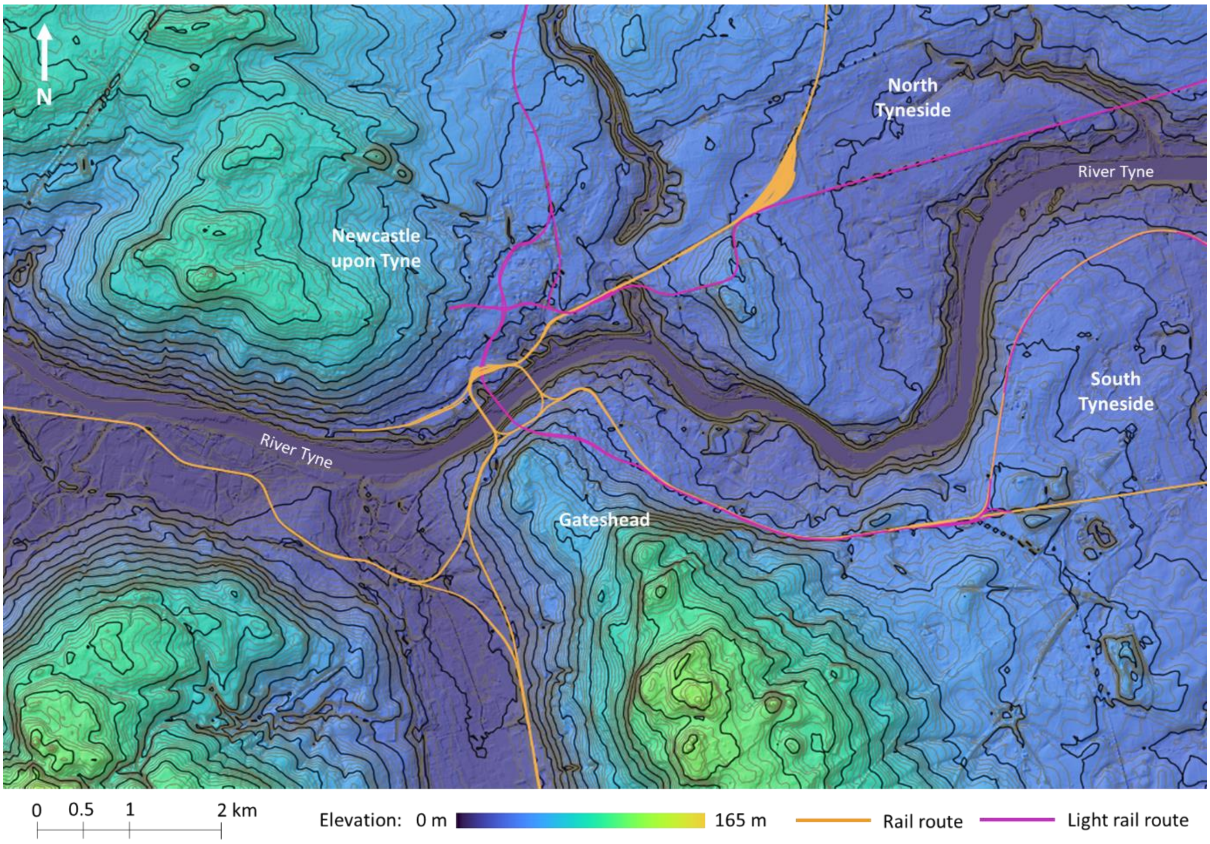


Figure 38 Geospatial representation of the generated DEM in a detailed area of the study area. Public transport networks (orange and purple lines) were added for context.

Gradient values were derived from digital elevation models (DEMs), quantitative representations of the Earth's surface that provide basic information about the terrain relief (Mukherjee *et al.*, 2012; Guth, 2013). DEFRA (2023) allows downloading data of the UK up to 1-metre resolution, while de Ferranti and Hormann (2023) of any region in the world up to 1 second of arc. For the purpose of this thesis, both DEMs were used. A 2-meter resolution DEM from the former covering the Tyne and Wear region was generated, while the remaining area of study used the 1-second of arc resolution from the latter. The reason for using initially different spatial resolutions was to simplify and reduce the file size and time needed to generate a very detailed DEM covering the whole study area. It was assumed that the majority of the active trips will be made within the urban area and those agents travelling from the surrounding areas will use either cars or public modes. In order to have a single DEM covering the whole study area, the files' resolutions were resampled to 10-metre and merged using QGIS (QGIS Development Team, 2023), making the final file manageable in terms of size and computational time. Figure 38 shows a detailed representation of the created DEM categorised in different colours based on the elevation value (dark values for low elevations and light for high elevations). Additionally, the rail (orange) and light rail (purple) networks were included in the area shown to add geospatial context.

The generated DEM was used to add the elevation (Z value) to each node and the gradient to each link in the network. GeNET (Arup, 2022a; Kozlowska *et al.*, 2023) was applied as well for this purpose, where the network, the DEM, a specific projected coordinate system code (EPSG) and the null value used in the DEM were considered as input data, obtaining a single network file as output.

Even though the *quietness* attribute calculated by CycleStreets includes an incline factor when rating links, it was decided to consider a more detailed external attribute using another DEM. Based on documentation from CycleStreets, the incline value was calculated using a 90-metre resolution DEM from NASA (Cyclestreets, 2022b). For the purpose of this thesis, the DEM resolution was considered insufficient as the steepness in urban areas could be underrepresented, as links below 90 metres would be treated as flat. Consequently, a more detailed DEM was used to resolve this issue.

3.4.4. Cycleability rating or quietness

Besides the knowledge of the gradient, it is important to identify roads' quality for cycling. This is a critical factor to consider when trying to incentivise the use of the bicycle within the population, as it is related to real and perceived safety. A road with a good cycling quality (e.g., segregated cycle paths) could attract new cyclists, while the opposite (e.g., roads shared with vehicles at high speed) could disincentivise them. Research made by Morrison *et al.* (2019) indicates that segregated cycle paths reduce real and perceived risks for cyclists and contribute to greater cycling participation. Additionally, Wegman *et al.* (2012) highlight the fact that the modern traffic system is designed largely from a car-user perspective, leaving cyclists relegated to the background, with the consequent high vulnerability of cyclists when sharing roads with motor vehicles, which could affect the transport choice between the use of a bicycle or any other mode.

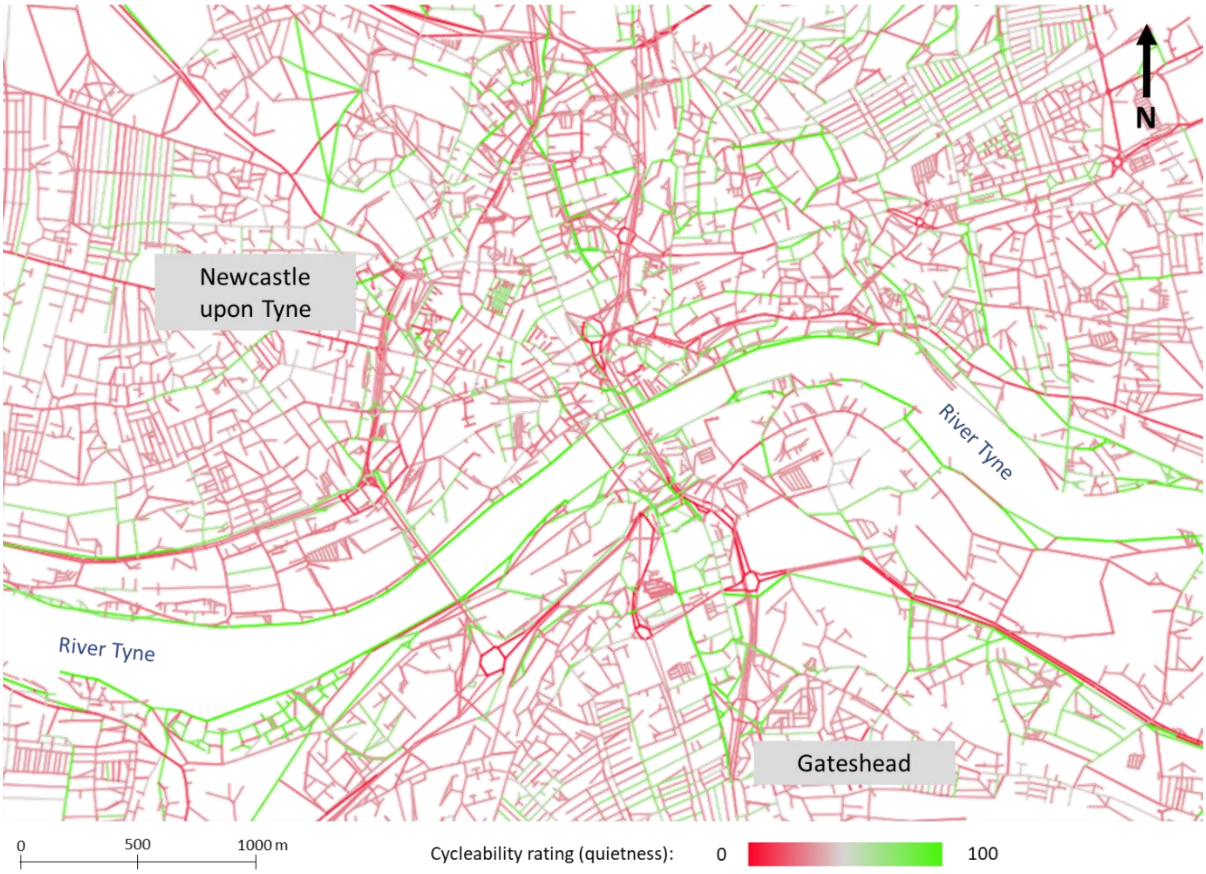


Figure 39 Geospatial classification of the cycleability rating or quietness of several roads in the city centres of Newcastle upon Tyne and Gateshead (OSM basemap).

Figure 39 shows the roads in areas of Newcastle upon Tyne and Gateshead, classified based on their *quietness* value, ranking from 0% (red) to 100% (green). It can be observed that most areas have a low value (i.e., below 50%), with exceptions where segregated cycle paths are built (e.g., along the river Tyne, as part of the National Cycle Network). Unfortunately, similar information for walking was not found.

Characteristics of the built environment (e.g., the existence of fully segregated cycle paths, the type of road, surface type, road quality and width) are key factors that could make the difference when choosing a cycling route, but also the use of an alternative transport mode in detriment of cycling. CycleStreets, a social enterprise keen on getting more people cycling, develops tools and datasets to improve and increase knowledge about cycling in the UK. One of their outcomes is a cycling road classifier, named cycleability rating or *quietness* (Cyclestreets, 2022a). A self-developed algorithm (Cyclestreets, 2022b) ranks roads as a percentage score depending on their built environment characteristics (e.g. road type, length, width, quality, surface, the existence of segregated cycle paths, barriers, kerbs, crossings and junctions, inclines), using OSM data and other sources.

Based on CycleStreets, the road type (e.g., major road, minor road) is the foundation attribute within the algorithm, while the remaining attributes increase or decrease the value when favouring or harming the use of the bicycle, respectively. Due to the proprietary nature of the original CycleStreets data, the full methodology for the development of this rating is not available. Examples of attributes that benefit cycling are the existence of at least 2-metre wide cycle paths, signed routes and paved surfaces (e.g., asphalt), whereas the existence of narrow cycle lanes (e.g., less than 1-metre), kerbs, inclines and traffic signals that delay the journey could penalise it.

In order to identify which attribute values are associated with high cycleability rating scores, several OSM attributes were analysed by comparing the cycleability score for each OSM road type. In terms of road type (figure 40), it was reaffirmed that segregated cycle paths achieve the highest average value (87), followed by living streets (85), pedestrianised areas (74), tracks (52) and residential streets (44). The worst types are major roads (21) and trunk roads (5), as in these types of roads are primarily focused on motor vehicles, with (normally) limited space and consideration for cyclists.

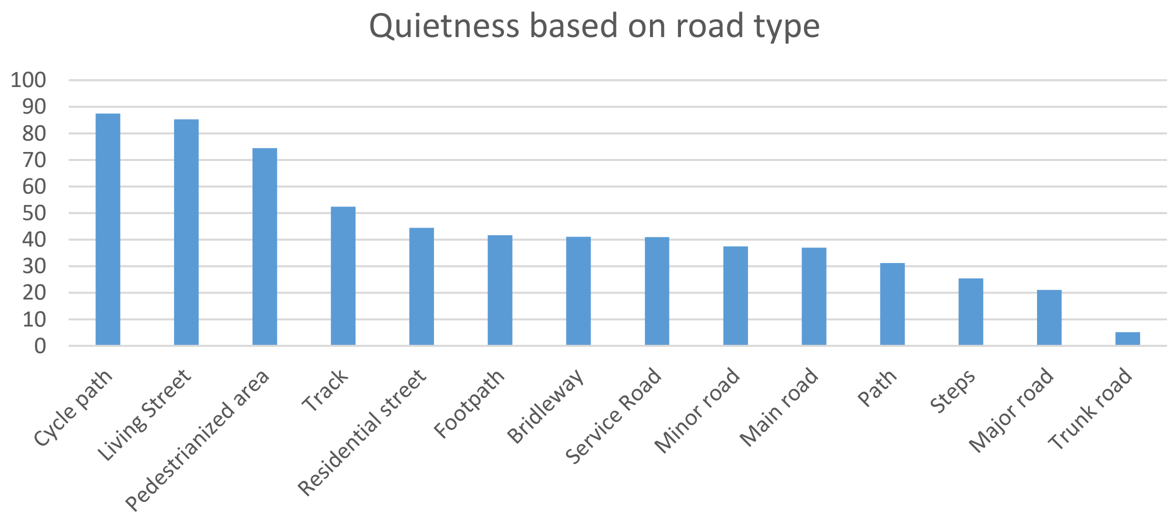


Figure 40 Quietness attribute values depending on the road type.

The analysis of cycle lane width could confirm that narrow cycle lanes penalise the cycleability rating, while those with at least 2.5 meters reach a high value, as shown in figure 41.

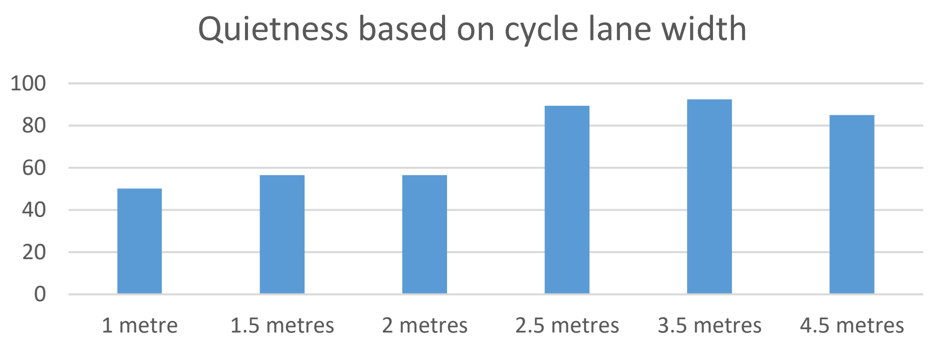


Figure 41 Quietness attribute values depending on road lanes' width.

In the case of surface types (figure 42), regular and compacted (e.g., sett, compacted, concrete, asphalt and paved) obtain the highest values (60-51). Irregular and paved surfaces (e.g., bricks, gravel, wood, metal and cobblestone) can be classified in a second group (40-29). The last and worst group is formed by unpaved or natural surfaces (e.g., unpaved, ground, grass and earth).

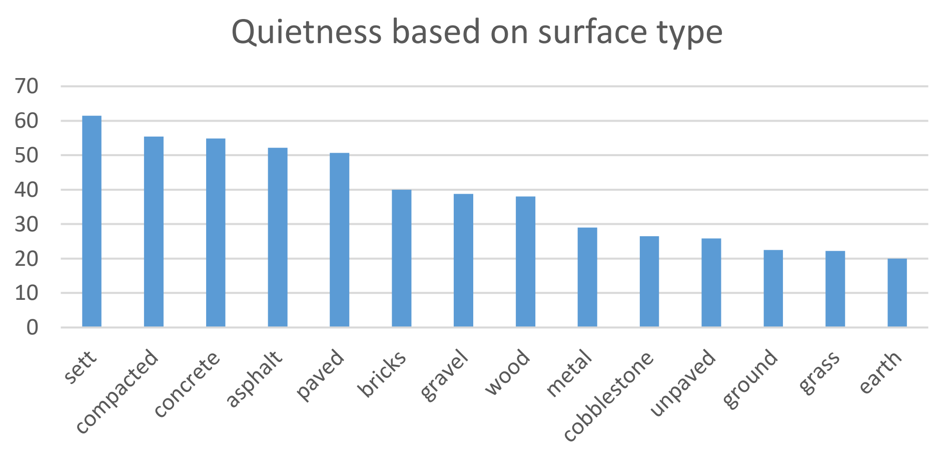


Figure 42 Quietness attribute values depending on surface type.

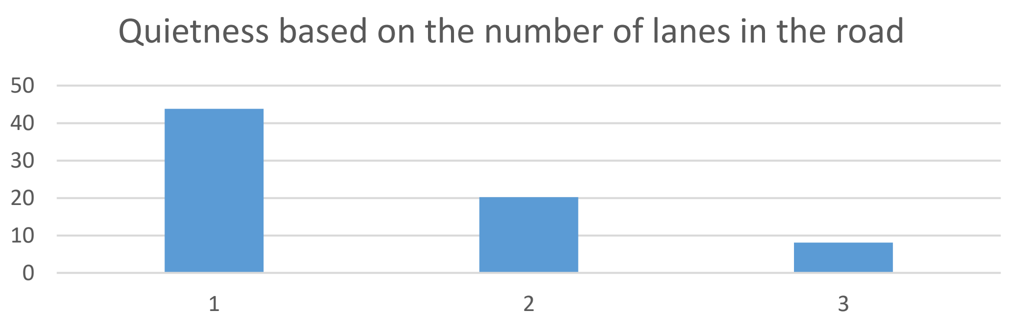


Figure 43 Quietness attribute values depending on the number of lanes.

The number of lanes also affects the *quietness* attribute (figure 43). This value is inversely proportional to the number of lanes, as roads with just one lane obtains double value than those with two lanes, and four times than those with three lines.

The analysis of allowed modes (figure 44) shows that the highest value is achieved in segregated cycle lanes (87); this is similar in the road type analysis. Secondly, an intermediate group where active modes (41) only and all modes (39) are allowed, while the worst case is where pedestrians are not allowed (27), indicating the limited space the bicycles have in these areas.

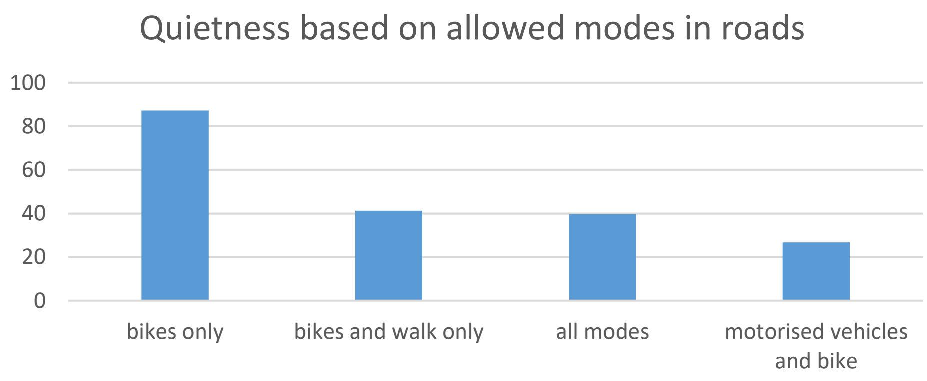


Figure 44 Quietness attribute values depending on allowed transport modes in roads

Lastly, the maximum allowed speed (figure 45) also affects the *quietness* attribute, as low speed roads (up to 20 km per hour) reach much higher values (44) than those where the maximum speed in higher (17). The built environment characteristics of the first group attract the use of bicycles, while the second restrict them.

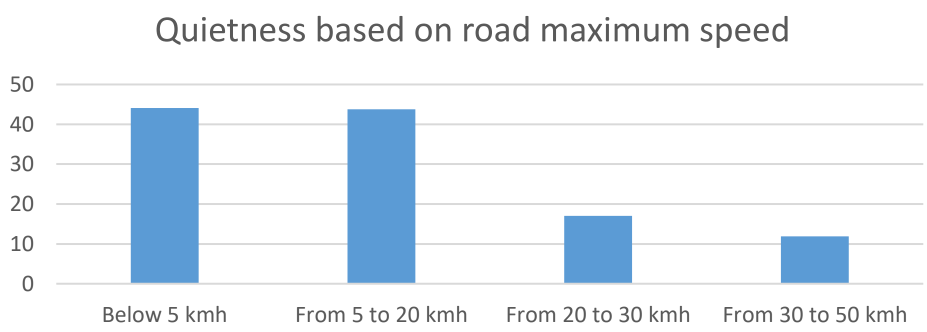


Figure 45 Quietness attribute values depending on the road maximum speed.

To sum up, these attributes allow quantification of how good roads are for cycling, providing a numeric value about how attractive they are for cyclists, based on their built environmental characteristics. Segregated cycle paths and slow roads (up to 20 km/h) with one lane per direction and at least 2.5m cycle line width are the type of roads with the highest *quietness* index, and therefore, the most cycling-friendly. This cycleability rating value is a very valuable factor to consider, as a more realistic simulation of the cycling individuals can be obtained.

This information was transferred into the network generated previously, by matching links with the same OSM identifier. The estimated time to transfer the *quietness* attribute to the network in the study area was around 10 hours, as individual matches between links from the OSM network generated in section 3.4.1 and the data collected from CycleStreets were required.

The output datasets obtained after generating the network (i.e., network, schedules and vehicles) were validated at different stages. Firstly, PUMA (Arup, 2022b) provides warnings and errors when merging the OSM road network with the GFTS public transport datasets. Several corrections in terms of public transport travel directions and times, besides self-developed artificial links to connect incorrect bus routes to the road network, among others, were highlighted as improvements for a fully connected public transport network. Secondly, the road network was validated visually using QGIS (QGIS Development Team, 2023), identifying wrong road directions, flow capacity or speed values, among others, as OSM volunteers digitised this information, and errors are expected. Thirdly, the network was improved during the simulation calibration stage, as the possibility of visual checking of the results obtained after each simulation using Simunto Via (Senozon AG, 2018) allowed the identification of wrong transport behaviours in different zones of the study area (e.g., unexpected car congestion, wrong vehicle direction, unrealistic speeds and wrong allowed transport modes to use the roads). Further details are explained in section 3.7.1, dedicated to the MATSim calibration.

3.5. MATSim configuration

Module name	Comment	Source
Global	Module that defines the coordinate reference system, number of threads and random seed	(Horni *et al.*, 2016)
Network	Module that identifies the directory location for the network.xml file	(Horni *et al.*, 2016)
Plans	Module that identifies the directory location for the synthetic travel demand file	(Horni *et al.*, 2016)
Vehicles	Module that identifies the directory location for the vehicles.xml file	(Horni *et al.*, 2016)
Transit	Module that defines public transport modes, besides providing directory locations for schedules.xml file	(Horni *et al.,* 2016)
Qsim	Module that identifies the mobility simulation controller used, besides the number of iterations, output formats and the interval when outputs are generated	(Gawron, 1998; Simon, 1999; Cetin *et al.*, 2003; Dobler, 2010; Dobler and Axhausen, 2011; Horni *et al.*, 2016)
SwissRailRaptor	A fast public transport router module	(Horni *et al.,* 2016; Swiss Federal Railway, 2020)
SBBPt	Module to simulate public transports as deterministic modes	(Horni *et al.*, 2016; Swiss Federal Railway, 2020)
Bicycle	Module that defines the characteristics cyclists consider when choosing the route	(Horni *et al.* , 2016; Ziemke *et al.*, 2017)
Planscalcroute	Module that defines teleported modes	(Horni *et al.*, 2016)
Counts	Module that calculates the vehicle (e.g., cars, bikes) counts in specific links and compares those against real data provided by the user.	(Horni, 2007; Horni *et al.,* 2016)
LinkStats	Module that calculates statistics of vehicles by link in the network	(Horni *et al.*, 2016)
PlanCalcScore	Module that defines parameters used for scoring (activities and trips depending on transport mode)	(Horni *et al.*, 2016)
Strategy	Module that defines a set of weighted strategies	(Horni *et al.*, 2016)
TimeAllocation Mutator	Module that defines the strategy when agents are allowed to modify their activity times	(Horni *et al.,* 2016)
SubtourMode Choice	Module that defines the strategy when agents are allowed to change routes	(Horni *et al.,* 2016)

Table 5 Modules used to calibrate the MATSim model.

Besides the development of the two main input datasets (i.e., synthetic travel demand and network), the definition of a config file is required to run the model and start the co-evolutionary framework (see section 3.2).

This is a structured XML file, used as the nexus between the input datasets and the simulation tool, also including other modules that define how the scenarios are simulated (e.g., the number of iterations, the simulator, the strategies that the agents can adopt through the co-evolutionary algorithm, counts). There is a wide variety of modules that can be used in MATSim, with the majority already being within the tool, while others need to be incorporated (e.g., bicycle contributions). Table 5 identifies the modules applied in this thesis.

3.6. MATSim bicycle contribution update

As shown in table 5, the bicycle contribution was considered in the simulations. This is an extension developed by Ziemke *et al.* (2017), where a set of characteristics from the built environment (e.g., road type, surface quality, gradient and the existence of cycle paths) are considered by cyclists when choosing the route. This is a valuable tool to simulate realistic cyclists' mobility patterns as bicycles were simulated as cars, teleported or even not included within the scenarios before its development.

These characteristics are fundamental factors to consider when cycling, as physical effort required when riding, in opposition to other vehicle types (e.g., cars, public transport~~s~~). Research has found that characteristics such as slopes (Menghini *et al.*, 2010; Hood *et al.,* 2011; Li *et al.*, 2012), pavement surface conditions and smoothness (Landis *et al.*, 1997; Hölzel *et al.*, 2012; Milakis and Athanasopoulos, 2014), and the existence of continuous cycle paths (Sener *et al.*, 2009; Li *et al.*, 2012) are important factors that influence the use of bicycles. Therefore, their consideration in transport simulations is essential to simulate realistic scenarios where cycling is a predominant objective to be achieved.

Ziemke *et al.* (2017) identify two open-access input datasets to collect these characteristics. The existence of cycle paths, types of roads and surface quality attributes can be obtained from OSM tags, while gradients can be obtained from DEMs (e.g., European DEM (EU-DEM) (European Environment Agency, 2023a) at 25-metre resolution). For the purpose of this research, different input datasets were considered, as better quality and quantity attributes were found for the study area, as described in section 3.4. Firstly, a very detailed attribute rating roads for cycling based on their built environment characteristics (*quietness*), was obtained from CycleStreets (Cyclestreets, 2022a). Secondly, a 10-metre resolution DEM was generated using data from DEFRA (DEFRA, 2023) and viewfinderpanorama (de Ferranti and Hormann, 2023).

The use of a different attribute (i.e., *quietness*) instead of the original OSM tags required a code update. A new marginal utility of quietness (βquietness (a)) was included in the code, similar to those generated for the comfort and infrastructure attributes in the original code. The effectively used marginal utility of *quietness* for a link *a* is computed as follows (equation 11):

$$\beta_{quietness\,(a)} = \beta^{\max quietness\,(a)} * (1 - quietness(a))$$

Equation 11 Marginal utility of quietness*.*

Where $\beta^{\max quietness\,(a)}$ is always 1.0 and $quietness(a)$ is the *quietness* value of each link divided by 100 (i.e., *quietness* values used in the equation range between 0 and 1).

This code improvement was developed in collaboration with Dr Ziemke, the main developer of the extension, during a three-month secondment at TU-Dresden (Germany). The input datasets (*quietness* and gradient attributes) were prepared by the author in the format required by MATSim, while Dr Ziemke was focused on the code-development. The methodology followed to generate the code based on the input datasets was done jointly. This engagement with an international University allowed for the possibility of simulating a more realistic cycling behaviour in areas of England.

An updated version of the MATSim tool was released (15.0-PR2396), which can be used by anyone having the *quietness* attribute or any other similar where a set of characteristics of the built environment for cycling are considered.

3.7. MATSim model

Once the config file is populated with the relevant modules and directory locations of each required input dataset, MATSim scenarios can be simulated. After that, the very first results are obtained. Initially, the achieved results are not representative of any normal mobility in the study area, as the scenario needs to be calibrated and validated.

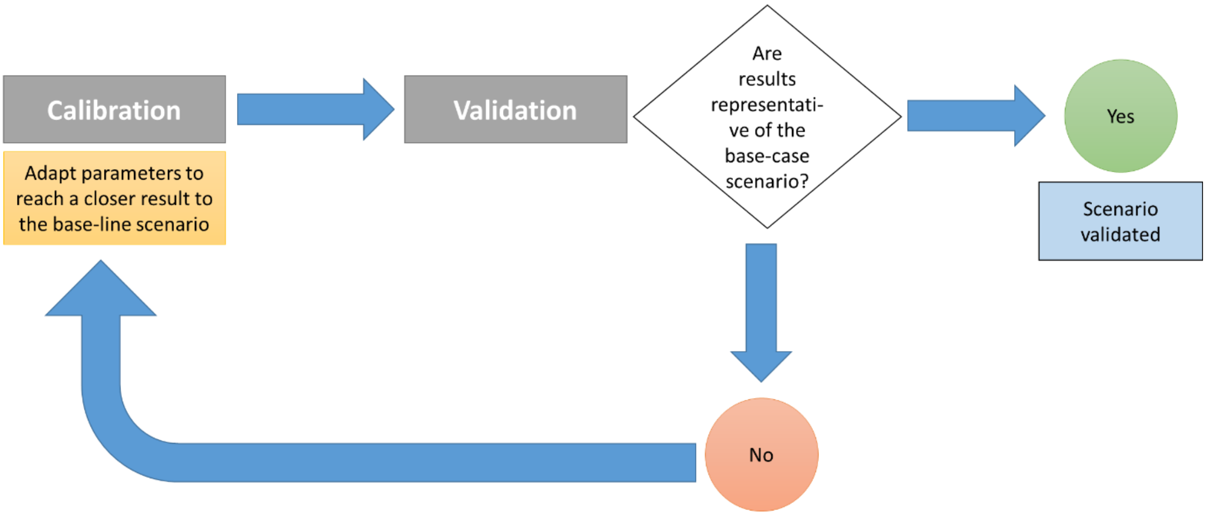


Figure 46 Relationship between calibration and validation stages.

Calibration and validation are fundamental stages when developing any model. Although these two concepts are sometimes not considered, confused or treated as equivalents (as described in the literature review (see section 2.6), they have different purposes, as shown in figure 46. The first consist of manipulating the set of parameters included in the config file that defines how the simulations are run. The goal is to adapt them until simulation results achieved are similar to the baseline scenario, (i.e., the normal mobility during a working weekday in the study area). The second consists of verifying if the achieved simulation results are representative of the baseline scenario, by comparing results against official datasets (e.g., NTS statistic and vehicle counts in different zones in the study area). Both stages are interconnected and perform an iterative loop that ends when the validation stage verifies that the simulation results are representative of the base-case scenario.

3.7.1. MATSim calibration

The MATSim model was calibrated at different paces and stages followed a trial-and-error procedure as this is an iterative process where many modules and parameters interact and are conditioned between them. The model was initialised with the minimum required modules and with a ridiculously small population sample (i.e., 1%), to know if the input datasets were in the correct format and structure. Once this first step was accomplished, other modules were included gradually (e.g., modules to route public modes, bicycle extension, vehicle counts, link statistics). After all required modules were working correctly together, the population size was increased and results were analysed in more detail, comparing them against official mobility datasets. Based on the initial results, updates on the network (e.g., speed reduction in urban areas, flow capacity increases in short links), transport mode parameters (e.g., alternative-specific constants (ASC)) and strategies (i.e., reroute, change transport mode, modify activity times) were applied until transport mode distribution and average score value reached equilibrium. As can be observed in table 6, the model was calibrated with a 20% population sample, running 1,500 iterations using the Qsim controller, MATSim's default mobility simulator module. Although there is currently a faster mobility simulator module (Hermes (Graur *et al.*, 2021)), this was discarded due to incompatibilities with the updated bicycle extension used.

Eight different transport modes were allowed to be used by the agents, although the use of cars as drivers was restricted to only those agents with access to a car in the household, based on their socio-demographic attributes (car_Access = True). This constraint prevents agents without access to a car from using them (especially children), providing a more realistic vision of drivers derived from the internally validated synthetic population, where attributes considering the number of cars in household and the possibility of holding a driving licence were generated.

Public transport modes were simulated as deterministic modes (i.e., they are not part of the road traffic, being only constrained by their schedules, routes and stops), their maximum capacities were not considered, and economic cost was not applied when using them. These three assumptions made public transport more attractive than other modes (especially slower modes), as they cannot be stuck in congestion, there is not any limit in the number of passengers in each vehicle and agents do not have any economic cost when using them.

Parameter	Value, constraint and assumptions
Population sample	20% of those agents interacting with the Tyne and Wear region within the NE of England
Number of iterations	1500
Controller	Qsim
Transport modes	car, car passenger, bike, walk, public transport (bus, rail, metro, ferry)
Cars	Only those agents with access to cars in their socio-demographic attributes (car_Access = True) were allowed to use the car in the simulation (considerCarAvailability (true)). Cars were allowed to overtake bicycles while the opposite was enabled (linkDynamics = PassingQ)
Public transport	Simulated as deterministic (modules SBBPT and SwissRailRaptor). Maximum vehicle capacity was not considered (useCapacityConstraints = false), Economic cost was not considered Access and egress to public stops allowed on foot and by bicycle.
Bicycle	Updated bicycle extension enabled where road gradient and *quietness* attributes are considered when choosing a route. Marginal utility of gradient (-0.02) and *quietness* (-0.035) values.
Walking	Simulated as teleported mode.
Strategies	Reroute (0.1) TimeAllocatorMutator (0.1) SubtourModeChoice (0.1) ChangeExpBeta (0.7)
Strategy criteria	80% of all iterations
Network	Road speed in urban areas reduce to half, assuming the effects of traffic lights and intersections. Road capacity increased in short links (< 50m) to avoid unrealistic traffic congestion
Transport ASC	car: -0.37 car passenger: -1.7 bike: -1.1 walk: 0.0 bus: -7.2 rail: -0.001 metro: -0.001 ferry: -0.001

Table 6 MATSim calibration values.

Although these three assumptions are not realistic, they were considered because public modes are not the main purpose of the analysis, besides knowing that in the study area, there is not important traffic congestion, and every public mode has always enough room for any individual that wants to use them. In terms of the economic cost (i.e., ticket price), it was assumed to be covered by the ASC value applied to each mode. Beyond the above, the decision was also supported by the computational complexity and excessive time required in case they were simulated in greater detail (i.e., stochastically). Additionally, access and egress to the stations were only allowed on foot and by bicycle as the possibility of adding other modes (e.g., cars as driver or passenger) was not allowed within the code, as unexpected code crashes were experienced. Although the bug was raised with the MATSim community, no solution was obtained, and it was decided to leave this issue for future work. Despite the previous assumptions, the calibration ensures that the mode split for public transport reflects reality.

Unlike the use of cars, the use of bicycles was not restricted to only those agents with access to a bicycle in the household, based on their socio-demographic attributes (i.e., bike_access = True), as this possibility is not currently available within MATSim. Consequently, it was assumed that anyone could use them, since the main barrier for owning a bicycle could be the need to buy one, which should not involve a large financial outlay and be within the reach of almost the entire population.

The walking mode was teleported. Even though increasing the use of this mode is considered one of the key objectives when applying urban mobility policies to reduce the use of private cars, the resources and datasets available to simulate it with reasonable accuracy are limited. In contrast to the case of cycling, the existence of a dataset with road walkability ratings and a tool to simulate the spatial mobility considering at least the road gradient have not been developed and/or found during the development of this thesis. The alternative was to calculate the Euclidean distances between origin and destination locations, multiplying them by 1.3 to consider potential detours within the route, which is the common procedure in MATSim. This solution has the positive aspect that allows reducing simulation computational time, as simpler routes and faster calculations are made. Another drawback considered when agents walk is the assumption that all the agents have the same abilities to walk (as when cycling), which is an unrealistic view of the world. This is a limitation the developed model has due to the lack of an attribute that classifies synthetic individuals in terms of mobility conditions (e.g., very good, good, bad and very bad mobility).

Regarding the strategies (i.e., the different possibilities agents have to modify their plans and improve their daily score after each iteration), four different types were established:

- 10% of the agents were allowed to change the route of any of their trips.
- 10% could alter the departure time of activities.
- 10% allowed to change the transport mode.
- The remaining percentage of agents chose an already simulated plan from their memory.

These strategies were applied to the first 80% of the iterations, considering only the last one for the remaining 20%. These allow the agents to learn through the iterations, as they are exposed to different experiences, being able to keep in memory (up to a maximum of five) those that increase their score and delete those that achieve a low score value. The percentages used were obtained after several trial-and-error phases and based on experiences from other researchers consulted.

Different ASC values were tested for each transport mode. These parameters were the most modified during the calibration stage in a trial-and-error process, as they define the attractiveness the synthetic agents have for each transport mode. The lowest value was assigned to the buses, as this mode was simulated as deterministic, being very attractive for the agents, due to the number of services and routes available, contrary to the other public transport modes. The second lowest value was assigned to car passengers, as it was the faster mode available to any agent in the simulation, contrary to car drivers, as only a small proportion of them were allowed to drive (i.e., based on the 'car access' socio-demographic attribute). Cycling ASC value was allocated between the previous values, while walking ASC value was set to 0, as it is the case in most MATSim models (e.g., Ziemke (2022)).

As highlighted in section 3.4, the developed network required extra calibration stages to simulate realistic travel times and routes. Two interventions were the most important: the maximum speed in urban areas (i.e., those links which maximum speed was up to 50 km/h) was reduced to half in order to account for the effects of traffic lights and intersections; and the flow capacity value in short links (i.e., those below 50 metres) was duplicated to avoid unrealistic traffic congestion. These two interventions allowed achievement of more realistic average trip times in the different transport modes simulated as stochastic (e.g., cars and bicycles), as well as the removal of very congested unexpected areas (e.g., roundabouts and very short links).

The computer used to calibrate and validate the baseline scenario, as well as different scenarios, has the following characteristics:

- Model: 11th Gen Intel(R) Core (TM) i9-11900KF @ 3.50GHz
- System: x86_64 x86_64 GNU/Linux
- Number of CPUs: 16

MATSim version used: 15.0-PR2396

Time required to simulate the baseline scenario (1500 iterations): 4 days and 6 hours.

3.7.2. MATSim validation

The validation stage is not an easy, standardised and structured process, as described in the literature review. There is not any specific methodology to follow, as it depends on the purpose and objectives of the model. This section describes the validation stages followed when aggregated values from the calibrated MATSim model were compared to external datasets from NTS, UK 2011 census, Traffic and Accident Data Unit (TADU) and stakeholders' advice. Six different validations were made:

- Modal split
- Vehicles counts
- Average trip distances and times by mode
- Percentage of commuting trips per range of age
- Bicycle routing
- Percentage of active travel trips below five kilometres

Modal split

Modal split is considered as the point of reference in calibration (Ziemke, 2022), accounting for the percentages of all trips made by different transport modes. Despite the existence of several official datasets containing information for different spatial distributions (e.g., national, regional), no specific dataset focused on the study area was found (i.e., individuals living in the NE of England and only interacting with the Tyne and Wear region), where all types of trip purposes were considered.

Therefore, national and regional statistics, and expert advice were considered to estimate the modal split. The 2011 UK census provides information about the method of travel to work per region (ONS, 2011e), while the NTS provides information about the methods of travel to work by region of residence (DfT, 2023d) and workplace (DfT, 2023e) from 2002 for each year. Additionally, the UK Government provides information about the modes of travel to school of individuals aged between 5 and 16 years in England between 2015 and 2019 (UK Government, 2023c). A combined analysis of these datasets allowed estimation of modal splits for working and educational trip purposes respectively, but the remaining trip purposes were unknown. To cover this gap of information, advice was requested from stakeholders involved in transport mobility, public transport analysis and consulting. Several discussions were established with Nexus, Transport North East, Arup CML and Newcastle University researchers.

Based on the dataset and knowledge collected, an iterative process to estimate the modal split for all trip purposes was established. This process was validated from several perspectives. Firstly, split modes of commuting trips and trips to school were compared against previous highlighted official statistics. Differences found between simulated results and the official statistics were used to adapt the ASC value of each transport mode, with the commuting trip values being more relevant, as they belong to the Tyne and Wear region during 2019, while the others are national values in a five-year range. Secondly, vehicles en-route were considered. Differences between the percentages of simulated cars per hour and those obtained at national scale from NTS (NTS, 2023c) allowed identification of the estimated proportion of cars to be expected, varying the cars' ASC values consequently to reach a more accurate percentage of trips (for all kinds of purpose) made by car.

Vehicle counts

The spatio-temporal distribution of vehicles in the study area is also an important factor to consider when validating a transport AgBM model, as both space and time are key components in transport mobility. The percentage of vehicles en-route per hour was compared against NTS values for England during 2019 (NTS, 2023c), while vehicle counts in different zones of the study area were compared with official counts (Gateshead Council, 2023), per hour and aggregated per day.

Average trip distances and time by transport mode

Two other fundamental components in transport mobility are associated with average trip distances and times by transport mode, as this information provides insight about the general mobility in the study area. Obtained average values by transport mode were compared with observed average distances (NTS, 2023d) and times (NTS, 2023b), at regional and national scales, respectively. Additionally, verifications of individual trips made by car and bicycle were compared with routes calculated by Google Maps (Google, 2024).

Percentage of commuting trips per range of distance

Beyond the validation of global average trip distances by mode, commuting trips were individually analysed to identify whether the workplace trips are geospatially distributed, based on their distances, in the study area. The percentage of simulated commuting trips per range of distance was compared with national statistics (ONS, 2023b).

Bicycle routing and counts

The use of bicycles is an important component in this thesis and its understanding is fundamental to simulate realistic scenarios to increase the number of cyclists on the roads.

The routes followed by cyclists were considered validated when routes followed avoided steep roads and used existing cycle paths, when possible. Parameters from the updated bicycle extension (i.e., gradient and *quietness*) were calibrated to achieve this goal. Several routes were analysed by cyclists from the study area with different backgrounds and experiences to determine if the behaviours simulated were realistic.

Active travel trips

The validation of the number of active travel trips is another milestone in this thesis, as the aim is to test different urban mobility policies to increase the use of active modes, starting from a realistic baseline.

The percentage of simulated short trips was compared with the ATE baseline, which has identified that 41% of short trips (i.e., below five miles) in urban areas were walked or cycled in 2018 to 2019 (ATE, 2023b).

3.8. Urban mobility scenarios

Once the MATSim model was validated, the baseline scenario for the study area was defined and ready to be used to test the effectiveness of several urban mobility policies. All previous efforts made were required to develop a realistic and representative geospatial and temporal transport model of the Tyne and Wear region. This section focuses on the definition and development of a set of diverse urban mobility policy scenarios aiming to shift journeys to active travel to reduce GHG emissions.

Kuss and Nicholas (2022) identified seven effective interventions to reduce the use of cars in urban areas and support climate goals, after screening almost 800 per-reviewed studies and case studies from 2010. These categories are charging and pricing (Börjesson and Kristoffersson, 2015; Beria, 2016; Metz, 2018; Dale *et al.*, 2019), time dependent access limitations (DeRobertis *et al.*, 2016), parking and traffic control (European Commission, 2024), mobility services for commuters (Nassisi *et al.*, 2013; European Commission, 2019), integrated car-sharing plans (Fred Dotter, 2015; Glotz-Richter, 2016), travel planning (Cairns *et al.*, 2010; Civitas, 2013; Bamberg and Rees, 2017), and gamification process to promote sustainable mobility (Giarandoni *et al.*, 2018). Within them, it was observed that the most studied categories were charging and pricing, and travel planning, although all interventions analysed consider multiple measures (e.g., cycle paths, awareness campaigns, funding for public transport, car-sharing schemes), the most effective being those including congestion charge, parking and traffic control, and limited traffic zone measures. Despite these measures and results, the understanding process of the applied policies is still under investigation (Kuss and Nicholas, 2022) and further research is needed.

The objective in this section is to define and develop urban mobility policy scenarios to estimate their efficiency in reducing the number of private and polluting vehicles on the roads by favouring the use of active travel modes or penalising the use of the former.

3.8.1. Definition of scenarios

Based on the literature and the expected actions to be developed by ATE to reach a 50% target of short trips in urban areas using active modes by 2030, five individual and a set of combined policy scenarios were defined, where 'stick' and 'carrot' or 'pull' and 'push' measures are applied. Some of the measures are focused on the first, others on the second, while another group in both.

Scenario 1: Fully segregated cycle paths

The implementation of fully segregated and safe cycle paths are two of the most common responses by individuals in England when asked about things that would encourage them to cycle more, even if their implementation reduced the road space for cars (DfT, 2021b). The scientific evidence supports the concept that cyclists prefer continuous cycling infrastructure (Sener *et al.*, 2009; Li *et al.*, 2012; Ziemke *et al.,* 2017).

In this context, the development of a fully segregated cycle network in Seville (Spain) was analysed by Marqués *et al.* (2015). The results showed that a connected, continuous, bi-directional and comfortable network achieved a 3.9%-point increase, doubling the number of cyclists in four years. Despite of the effectiveness of the measure, seasonality considerations need to be addressed, as different values were obtained depending on the climate conditions (i.e., warm months showed low values, while previous and posterior months showed strong peaks).

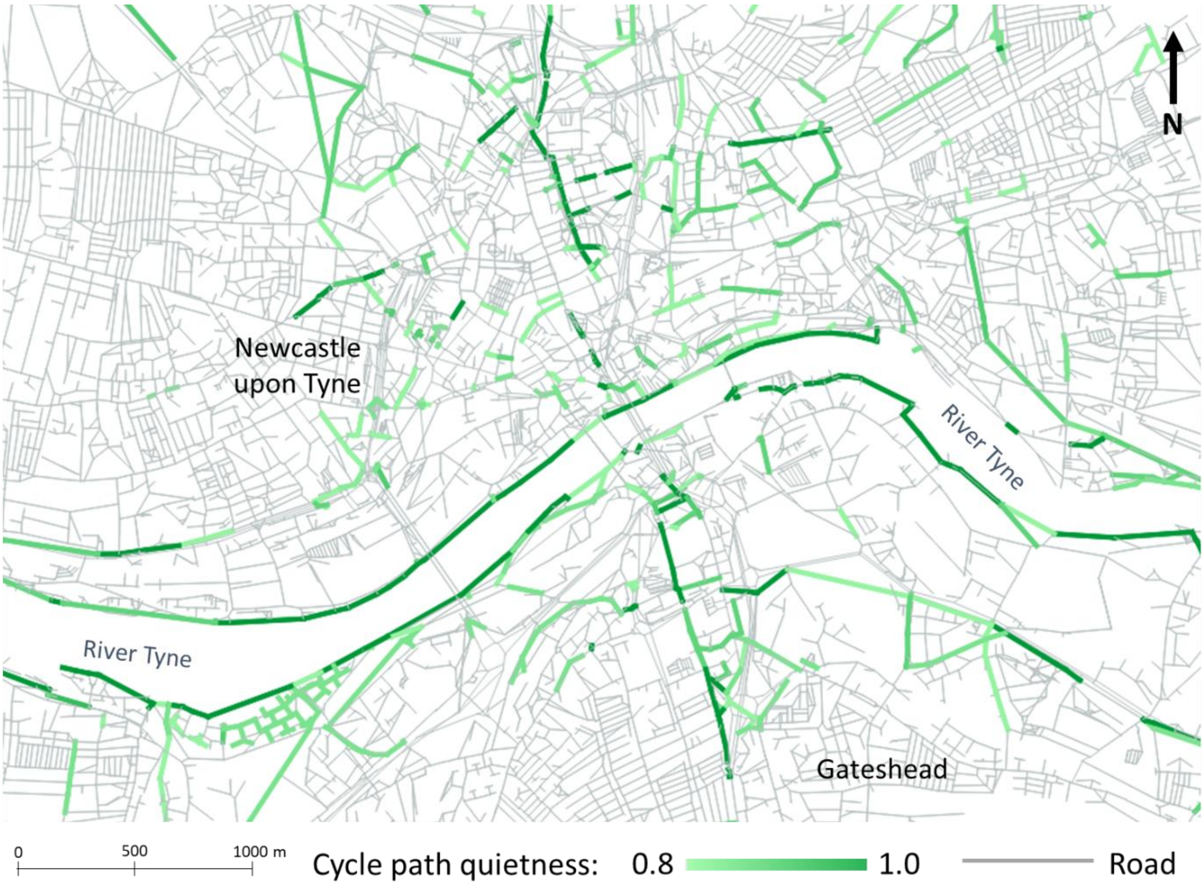


Figure 47 Example of the road network quality for cycling, based on data from CycleStreets (OSM basemap).

In the Tyne and Wear region context, the existing cycle path network is patchy and poorly maintained with many different types (e.g., segregated lanes, shared paths, shared roads), besides the non-existence of explicit cycle routes between different zones, resembling disconnected islands. These characteristics make cycling difficult, unpleasant and insecure for cyclists, it not being attractive as a result. Figure 47 shows the cycleability rating or *quietness* of the roads in the city centres of Newcastle and Gateshead (above 0.8 only), where the uneven characteristics of the network is observed.

In this thesis, a proposal is made for an extreme and currently unrealistic scenario where every road in the study area has a fully segregated and safe cycle path. This scenario provides a secure infrastructure connecting all the activities through direct routes, being available to everyone, creating comfortable riding conditions. The goal is to estimate the increase of cyclists when a coherent, connected, direct, continuous, comfortable and safe network is available for cycling.

To enable the agents to use fully segregated and safe cycle paths in the urban region, a new network was developed. The original road network was duplicated and allowed to be used by cyclists only, updating the *quietness* attribute to the maximum value (i.e., 1.0). Consequently, the flow capacity attribute of the original roads used by cars was reduced proportionally to the number of lanes, to allocate the new segregated cycle paths within the existing road space. Each lane was assumed to be 3.65 metres wide (DfT *et al.*, 2009), while the new cycle path is one metre. Both networks were merged, and the result was a combined network file containing a fully connected, segregated and safe cycle path network allocated within a reduced flow capacity road network.

Scenario 2: Low Traffic Neighbourhoods (LTNs)

Low Traffic Neighbourhoods (LTNs) are schemes that remove through motor traffic from residential streets (except for residents) using 'modal filter' measures such as planters or lockable bollards (Goodman *et al.*, 2021) to disincentivise the use of those vehicles and enable the use of more sustainable modes. Although this policy is facing great controversy in several regions in the UK (Dudley *et al.*, 2022), LTNs are now being trialled at pace in some cities (Laverty *et al.*, 2021).

Surveys developed by DfT in 2021 (DfT, 2021a), based on interventions in Birmingham, Bournemouth, Ipswich and Salford achieved the following results:

- Only a third agreed that they had noticed fewer cars driving through their neighbourhood.
- A third considers the LTN encourages people to switch trips from car to other modes of transport.
- Three in ten agreed the LTN helps create a sense of community in the local neighbourhood, while half disagreed with it.
- A third of respondents who had used a cycle to get around their local area reported cycling more as a result of the LTN intervention, a quarter of those who walked said

they travelled more on foot since the LTN intervention, and a similar proportion of runners reported running more as a result of their local LTN.

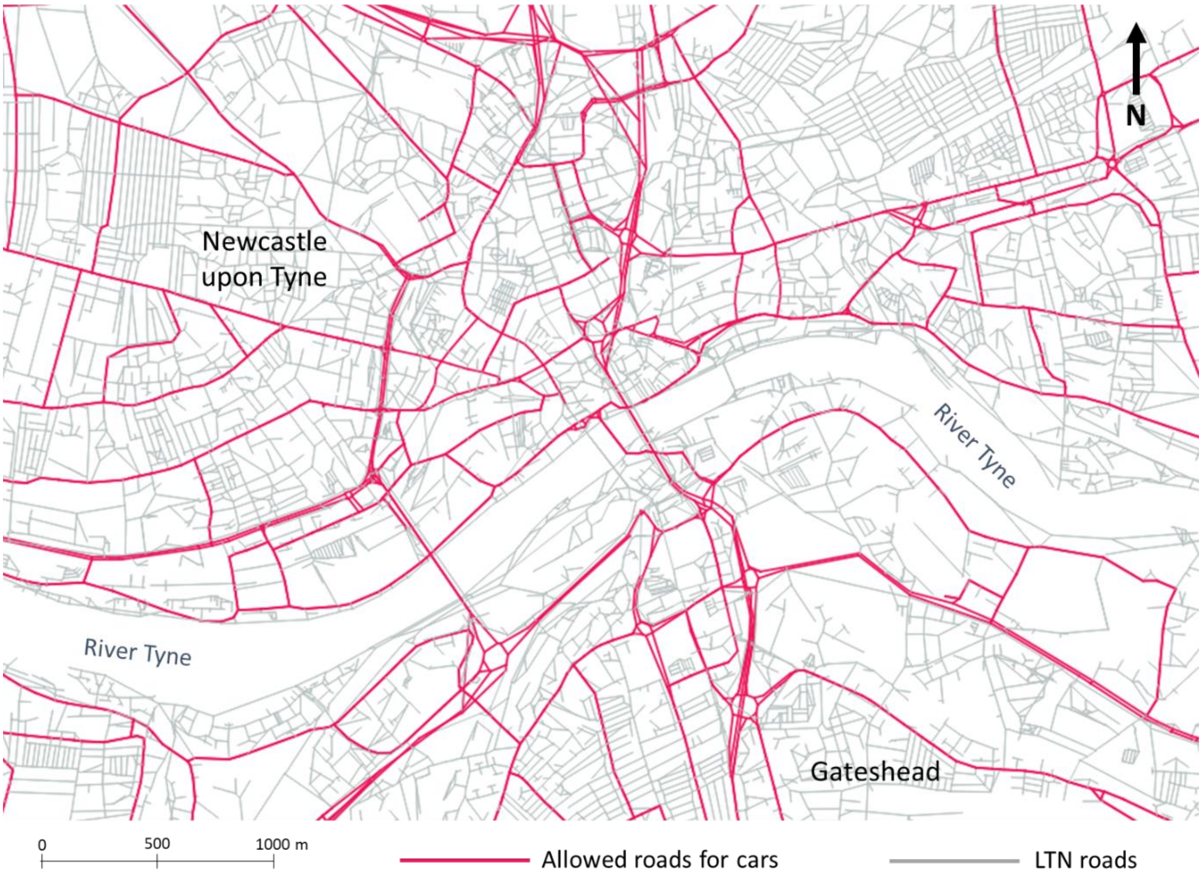


Figure 48 Definition of LTNs based on the allowed roads for cars (OSM basemap).

In this thesis, a LTN scenario was generated where the areas were defined based on the type of roads. It required the creation of a new network, where car users were only allowed to use main roads (i.e., OSM links classified as trunk, motorway, primary, secondary, tertiary), while the remaining roads were restricted to them and the *quietness* value updated to the maximum value (i.e., 1.0), assuming perfect conditions for cycling due to the lack of cars. In case the destination of an agent using a car is within a LTN, the agent is allowed to use the car up to the closest link that surrounds the area, while the remainder of the trip is walked (i.e., teleported in this case). Figure 48 shows the generated network, highlighting in red the only roads allowed for cars.

Scenario 3: Active travel rewards

Beyond modifications in the network to incentivise cycling (Scenario 1) or penalise the use of cars (Scenarios 1 and 2), there is the possibility of incentivising those agents using active modes economically. Reward-based instruments have the potential to encourage individuals' shift towards multimodal mobility options, thus contributing to a more sustainable and resilient transport environment (Tsirimpa *et al.*, 2019).

Currently, there are some mobile phone apps that allow collecting points when walking and/or cycling to redeem discounts, gift cards, free items and raise money for charities. Examples are Sweatcoin (Sweatcoin, 2023), WinWalk (winwalk, 2023) and WeWard (WeWard, 2023) for walking, and BetterPoints (BetterPoints, 2024) and Charity Miles (Charity, 2023) for walking and cycling.

Additionally, there are some countries rewarding individuals when commuting by bicycle. One example is the Netherlands, which is currently providing a mileage allowance of up to 0.19 euros per kilometre when commuting to work (Government of The Netherlands, 2023). Others are Belgium, rewarding 0.27 euros per kilometres up to a daily cap of 40 kilometres from the 1st of May 2023 (The Brussels Times, 2023) and France, which provided 0.25 euros per kilometre cycled in a trial for 10,000 employees in 2015 (Macmichael, 2014; Ng, 2015). Results from the French trial showed a marginal impact as only 419 people agreed to ride to work by the end of the trial (CityLabTransportation and Jaffe, 2015), while outcomes from other countries were not found. Máca *et al.* (2020) developed an experiment to increase regular commuter cycling in cities providing financial and non-financial (i.e., gamification) motivational features randomly between the participants. Results suggest that these features can motivate individuals, being more effective when financial rewards are given, although when combined, results could be even better.

Based on previous approaches, a similar scenario was developed for the area of study, extended to both active modes. In this scenario, all trips made by bicycle or on foot were rewarded with £0.15 per kilometre, as a measure to incentivise them for any type of trip. For this scenario, only economic parameters were required to be updated within the config file. Firstly, the marginal utility of money was updated to 1 (standard MATSim value (Horni *et al.*, 2023)), as previously the value was set to 0 due to economic factors not being considered (only time factors were taken into account when agents were simulated in the baseline). Secondly, the parameter that converts distance into money (monetary Distance Rate) (unit of money / metre)) was modified. As this parameter does not allow the use of positive values, it was required to penalise the other transport modes instead of rewarding the active modes. Therefore, the parameters for all modes except bike and walk were set to -0.00015 (i.e., £-0.15 per kilometre). In this case, beyond a time constraint, the score value achieved is dependent of the possibility of earning money when walking or cycling.

Scenario 4: Pay-when you drive

Opposite to economic rewards, there is the possibility of applying economic penalties to influence a behavioural change in mobility. This is the case of tolls and charging zones, among other options, where economic charges are applied to car users to disincentivise their use and reduce GHG emissions in urban areas, as road pricing is considered an effective strategy for reducing traffic congestion on transportation networks (Bastarianto *et al.*, 2023).

An example is the Ultra-Low Emission Zone (ULEZ) in London, deployed in 2019. This measure operates all the time and requires car users to pay a £12.50 daily charge to drive within the zone (TfL, 2024b), currently covering all London boroughs and the City of London (TfL, 2024a). Ma *et al.* (2021) analysed the impact of the policy in terms of air quality in 2019. They concluded that only small improvements were achieved in a longer-term downward trend, although its combination with other measures (e.g., Low Emission Bus Zones, bus retrofit, Taxi Delicensing Scheme, zero emission capable requirement on new taxis, and Euro vehicle emissions standards (Greater London Authority, 2019; Ma *et al.*, 2021)) has led to more observable improvements. Because of the reduction in the number of cars on the roads, an increase of bicycle use was observed. Ding *et al.* (2023) analysed the impact of ULEZ in the use of public bicycle sharing and identified a significant increase in demand up to 27.9%, principally for short (less than 15 minute) and intermediate (between 15 and 30 minutes) trips, between May and October 2019.

Based on the results achieved in London, a similar scenario was defined for the area of study. The complete NE region was considered as a ULEZ, where agents using the car, either as a driver or passenger, were required to pay a £2.5 daily charge. This extreme scenario considers areas beyond urban zones. Although a more detailed geographic definition could be specified, it was decided to consider the whole extension to simplify the methodology and procedures followed to simulate this case scenario. Additionally, the economic daily charge was assigned as a symbolic value, without any other consideration. These limitations imply that further investigation is required to identify realistic areas and economic values to the study area, based on research of transport plans developed by the Government or LAs.

The scenario was designed analogous to the previous one, where only economic parameters were modified in the config file. The marginal utility of money parameter was set to 1 and the daily monetary constant (i.e., fixed cost of mode per day (unit of money/day)) for car users (both drivers and passengers) was updated to 2.5. Although a monetary distance rate value (i.e., £0.15 penalty per kilometre driven) was also simulated as an alternative scenario, it was discarded as short trip distances would not be affected in the same way as longer ones, the former being the most likely to be walked or cycled.

Scenario 5: Cycle hubs next to metro stations

Additional to the implementation of network improvements and restrictions, economic rewards and penalties, alternative policies could imply the possibility of combining active with public modes.

EuroVelo, the European network of long-distance cycle routes that cross and connect the whole continent, consider that the combination of cycling and public transport journeys is the ideal solution for sustainable mobility, being a genuine alternative to private and polluting vehicles (European Cyclists' Federation, 2024).

Scientific research has also been analysing this combination of transport modes, where station accessibility, distance to the station and bicycle facilities at stations (Heinen and Bohte, 2014) are fundamental factors to consider, as the combination of these modes could be seen as an extend cycling's speed and spatial reach (Kager *et al.,* 2016). However, this connection is not highly promoted. Although transit agencies have installed bicycle racks, implemented bicycles-on-trains policies to facilitate bicycle-transit integration (Flamm and

Rivasplata, 2014), citizens are not fully engaged, with exceptions such as the Netherlands (Kager *et al.*, 2016).

In 2018, Nexus, the transport agency for the Tyne and Wear region, conducted a survey asking citizens about their opinions, experiences and attitudes towards the use of public transport modes. Within them, they were asked about cycle storage areas, the existence of cycle paths near the stations, the possibility of taking bicycles on public transport vehicles and the information provided related to cycling routes to the stations. Results showed a very poor consideration from the public, as more than half (53%) consider cycle storage facilities as fairly poor or very poor (only one in five (19%) consider them as fairly good or very good). Similar proportions were obtained when considering the existence of cycle paths, while the ability to take the bicycle on public vehicles was even worse rated (three in four (76%) consider it fairly poor or very poor, while only one in 20 (5%) fairly good or very good). Lastly, access to information related to cycle routes to reach stops was considered as fairly poor or very poor by more than half (55%), being categorised as fairly good or very good by only one in five (17%). As a conclusion, results highlight the lack of infrastructures, facilities and information that people have in order to combine the use of bicycle and public modes in the region.

Based on the previous outcomes, a scenario where agents in the Tyne and Wear region are allowed to use the bicycle to access and egress metro (i.e., light rail) stations, assuming the existence of safe and secure cycle hubs near the stations, was developed (figure 49). The goal is to identify how many agents would combine the use of the bicycle and metro when secure and safe facilities to park or hire the bikes are facilitated. Previously, the validated model allowed the access and egress to railway stations on foot and by bicycle, as these stops usually allow both modes (the option to include cars was not possible due to issues with the program, as explained in section 3.5). The methodology followed to achieve this goal consists of updating the schedule file generated after merging the OSM network and the GTFS datasets (see section 3.4.2). The metro stations were identified, and two new attributes were added: bikeAccesible = true; and accessLinkId_bike = link_id. The first allows bicycles to be connected to the metro station, while the second identifies the network link from where the metro station is connected to the network. This procedure was followed for the 60 metro stations in the study area.

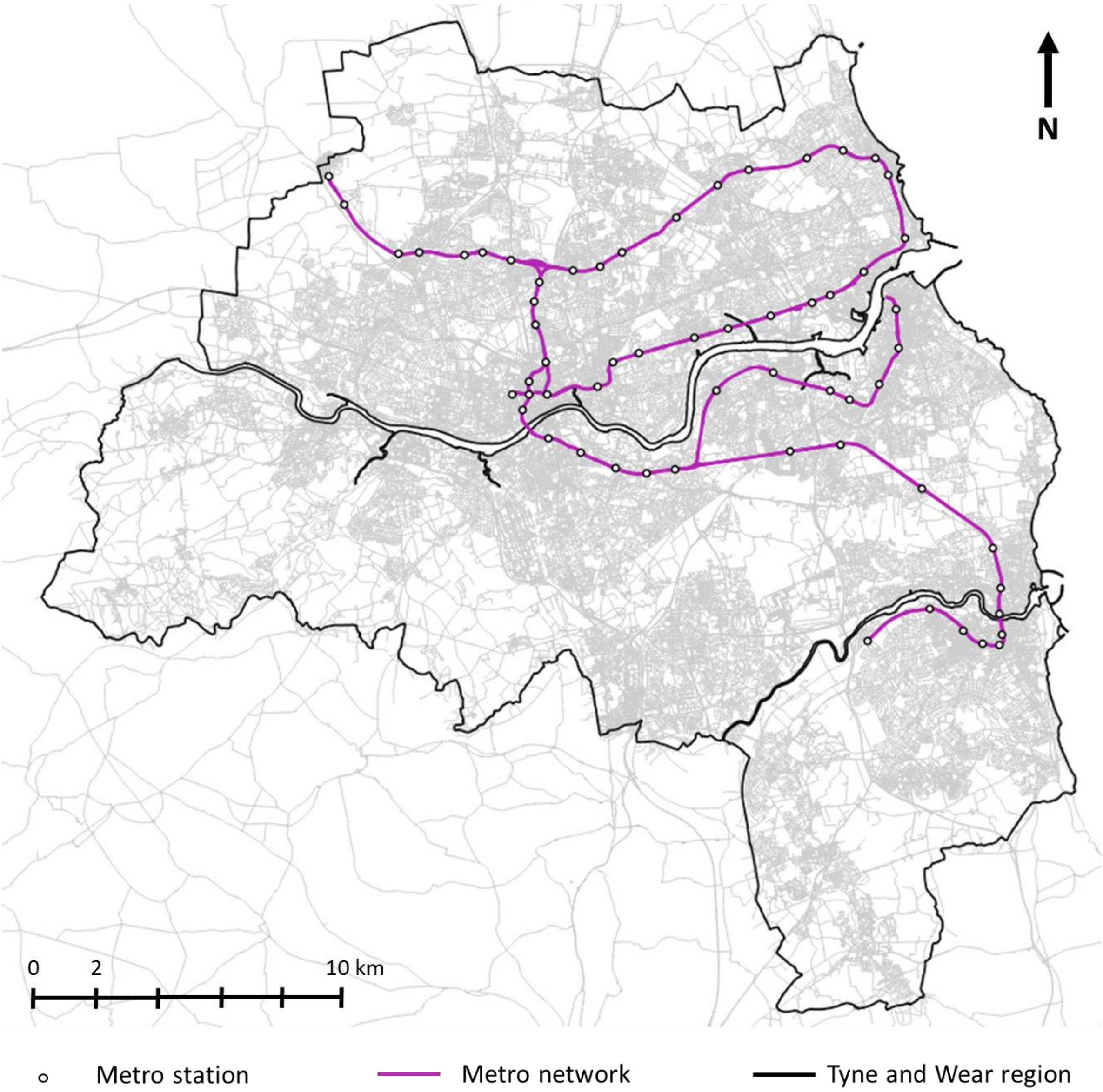


Figure 49 Definition of the metro network in the Tyne and Wear region.

Scenario 6: Combinations of previous individual scenarios

After individual policies were defined and set up, several combinations of them were considered to test if their integration performs better than when applied individually. Combined policies for an ambitious network upgrade in favour of active modes (scenario 6.1), the addition of economic rewards when using active modes (scenario 6.2) or penalties when using the car (scenario 6.3) and a global combination of policies (scenario 6.4) were developed. The following sections describe each of these cases. These are just some of the combinations and more possibilities in different proportions should be analysed in future research.

Scenario 6.1: Cycle paths – LTN – cycle hubs

This scenario combines the implementation of fully segregated cycle paths with the consequent space reduction for cars (scenario 1), the restriction of cars in residential areas defined by LTNs (scenario 2) and the possibility of using the bicycle to access and egress metro stations (scenario 5). As a result, it is a scenario that could benefit active travel (especially cyclists) and harm car users.

From the cycling perspective, agents have the possibility of using fully segregated and safe cycle paths to any destination following direct routes, with special relevance to metro stations, as all of them can be reached safely. Car users are affected mainly by the combination of the first two policies, where less road space and road restrictions apply to them. Public transport users and walkers are not harmed or benefited directly, but indirect consequences of the implemented policies may affect them positively or negatively.

The methodology followed to run this scenario was the combination of networks from scenarios 1 and 2 and the use of the schedule file generated in scenario 5.

Scenario 6.2: Cycle paths – LTN – cycle hubs – economic reward

This scenario was built from the previous scenario, adding economic rewards to those agents using active modes, as described in scenario 3. This scenario tries to boost the use of active modes, as all possible simulated measures that can benefit them are combined.

The methodology developed upgraded the one generated in the previous scenario, where the economic parameters described in scenario 3 were added.

Scenario 6.3: Cycle paths – LTN – cycle hubs – economic penalty

Scenario 6.3 extends scenario 6.1 by adding a £2.5 daily penalty to car users. This is the most restrictive policy combination for car users up to now, as three of the combined policies penalise their use (scenarios 1, 2 and 4), although two of them also benefit the use of the bicycle (scenarios 1 and 2). This scenario tries to reduce car usage when spatial (scenarios 1 and 2) and economic (scenario 4) restrictions are combined with fully segregated cycle paths (scenario 1).

The methodology in this case is similar to the one developed for scenario 6.3, although parameters described in scenario 4 were updated, instead of those described in scenario 3.

Scenario 6.4: Full combination

Scenario 6.4 is the combination of all individual policies at once, being the most complete but also extreme scenario which tries to identify the potential maximum transport mobility effect.

This scenario was developed using the network generated for all previous combined scenarios, then the schedule file from scenario 5 and the economic parameters from scenarios 3 and 4.

3.8.2. Analysis of scenarios

Results obtained from each scenario show the potential achievements that could be obtained from the different urban mobility policies simulated to reduce the number of private and polluting vehicles on the roads in favour of active modes. Aggregated and geospatial results were compared in the following eleven diverse groups against the baseline scenario (see section 4.4) to test their estimated efficiency:

- Transport modal share (section 4.4.1).
- Sankey diagrams identifying the changes in transport mode shares between baseline and the simulated scenarios (section 4.4.2).
- CO_2 emissions reductions (section 4.4.3).
- The geospatial distribution of cars and bicycles (section 4.4.4).

- Walking and cycling statistics (section 4.4.5).
- The percentage of trips made by active modes and a comparison with the ATE target for 2030 (section 4.4.6).
- Socio-demographic analysis (section 4.4.7).
- Health benefits analysis (section 4.4.8).
- Built environmental characteristics analysis (section 4.4.9).
- Economic analysis (section 4.4.10).
- The use of cycle hubs allocated next to metro stations (section 4.4.11).

It is worth adding that all scenarios described above can be easily transferred to any other study region. The developed code should be updated by simply pointing to the correct network file of the desired study area.

Chapter 4 will show the results obtained when the methodology explained in this chapter is applied to the Tyne and Wear region. Results of the main MATSim input datasets (i.e., synthetic travel demand and network), as well as the calibration and validation stages are shown. The chapter concludes with the results obtained from each simulated scenario, providing them from different approaches (e.g., transport, geospatial, temporal and statistical).

Chapter 4. Results

Men of learning suspect it little and ignore it mostly. Wise men have interpreted dreams, and the gods have laughed. Howard Phillips Lovecraft

The previous chapter explained the stages followed to develop a transport MATSim model and to simulate different scenarios to increase the use of active modes. This chapter shows the results obtained after applying the previously described methodology to the area of study (i.e., Tyne and Wear) during a normal working day in 2019.

This chapter has been structured as follows. Firstly, the results obtained from the synthetic travel demand are presented (section 4.1). Secondly, the network developed to allow agents to move between their daily activities is shown (section 4.2). Thirdly, the stages followed to calibrate and validate the MATSim baseline scenario and results obtained are described (section 4.3). Lastly, the results obtained from the different scenarios simulated are compared with the baseline, identifying differences in modal share, CO_2 emissions, geospatial distribution, active mode use, achievement of the ATE goal, socio-demographic distribution, health benefits, use of roads depending on the built environment characteristics, economic analysis and cycle hubs usage (section 4.4).

4.1. Synthetic demand

The results obtained in the development of the synthetic travel demand for the study area have been divided in two: synthetic population and activity plan. Both results were compared and validated against internal and external datasets, when possible. Section 4.1.1 describes the results achieved when developing the synthetic population of the entire NE of England, while section 4.1.2 describes the results obtained when the activity plans were assigned to each individual in the synthetic population.

4.1.1. Synthetic population

The application of the methodology explained in section 3.3.1 allowed the development of a very detailed synthetic population, consisting of 12 attributes for each individual (see section 3.3.4). In total, 2,645,517 individuals were generated. Attributes obtained from SPENSER were assumed to be correct, while the eight attributes generated with the synthPopEng tool developed in this work were validated against statistical datasets, as shown below.

Marital status

The marital status attribute classifies individuals in two categories (married or single) based on age and sex attributes and the internal relationships that individuals from the same household can have between them, assuming that those attributes were correctly calculated by SPENSER. In total, 45.64% of individuals were classified as married (aged 16 or over), while the remaining 54.36% were considered as single. Official statistics from ONS for England in 2019 (ONS, 2020) identify that 50.4% of adults are 'married'. Figure 50 shows this comparison, where blue bars represent results obtained from the synthetic population, while orange bars represent values from the ONS statistics.

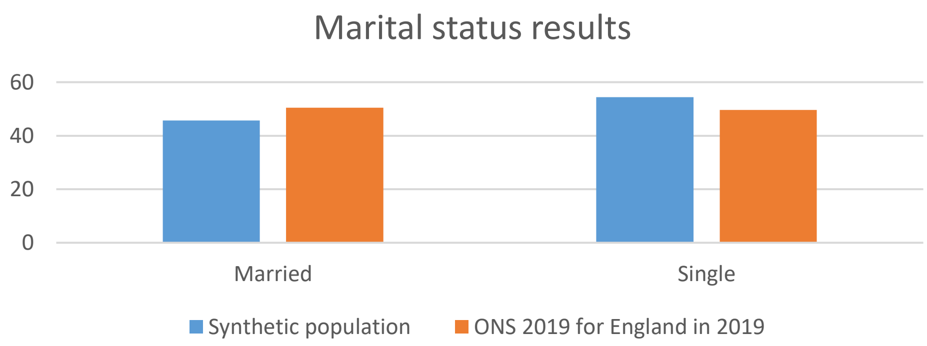


Figure 50 Comparison of the percentage of marital status between results from the synthetic population (blue) and ONS data (orange).

Results obtained are very similar to national statistics, where a 4.76% difference was achieved between the two possible values. Although the achieved result can be considered realistic, a closer outcome could be obtained by modifying or altering the assumptions made when considering married or single individuals in the developed tool, where the age, sex, marital status of the HRP and an up to ten-year difference gap between individuals in the same household were considered. Despite this, the results achieved can be considered as satisfactory for the purpose of this thesis. Further investigation would be required to reduce the difference gap, considering other attributes (e.g., ethnicity group) or external statistic datasets from ONS.

Children dependency

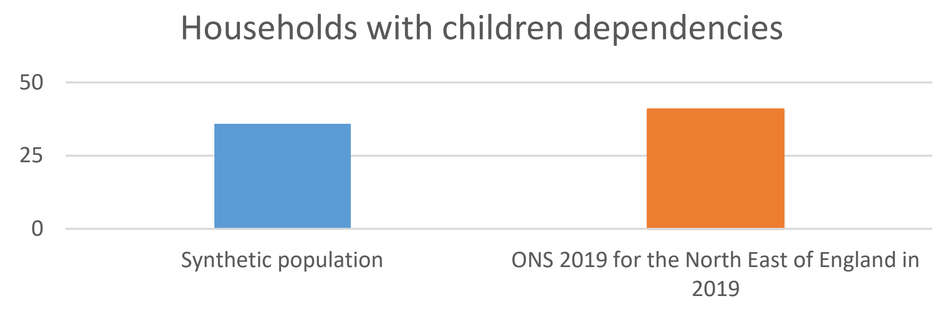


Figure 51 Comparison of the percentage of households with children dependencies between results achieved in the synthetic population (blue) and ONS data (orange).

Similarly, this attribute is entirely derived from SPENSER outcomes, where family relationships between individuals from the same household based on their sociodemographic attributes were considered. Figure 51 shows that 35.9% of households have children dependencies in the area of study (blue bar), while ONS statistics (ONS, 2019) shown a 40.8% (orange bar).

This difference is in line with results achieved in the marital status attribute, as both attributes are significantly related. Similarly, the use of more attributes, external datasets and/or a different set of assumptions would achieve results that are more accurate. It is expected that in a future investigation, the improvement of one of these attributes would improve the other.

Economic activity

Economic activity attribute classifies individuals in three categories (employed, unemployed, inactive), based on their OA area household location, age and sex. The assignment of economic activity to individuals was conducted with a process that iterates until the difference between modelled and observed values is less than a 1%-point. This is achieved in all cases, except for unemployed males over 65 years old, as it was the last category to be assigned and as such, is the remainder after all other individuals have been assigned. Figure 52 summarises the results achieved when compared with ONS statistics (ONS, 2023c), per range of age and sex.

		Range of age				
		16 - 24	25 - 34	35 - 49	50 - 64	65 +
Employed	Males calculated	50.82	83.56	87.25	68.54	9.23
	ONS NE males observed	51.35	84.18	87.79	68.8	9.61
	Difference males	**-0.53**	**-0.62**	**-0.54**	**-0.26**	**-0.38**
	Females calculated	47.66	73.49	78.19	65.26	4.54
	ONS NE females observed	48.65	73.05	77.93	66.22	5.13
	Difference females	**-0.99**	**0.44**	**0.26**	**-0.96**	**-0.59**
Unemployed	Males calculated	15.84	6.49	3.43	6.88	2.5
	ONS NE males observed	15.97	6.44	3.45	5.95	1.03
	Difference males	**-0.13**	**0.05**	**-0.02**	**0.93**	**1.47**
	Females calculated	13.04	4.48	3.75	3.49	N/A
	ONS NE females observed	12.28	5.06	3.45	3.21	No data
	Difference females	**0.76**	**-0.58**	**0.3**	**0.28**	**N/A**
Inactive	Males calculated	39.26	10.63	9.65	26.4	90.53
	ONS NE males observed	38.29	10.02	9.08	26.84	90.29
	Difference males	**0.97**	**0.61**	**0.57**	**-0.44**	**0.24**
	Females calculated	45.21	23.06	18.76	32.37	95.02
	ONS NE females observed	44.54	23.05	19.29	31.58	94.8
	Difference females	**0.67**	**0.01**	**-0.53**	**0.79**	**0.22**

Figure 52 Comparison of economic activity results with observed data.

The proposed methodology assumes a linear projection in the percentage of individuals in each economic activity category per OA Area, as the 2011 UK census data is projected evenly in all OA areas based on regional ONS data. External circumstances such as the establishment of new factories, offices and any other work developments in specific areas are not considered.

Occupation

The occupation attribute classifies individuals in nine categories when employed or unemployed, considering their OA area household location, age, sex and economic activity attributes. Figure 53 shows the results obtained, where aggregated results are compared with official UK regional statistical of the area of study (ONS, 2022a).

		Global			Sex		
		ONS NE 2019	Results	Differences	ONS NE 2019	Results	Differences
1: Managers, Directors and Senior Officials (SOC2010)	Total	8.45	10.93	2.48			
	Males				61.97	62.39	0.42
	Females				38.03	37.61	-0.42
2 Professional Occupations (SOC2010)	Total	20.66	17.88	-2.78			
	Males				43.74	43.26	-0.49
	Females				56.26	56.74	0.49
3 Associate Prof & Tech Occupations (SOC2010)	Total	12.59	12.47	-0.12			
	Males				51.57	56.04	4.47
	Females				48.43	43.96	-4.47
4 Administrative and Secretarial Occupations (SOC2010)	Total	11.24	8.61	-2.63			
	Males				22.18	40.86	18.69
	Females				77.82	59.14	-18.69
5 Skilled Trades Occupations (SOC2010)	Total	8.29	11.78	3.49			
	Males				92.85	94.56	1.71
	Females				7.15	5.44	-1.71
6 Caring, Leisure and Other Service Occupations (SOC2010)	Total	11.55	10.97	-0.57			
	Males				14.65	13.51	-1.14
	Females				85.35	86.49	1.14
7 Sales and Customer Service Occupations (SOC2010)	Total	9.53	7.45	-2.08			
	Males				31.60	28.43	-3.17
	Females				68.40	71.57	3.17
8 Process, Plant and Machine Operatives (SOC2010)	Total	5.82	7.94	2.12			
	Males				95.89	90.40	-5.49
	Females				4.11	9.60	5.49
9 Elementary occupations (SOC2010)	Total	11.87	11.97	0.10			
	Males				48.66	46.06	-2.61
	Females				51.34	53.94	2.61

Figure 53 Comparison between the occupation types for employed and unemployed synthetic individuals and observed values.

Differences achieved in aggregated results per occupation type were always below 3.5%-points when compared against ONS statistical data (ONS, 2022a), while when grouped by occupation and sex, differences were up to 18.7%-points in the worst case (i.e., category 4). In the remaining cases, gender differences were below 5.5%. As the percentage of occupations per range of age are not known from official statistics, this validation was not possible. Lastly, external circumstances, such as those highlighted for the previous attribute, were not considered either.

In the case of inactive individuals, five different occupation categories were considered based on age, sex, economic activity and household attributes. Figure 54 shows the aggregated results when compared with official regional statistics (ONS, 2023c). In all cases, the aggregated values were below 1%-point difference, although when grouped by sex, the differences were up to 5%-points.

		Global			Sex		
		ONS NE 2019	Results	Differences	ONS NE 2019	Results	Differences
Student	Total	25.13	25.1	0.03			
	Males				29.37	34.16	-4.79
	Females				22.17	18.76	3.41
Retired	Total	13.7	13.8	-0.1			
	Males				15.2	17.94	-2.74
	Females				12.7	10.88	1.82
Looking after home / family	Total	21.34	21.35	-0.01			
	Males				7.8	10.25	-2.45
	Females				30.82	29.22	1.6
Sick	Total	30.4	30.38	0.02			
	Males				36.5	34.34	2.16
	Females				26	27.57	-1.57
Other	Total	9.47	9.32	0.15			
	Males				11.12	3.32	7.8
	Females				8.31	3.45	4.86

Figure 54 Comparison between the occupation types for inactive synthetic individuals and observed values.

The occupation attribute for inactive individuals was assigned considering a greater number of attributes than previous cases (i.e., sex, range of age, OA area, household characteristics and marital status). Additionally, the proposed methodology assumes a linear projection in the percentage of individuals in each occupation type per OA area, as it was similarly defined for the economic activity attribute. Therefore, a higher complexity and difficulty to match values from official statistics is acknowledged.

Annual gross income

The annual gross income quantifies the amount of money earned based on age, sex and occupation attributes. Although unemployed individuals do not receive any income when unemployed, they are assumed to have a similar economic wealth as if they were working, due to the likelihood of getting another job with a similar income.

Results shown in table 7 are grouped by deciles and compared against regional statistics of the study area (ONS, 2022d), with differences per decile being below £1,000 in all cases. A relative error threshold was calculated for each decile considering the obtained value and the ONS statistical value. In all cases, the error was below 0.1 in absolute value.

Percentile	Results	ONS NE 2019	Difference	error = (observed-calculated)/observed
p10	8790	7993	-797	-0.100
p20	13080	12607	-473	-0.038
p30	16560	16679	119	0.007
p40	20080	19560	-520	-0.027
p50	23060	22602	-458	-0.020
p60	26260	26126	-134	-0.005
p70	30430	30605	175	0.006
p80	36330	36523	193	0.005
p90	45620	45580	-40	-0.001
mean	25650	26339	689	0.026

Table 7 Comparison results between the annual gross incomes obtained in the synthetic population and observed data.

When results were grouped by range of age and compared against national statistics (figure 55), lower mean incomes per range of age (blue bars) were found in the NE than the whole UK (orange bars), but there was consistency in the differences. Discrepancies up to £2,000 were identified, which could be reasonable as results obtained from the synthetic population were compared with UK median income values per range of age (ONS, 2022b), however, incomes in the NE of England are generally lower than the UK average (ONS, 2022c).

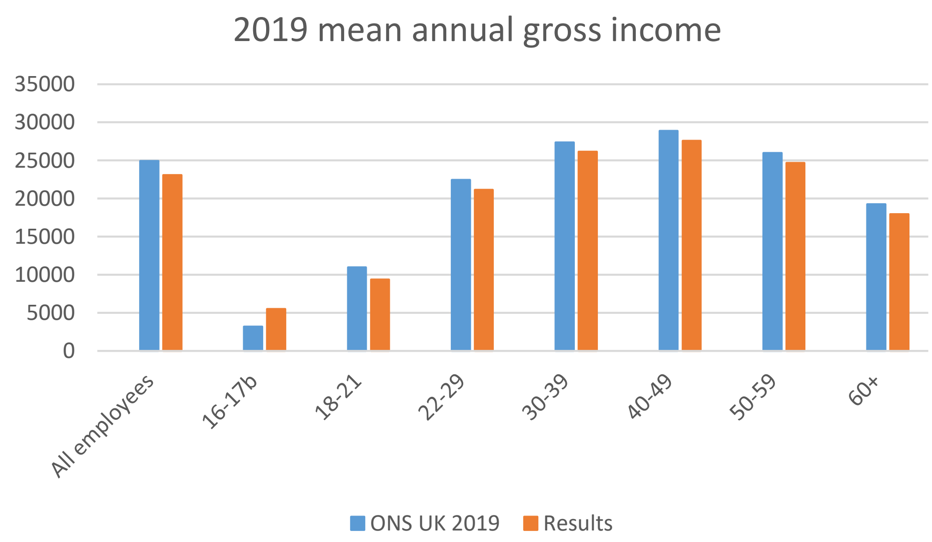


Figure 55 Annual gross income comparison between results achieved in the synthetic population (blue) and ONS data (orange) at UK scale, grouped by range of age.

The methodology proposed for employed and unemployed individuals heavily depends on estimated values (although based on ONS data) that need to be iterated until results achieved are similar to ONS statistics (see section 3.3.3).

In the case of inactive individuals, the annual gross income values were assigned based on their socio-demographic characteristics and UK statistical values that quantify their annual gross income depending on the potential benefits that they are eligible to receive. Due to lack of more granulated UK official data, it was not possible to validate the accuracy and precision of these values.

Driving license

Driving licence is a Boolean attribute that identifies those driving licence holders based on their age and sex attributes. Figure 56 shows the comparison between the obtained results (light blue and red bars) and regional statistics (dark blue and red bars) (NTS, 2023e).

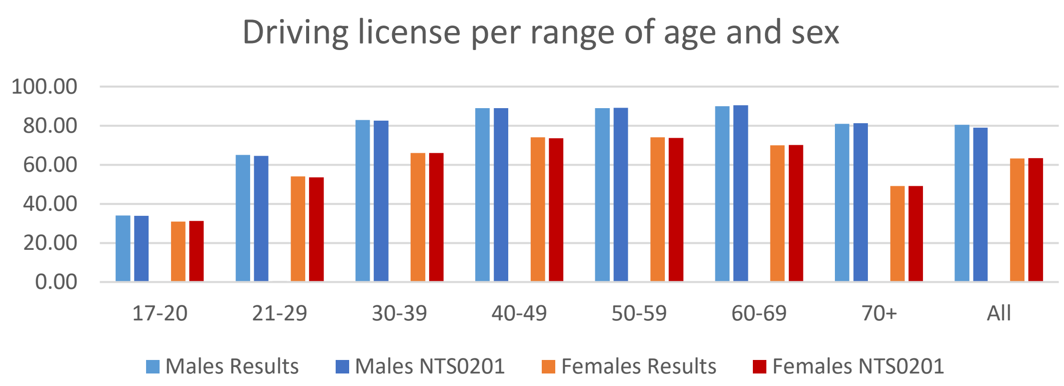


Figure 56 Driving license comparison per range of age and sex between results obtained from the synthetic population and NTS datasets.

Results were remarkably similar to those provided by NTS (2023e), with differences always below 1%-point when grouped by sex and range of age, and below 1.5%-points when grouped only by sex. The developed methodology assumes that at least one person per household with at least one car holds a driving licence, while the remaining driving licences are assigned based on the individuals' characteristics (i.e., age and sex) and probability values dependent on the number of cars in the household. The assignment of these probability values is an iterative process that requires a trial-and-error strategy, until results are similar to those provided by the ONS.

Unfortunately, it was not possible to consider any spatial resolution, as official datasets were obtained only at region level.

Car access

Car access is also a Boolean attribute derived from two other attributes: the number of cars in the household (attribute assigned to the household where the individual lives) and the possession of a driving licence. In total, 68.5% of the households in the NE have access to a car, while national statistics for 2019 estimate 76.0% (figure 57). Official statistical data of the study area was not found.

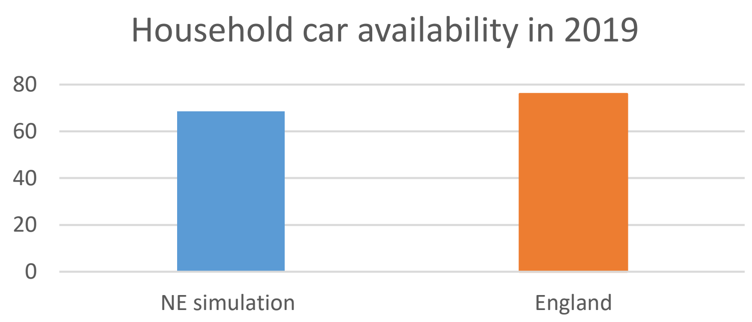


Figure 57 Comparison of household car availability in 2019 between results achieved in the synthetic population (blue) and statistics for England (orange).

Similarly, as in the case of the marital status and children dependency attributes, the result obtained in the synthetic population is lower than official statistics, although the validation is made comparing different scales as a consequence of lack of information at a regional level.

Bicycle access

Bicycle access is also a Boolean attribute that identifies those individuals with access to a bicycle in the household, based on their age only. The definition of this attribute was overly simplistic since the available data was only structured per range of age, so those NTS statistical values were assigned proportionally to the individuals based on their age, which implies the impossibility of validating them against any other data. Future work could include the validation of this attribute based on several socio-demographic attributes, once official information is released.

Spatial validation

Besides previous internal validations, results were also spatially grouped to check their distribution in space, at OA level. This is an important concept, as the spatial distribution needs to be considered when analysing the accuracy of the results. Three attributes were spatially represented to verify the outcomes: children dependency, car access and students at college or university.

Figure 58 shows the percentage of adults with children dependencies in the Tyne and Wear region (right) and more detail of Newcastle city centre (left). Light colours represent very low percentage values, while darker colours identify OA areas with higher percentage of adults with children dependencies. It can be observed that they are mainly allocated on the outskirts of the city centres, where more family dwellings are found.

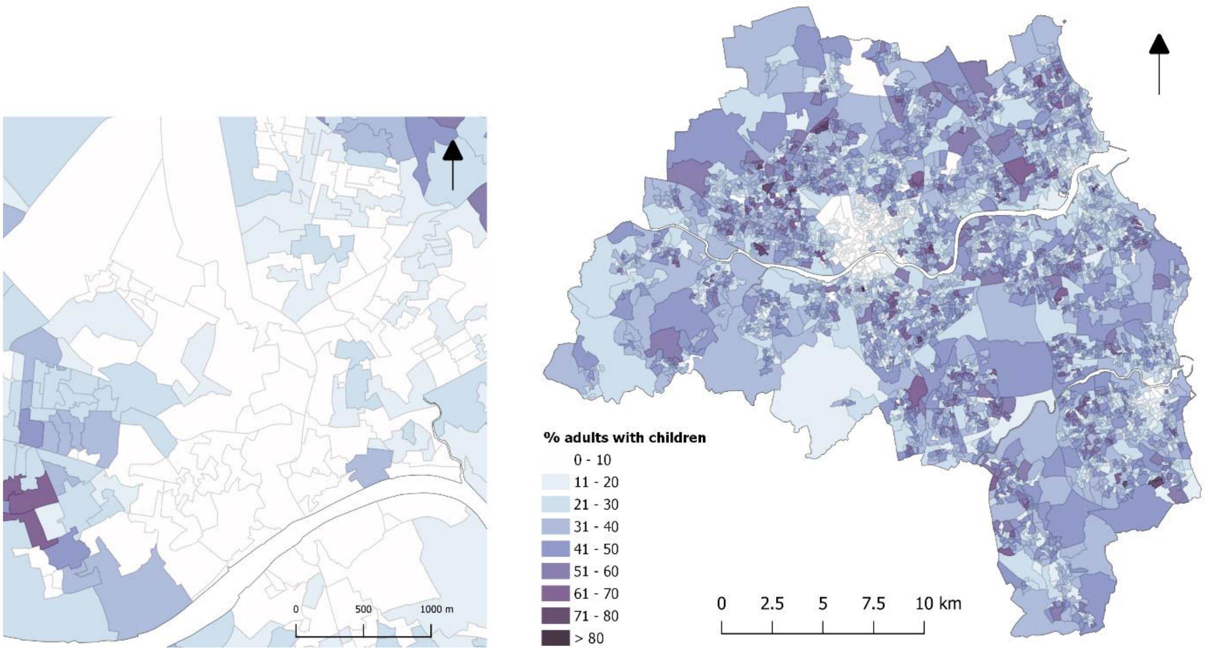


Figure 58 Geospatial representation of the percentage of adults with children dependencies per OA area in the Tyne and Wear region (right) and a detailed perspective of Newcastle city centre (left).

Figure 59 shows the percentage of adults with car access in the Tyne and Wear region (right) and highlights the city centre of Newcastle (left). Light yellow colours represent very low percentage values, while dark blue identifies OA areas with a higher percentage of adults with access to a car in the households. Similarly, as in previous figure 58, individuals with car access are found on the outskirts as people in the city centres usually have more transport options (e.g., bus, metro), with less need for a car (Transport for the North, 2022).

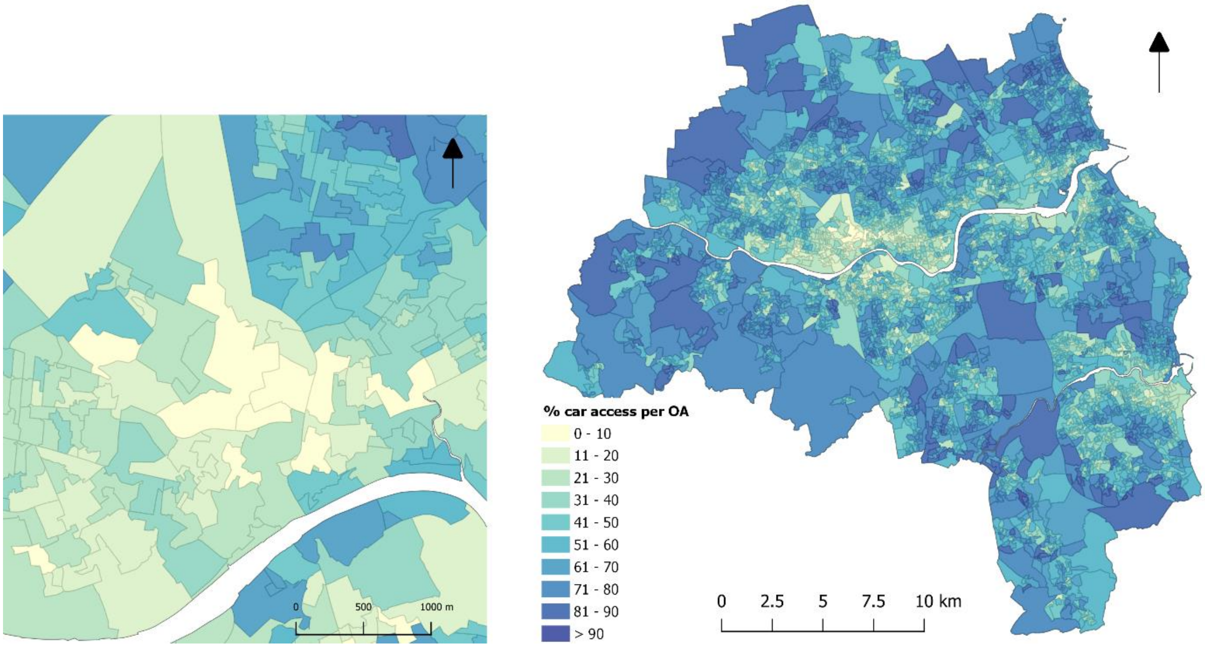


Figure 59 Geospatial representation of the percentage of adults with car access per OA area in the Tyne and Wear region (right) and a detailed perspective of Newcastle city centre (left).

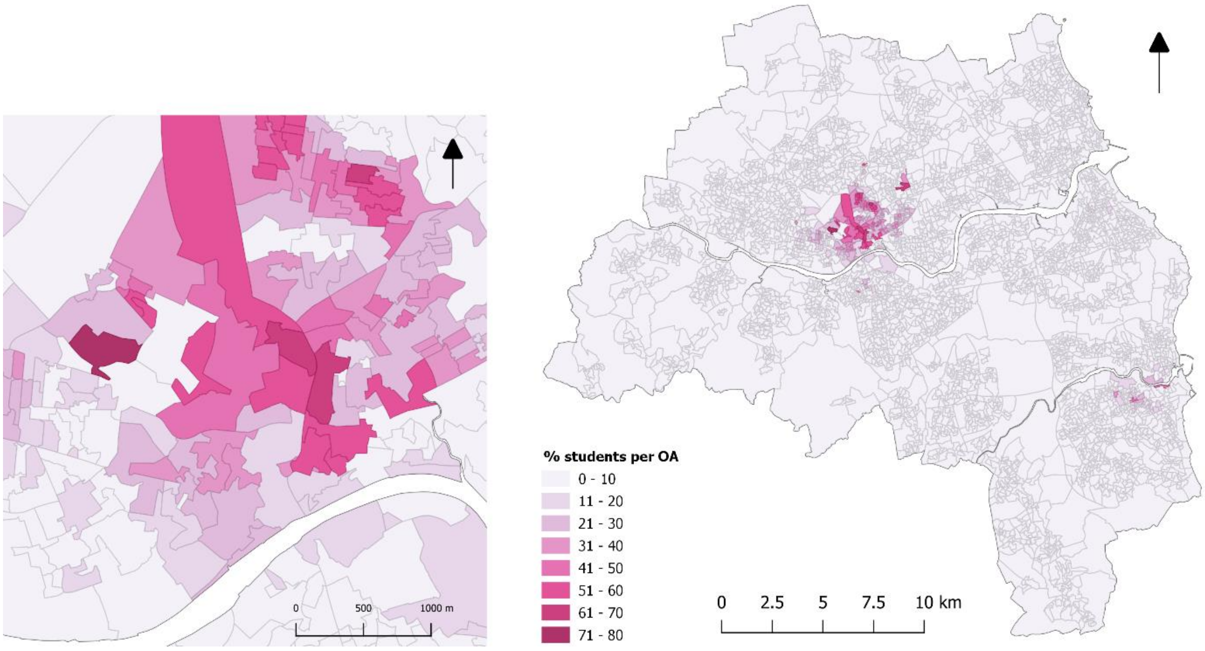


Figure 60 Geospatial representation of the percentage of students at college or university per OA area in the Tyne and Wear region (right) and a detailed perspective of Newcastle city centre (left).

Figure 60 shows the percentage of students at university or college in the Tyne and Wear region (right) and more detail of the city centre of Newcastle (left). Light red colours represent very low percentage values, while dark red identifies OA areas with a higher percentage of students in the area. Students are mainly found where student accommodations are allocated, especially in the surrounding areas of the main universities in Newcastle upon Tyne and Sunderland. Results achieved are a consequence of the methodology developed in the code, as students were forced to live in households with specific characteristics that resemble those where the student population lives (i.e., student accommodations, multi-person households).

4.1.2. Activity plan

This section shows the internal validation results when aggregated activity plans assigned to the synthetic individuals in the study area were compared to those obtained from the original travel diaries in the same area and time. Due to the small number of individuals surveyed in the NE during 2019 (839), results were also compared against all surveyed individuals in England except London in 2019 (13,797 surveyed individuals), as similar patterns were identified within other areas, as shown previously in section 3.3.5.

The percentage of trips by transport mode quantifies the distribution of trips in the different transport modes available. Figure 61 shows the results achieved in this thesis (blue bars), compared with those surveyed individuals in 2019 (orange bars) and in the NE in 2019 (grey bars). Seven different transport modes were considered (bicycle, bus, car driver, car passenger, metro, train and walk). Major discrepancies were found in the number of individuals using cars, having fewer car drivers in the synthetic population than in the surveyed individuals (8% difference with NE and 6% with the UK) and more car passengers (3% in both cases). Furthermore, more synthetic individuals use the bus and walk more than in 2019 (2.4 and 1.6% respectively) and in the NE in 2019 (1.6 and 2.9%). Despite these results, the accuracy obtained is not relevant, as the synthetic individuals will be allowed to change the transport mode at the simulation stage, until results achieved show a realistic proportion of transport modes uses in the study area.

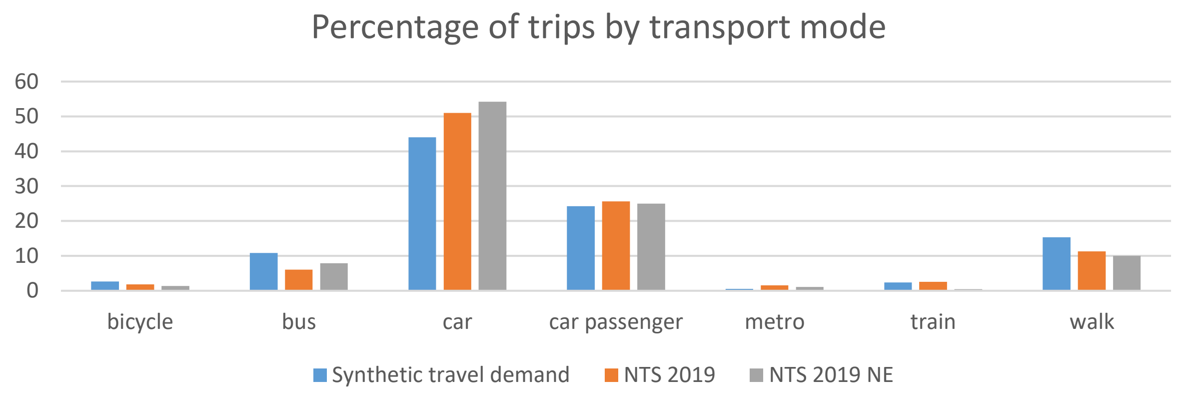


Figure 61 Comparison of the percentage of trips by transport mode between results achieved in the synthetic population (blue), NTS 2019 results (orange) and NTS results for the NE of England only, in the 2019.

Figure 62 shows the percentage of trips in distance by ranges. Similar to previous figures, results achieved with the synthetic travel demand are shown in blue, while values from the 2019 NTS surveys are in orange, and those individuals surveyed in the NE of England in 2019, in grey.

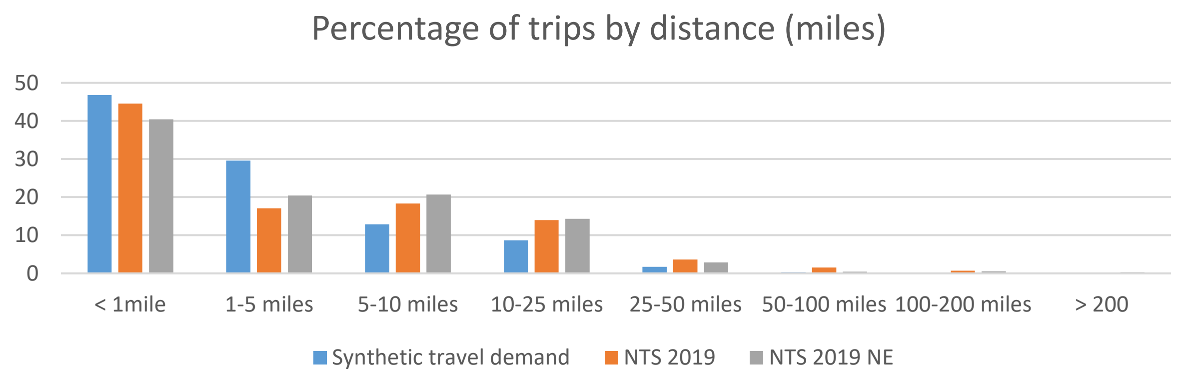


Figure 62 Comparison of the percentage of trips by distance (in miles) between results achieved in the synthetic population (blue), NTS 2019 results (orange) and NTS results for the NE of England only, in 2019.

Eight different ranges of distances were compared: from trips below 1 mile up to trips of more than 200 miles. Results from the synthetic travel demand contains more short trips than expected (especially up to five miles). Despite this, the amount of obtained short trips could be beneficial as they are commonly forgotten when doing travel diaries, as mentioned in section 3.3.5. This increased number of short trips could be a consequence of the methodology when identifying the building locations and applying the developed spatial interaction modelling (SIM) technique, as the distance to the household is also considered to make the activities in an area relatively close to the household. This parameter could be modified to adjust its importance when choosing the activity location in future work, as well as the possibility of using alternatives models, such as SILO (Ziemke *et al.,* 2016), which simulates household and workplace location choices based on transport costs.

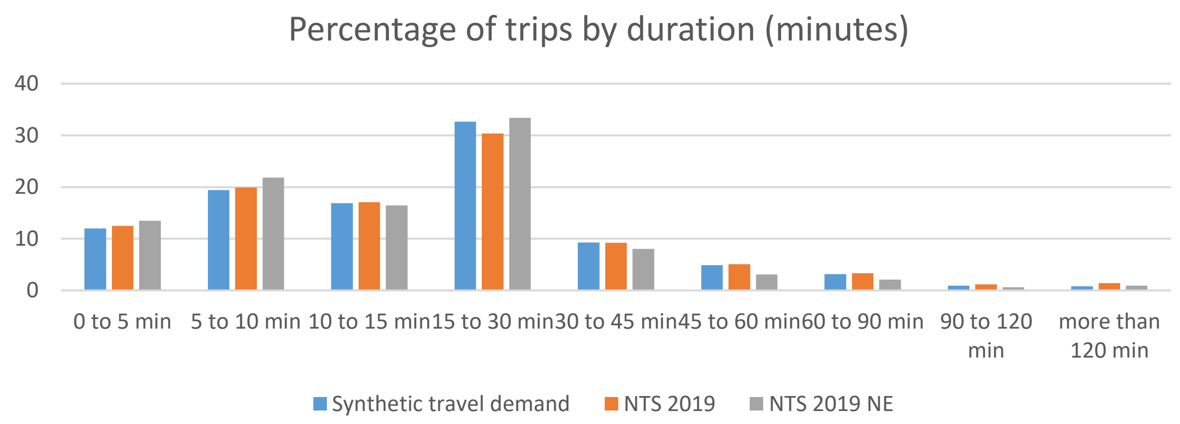


Figure 63 Comparison of the percentage of trips by duration between results achieved in the synthetic population (blue), NTS 2019 results (orange) and NTS results for the NE of England only, in 2019.

Figure 63 shows the percentage of trips by duration, in minutes. Results obtained (blue bars) are compared with those obtained in 2019 (orange) and in the NE in 2019 (grey). Nine time ranges were analysed: from very short trips up to five minutes, to long trips of more than two hours. As can be observed, trip durations are within 3% in all ranges, having the highest discrepancies in the 15-30 min range, being below three minutes.

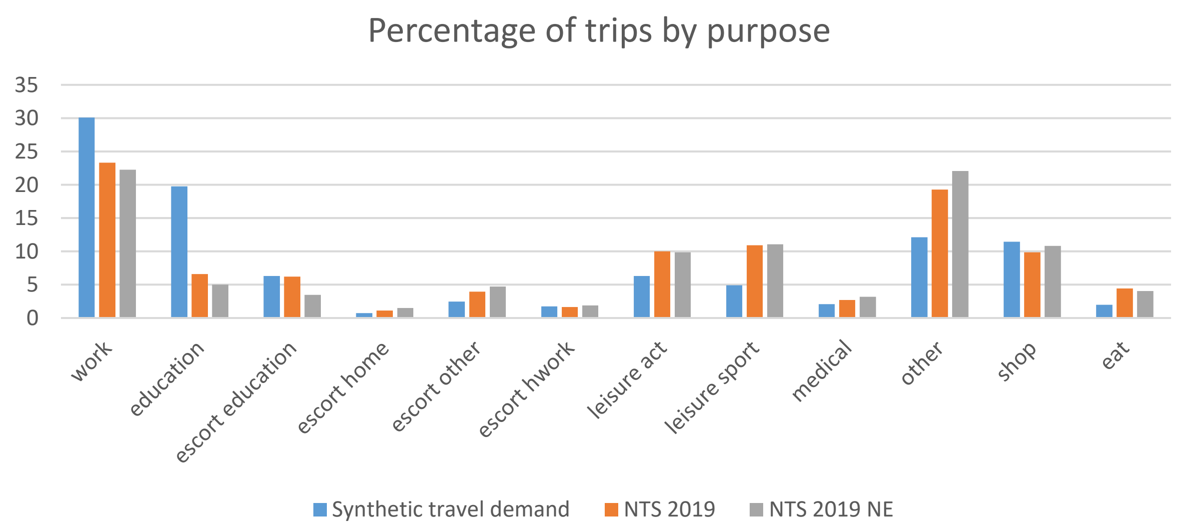


Figure 64 Comparison of the percentage of trips by purpose between results achieved in the synthetic population (blue), NTS 2019 results (orange) and NTS results for the NE of England only, in 2019.

Figure 64 shows the percentage of trips by purpose. In this case, 12 different trip purposes were compared between the results achieved (blue bars), the NTS statistics in 2019 (orange bars), and only those NTS statistics in the NE in 2019 (grey bars).

More work (6.8% and 7.8%) and education (13.1 and 14.7%) trips were obtained than those expected in 2019 and in the NE in 2019, respectively, while the percentage of the other activities were below the expected values (mainly 'leisure' and 'other' activities), except escort education, escort work and shopping. The reasons for these discrepancies could be various, although the lack of workers and children submitting the NTS travel diaries could be the most feasible. Based on results achieved, 77.6% of those synthetic employed individuals were assigned an activity plan containing a workplace and it was assumed that the remaining 22.4% work outside the area of study. These values are similar to those derived from the 2011 census (ONS, 2011c), where the percentage of people living and working in the NE was 80.1%.

Finally, figure 65 shows the percentage of commuting trips by sex and range of age. Results achieved (blue bars) are compared with the NTS statistics in 2019 (orange bars) and those NTS statistics in the NE in 2019 (grey bars).

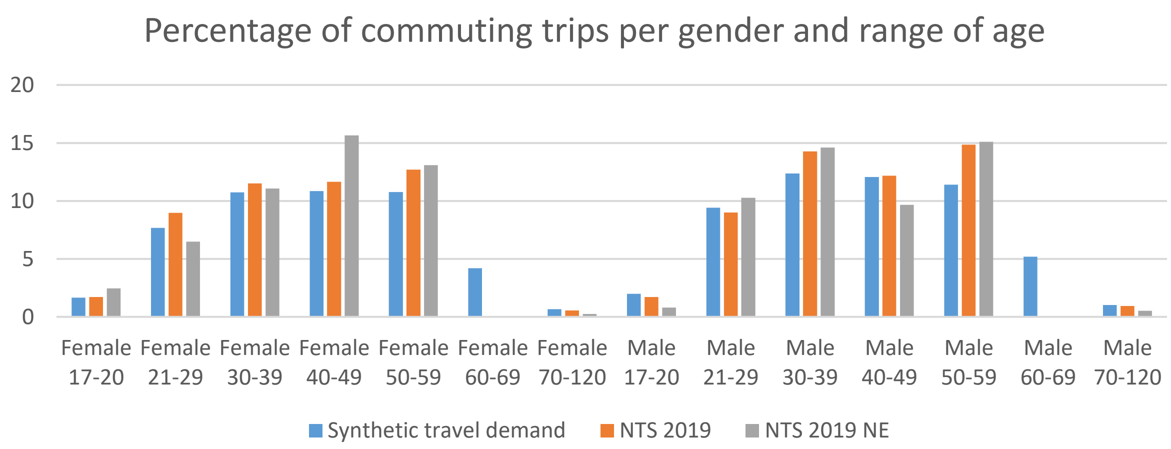


Figure 65 Comparison of the percentage of commuting trips by gender and range of age between results achieved in the synthetic population (blue), NTS 2019 results (orange) and NTS results for the NE of England only, in 2019.

An even distribution of trips is observed in all groups when compared against NTS values, although gaps for individuals between 60 and 69 years were observed. Major discrepancies can be observed in females between 40 and 49 years, which found around 5% less females in the synthetic travel demand than in the NE in 2019, although when compared against 2019, the difference is only about 1%. This can be caused by the very low number of surveyed individuals in the NE, which could explain the lack of data for females and males between 60 and 69 years. Therefore, it was impossible to compare them with NTS datasets.

4.2. Network

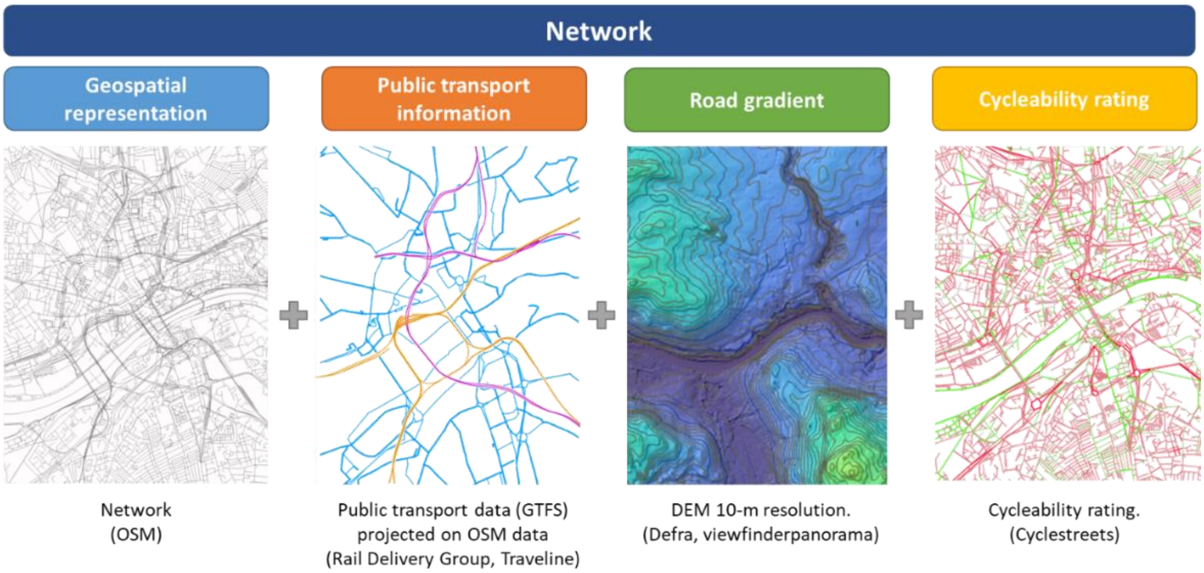


Figure 66 Network composition. A combination of geospatial road representation, public transport data, DEM and cycleability rating values.

The developed network consists of the geospatial representation of the OSM road and public transport network in the study area, where characteristics such as the type of feature (e.g., residential, motorway, railway), flow capacity, maximum speed and allowed modes (e.g., pedestrian, car, bicycle, rail) were defined. Additionally, three more components were added. Firstly, information about the public transport services (e.g., routes, stops, schedules and vehicle types) was obtained from GTFS datasets. Secondly, elevation values (i.e., coordinate Z) for nodes and gradients for the links, were obtained from a very detailed 10-metre resolution generated DEM. The third was the cycleability ratings or *quietness* values, which define the roads' quality for cycling, based on the built environment characteristics. Figure 66 summarises the four different datasets combined in the developed network.

As a result, three files were generated: the network (network.xml) defining the road and public transport network with information of gradients and cycleability ratings, the schedules of each public transport route (schedule.xml), and the vehicles' characteristics (vehicles.xml).

4.3. MATSim validation

The MATSim model was validated with official datasets from NTS and vehicle counts from TADU (Gateshead Council, 2023), besides other complementary datasets (e.g., expert advice, Google maps). Six validations steps were considered, covering the mode splits (section 4.3.1), vehicles en-route (section 4.3.2), average trip distances and times by transport mode (section 4.3.3), the percentage of commuting trips per range of distance (section 4.3.4), bicycle routing (section 4.3.5), the percentage of trips below five kilometres using active modes (section 4.3.6). Concepts of transport modes usage, geospatial distribution and average trip statistics were analysed to check if the generated MATSim model is representative of a regular working day in the Tyne and Wear region.

4.3.1. Modal split

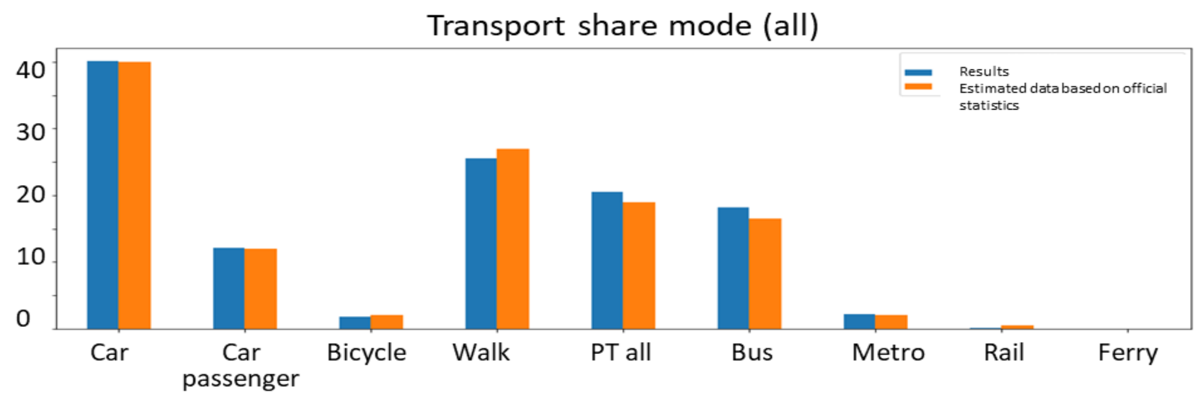


Figure 67 Comparison of the percentage of trips by transport mode between results achieved in the synthetic population (blue) and estimated results based on official datasets and expert advice (orange).

Modal split represents the percentage of trips made by the different transport modes. Figure 67 shows the simulated modal split results (blue bars) when compared against those values (orange) obtained through the combination of official NTS (DfT, 2023e) and census (ONS, 2011e) statistics. This also included expert advice from several transport stakeholders (e.g., Nexus, Transport North East, Newcastle University), as described in the previous chapter.

Differences achieved were always below 2% when compared against the estimated modal split. Results show that the most common mode is the car (as driver) (40.1%), followed by walking (25.5%), public transport (20.5% split in 18.1% for bus, 2.2% light rail, 0.2% rail and almost 0% for the ferry), car as a passenger (12.1%) and cycling (1.8%). These values coincide with the analysis performed in section 2.1, where it was shown that England exhibits a strong car dependency and a weak bicycle culture.

Figure 68 compares the simulated main mode of travel to work (blue), with the NTS main mode of travel to work when working (orange) (DfT, 2023e) and living (green) (DfT, 2023d) in the Tyne and Wear region.

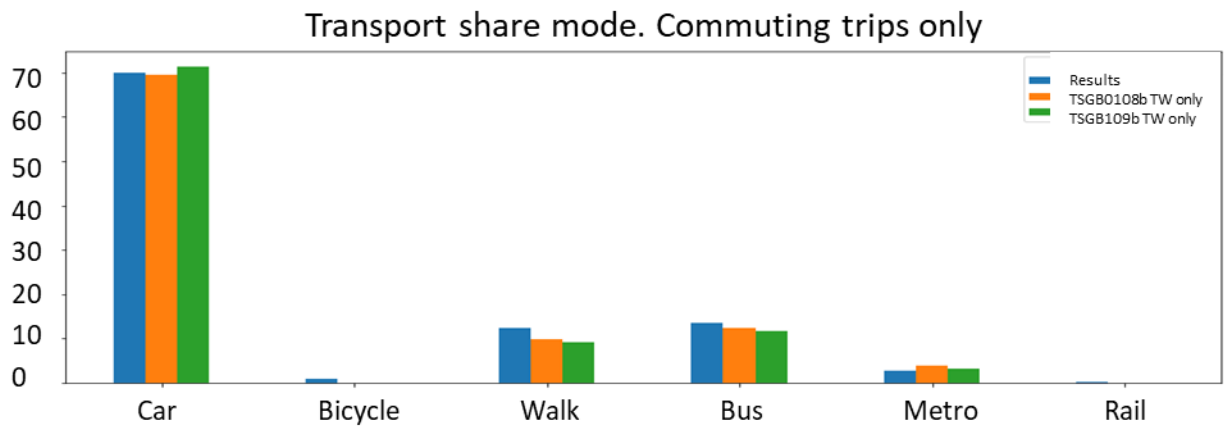


Figure 68 Comparison of the percentage of commuting trips by transport modes between results achieved in the validated MATSim mode (blue) and observed results of individuals working (orange) and living (green) in the Tyne and Wear region.

Results obtained show differences below 3% and 3.5% when compared against commuting trips of individuals living and working in Tyne and Wear, respectively. Greater values were found when walking (2.5% and 3.4% respectively) and using the bus (1.2% and 1.9%, respectively), and lower results in the use of the metro (-1.0% and -0.5%). The percentage of car trips was between the two observed values, while the use of the bicycle and rail were not possible to be compared, as no-data was obtained from the statistics. Similarly, as in figure 67, the use of cars when commuting is the predominant mode of transport (70%), followed by the use of buses (13.6%), walking (12.5%), metro (2.8%), cycling (1.0%) and rail (0.3%) The same conclusion of a strong car dependency culture when commuting as in figure 67 could be applied into this case.

Figure 69 compares the percentage of simulated trips by different modes when travelling to school (blue bars) with statistical values of modes of travel to school of individuals aged between 5 and 16 years in England between 2015 and 2019 (orange) (UK Government, 2023c).

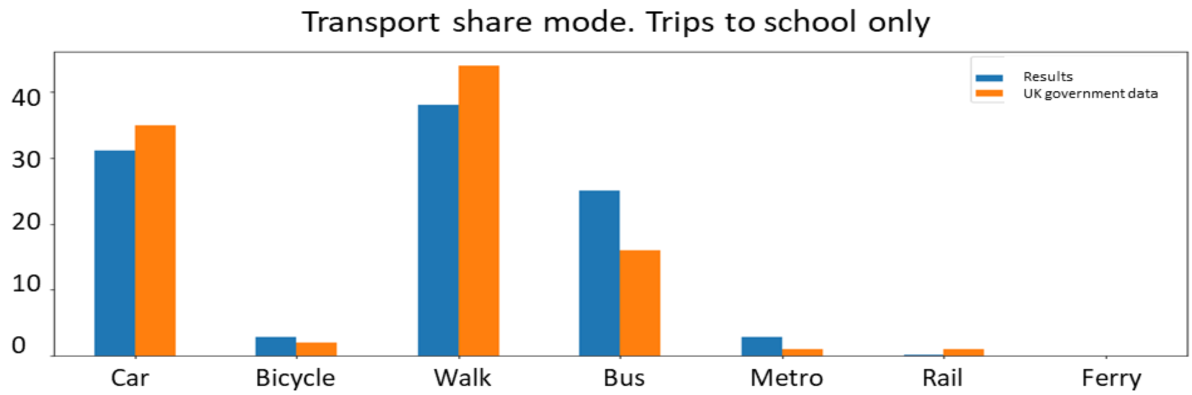


Figure 69 Comparison of the percentage of trips to school by transport modes between results achieved in the validated MATSim mode (blue) and observed results in England (orange).

Obtained differences were below 10% in all cases, with the value for the use of buses being the greatest. Despite this difference, results were considered as realistic because simulated results were compared with national statistics, due to the lack of information for the NE or the Tyne and Wear regions, and knowing that the use of buses in the NE is greater than the average in England, as indicated in figure 23. Conversely, lower percentage values were obtained when using the car (as passenger) (3.8%-points) and walking (6%-points), while the differences in the use of bicycles and rail were below 1%. In this case, most trips are made walking (38.1%), followed by car (31.2%) and bus (25.1%), accounting for 95% of trips.

4.3.2. Vehicle counts

Figure 70 shows the percentages of cars en-route per hour. Simulated results (blue bars) are compared with NTS values (orange) for the whole of England during 2019 (NTS, 2023c).

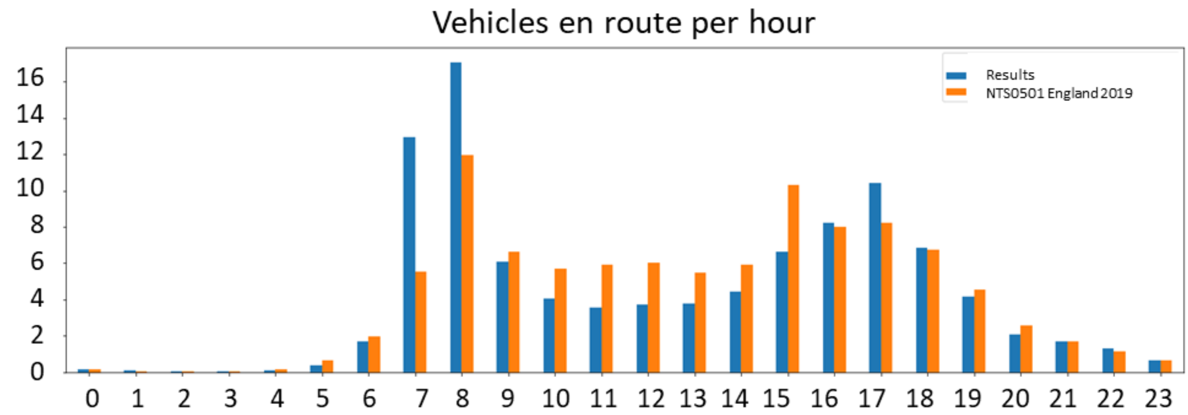


Figure 70 Comparison of the percentage of vehicles en-route per hour, between results obtained in the MATSim validated model (blue) and observed values from NTS (orange).

The simulated temporal distribution of vehicles en-route is similar to the national values, with discrepancies below 7.5%. The greatest differences are found during the morning peak (i.e., between 7 and 8am), where more simulated vehicles were found in movement than expected (7.42%), although lower percentage values were obtained during the late morning and early afternoon (around 2% below expected, on average). Finally, the evening peak (i.e., 5pm) is higher than expected (2%), while early morning, late evening and night values are below 1% difference. These discrepancies are a consequence of the following configuration parameters, assumptions and the data used to check the simulated results:

- Trips made by freight and other vehicles transiting the study area but starting or ending outside of it were not considered, having the highest impact during the late morning and early afternoon, as this period of time is when most agents are doing some of their activities (e.g., work, education, shop).
- Each activity is defined by a set of attributes, where the starting time and typical duration values are defined, among others. Although these values can be left as 'undefined', it was found that the most realistic results were obtained when the starting time, for work purpose, was set to 8am and the typical duration was dependent on each agent's work activity. Consequently, the morning peak was reached around 8am, as it is in the observed data, but greater than expected.
- The official data used to compare the model results is at national scale, as data containing only information of the study area was not found.

The combination of these factors achieved higher percentage values during the morning peak and lower during the middle of the day. Additionally, it was observed that the school run (i.e., between 3 and 4pm) was not captured, having a discrepancy around 4% below the expected value. A derived consequence of a lower percentage of children going by car as passengers to education trips could have produced this difference, as was discussed earlier.

Figure 71 compares vehicle counts (i.e., cars) from different roads in the study area. Simulated results (y-axis) are compared against official vehicle counts from TADU (Gateshead Council, 2023) (x-axis).

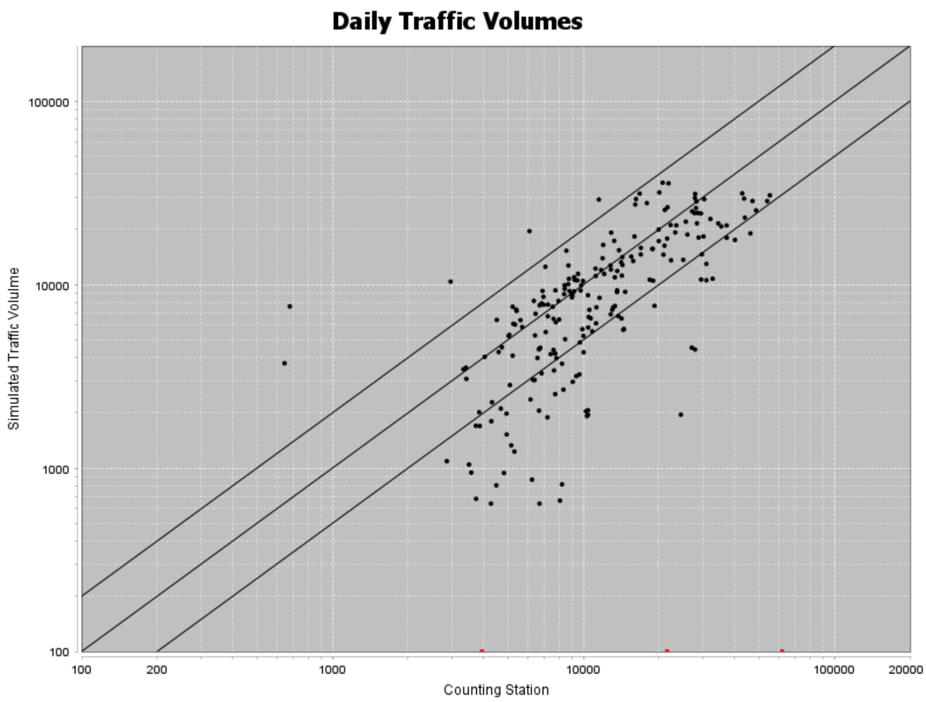


Figure 71 Comparison of the daily traffic volumes at different areas of the study area, between results achieved in the MATSim validated model (y-axis) and observed TADU data (x-axis).

The result shows that most of the zones reach similar daily traffic volumes, with the outliers potentially being caused by one of two effects, either motorways with less simulated cars than those in reality, or main urban roads with more simulated cars than those in reality. The former is explained with the same arguments as described for figure 70 (i.e., freight and trips starting and/or ending in other regions but passing through Tyne and Wear were not considered in the simulation). The latter is considered because agents try to minimise their trip duration, preferring direct routes rather than longer alternative routes. The first could be amended by including those missing trips, while the second by generating a more precise and detailed network, where the flow capacity and other attributes (e.g. speed) of those links are updated until results show a more realistic vehicle mobility in time.

Figure 72 shows the vehicle count comparison between simulated results (blue) and TADU counts (red), distinguishing motorways (a, b) and urban areas (c, d).

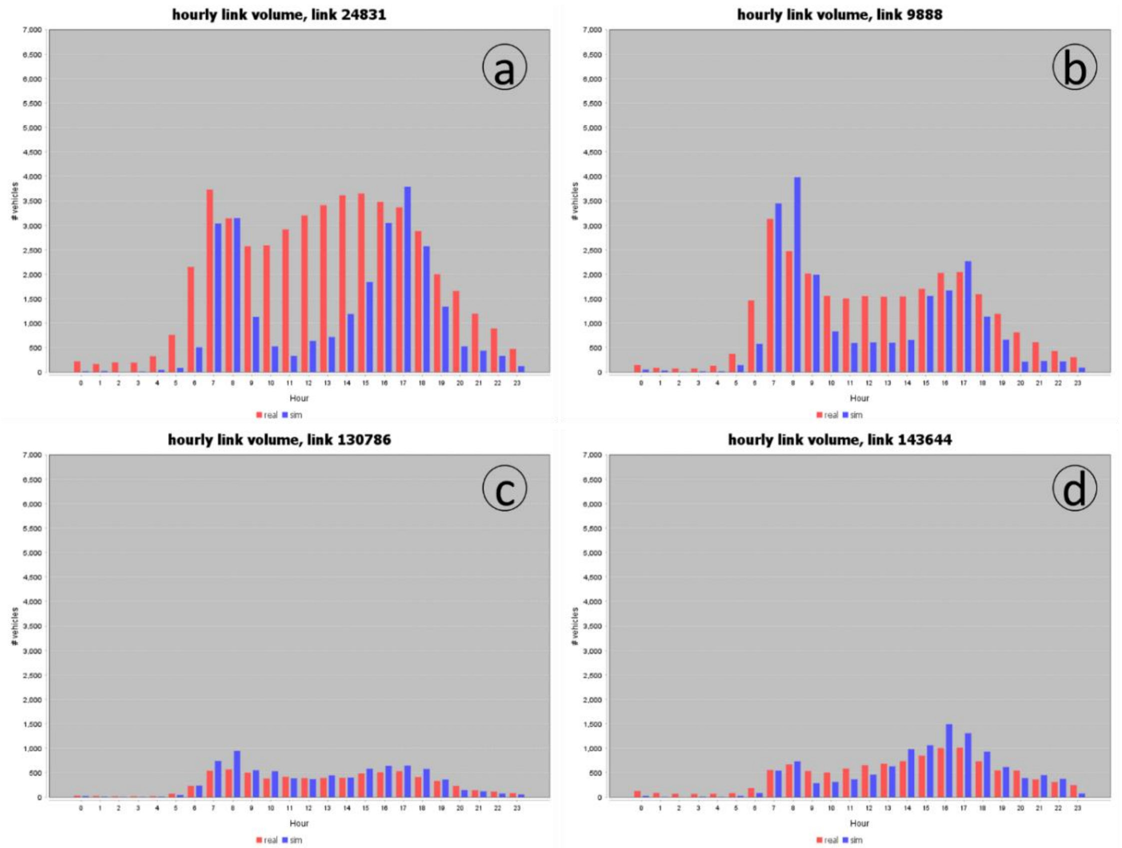


Figure 72 Comparison of the vehicle counts in motorways (a, b) and in urban areas (c, d) between results achieved in the validated MATSim model (blue) and observed values from TADU (red).

Results show remarkably similar outcomes in urban areas (c, d), while some differences were found on motorways (a, b) due to the same reasons highlighted before (i.e., lack of freight and other trips starting/ending outside the study area).

Whilst the lack of data of freight and other trips passing through the study area could be considered a limitation of the model, it is also beneficial as the purpose of the validated model is to test policies to reduce the use of cars in favour of active modes. In this case, the main trips to adapt would come from short trip distances, principally from urban areas, where the global traffic flow in space and time is analogous to the normal mobility in a regular day.

4.3.3. Average trip distance and time by transport mode

The knowledge of the mean distances is also important to know if the achieved results are representative of the mobility in the study area. Figure 73 compares the average simulated trip distance by transport mode (blue bars) with official NTS datasets of the NE of England (NTS, 2023d) (orange).

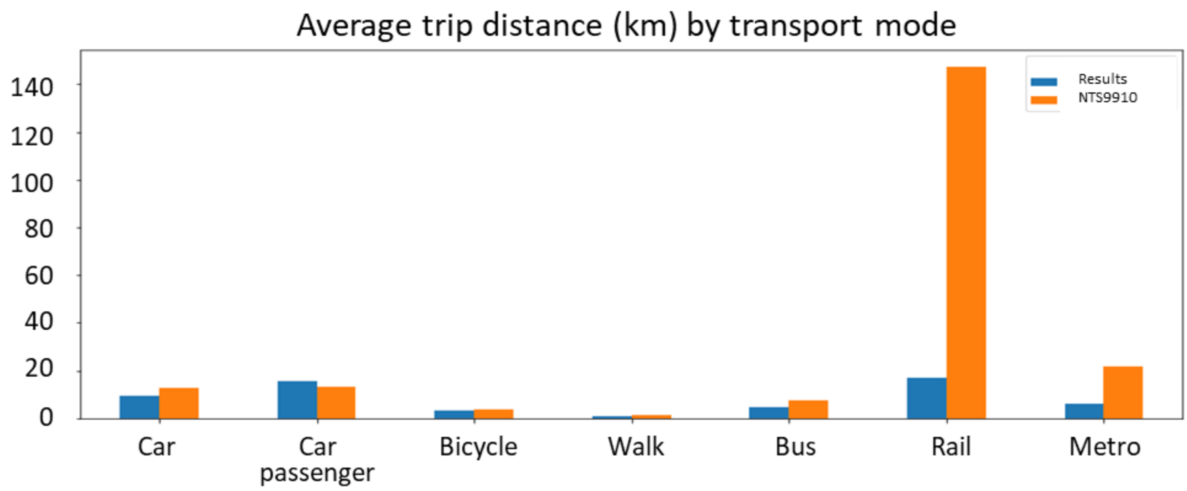


Figure 73 Comparison of the average trip distance by transport mode between results obtained from the validated MATSim model (blue) and observed NTS values (orange).

Differences vary depending on the transport mode used, although a similar pattern can be observed. Average car distances are unbalanced, as drivers use the car for three kilometres less than expected, while passengers use it for two more. Differences found in the average distances by car, both as a driver and passenger can be due to the activity plans assigned to the agents, as they were collected from surveys covering the whole England except London. In contrast, the average distances for active modes are very similar to observed values, with differences below half a kilometre in both cases, making the cycling and walking routes choices realistic, even when walking trips were teleported. In terms of public modes, differences obtained depend on the mode. Simulated average rail distance has great discrepancies with observed values because long rail trips connecting the NE with other UK regions are considered in the latter (e.g., trip from Newcastle to London), but not in the model. In the case of light rail, official statistics are combined with ferries and air trips (NTS, 2023d), making it impossible to compare them, although sensitivity checks based on the network length suggests that the obtained average distance is realistic. In the case of bus distances, the average is three kilometres shorter than expected, which could be related to its high attractiveness for the agents, as buses are the fastest mode not affected by traffic congestion. The implementation of an economic fare (e.g., £2 ticket) could make this mode less attractive and force the agents to find an alternative mode, especially in short distances, which could increase the average trip distance.

Figure 74 compares the average simulated trip duration by transport mode (blue bars) against official NTS datasets for England (NTS, 2023b) (orange).

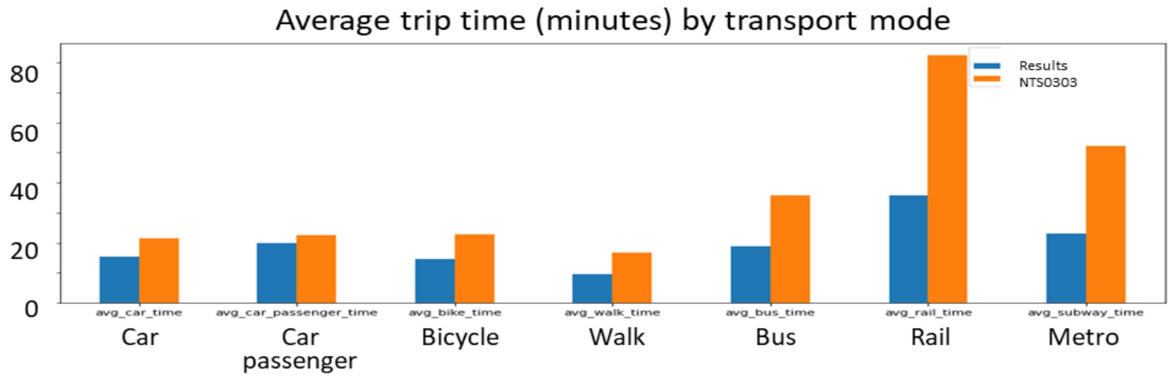


Figure 74 Comparison of the average trip time by transport mode between results obtained from the validated MATSim model (blue) and observed NTS values (orange).

Average trip times are dependant values of the average trip distances and speed by each mode. In this case, results were compared against national statistics, as values of the study area were not found. Similarly, as it was found with the average trip distances by mode, discrepancies were obtained, even for active modes. In all cases, all average trip times were shorter than the expected values at national scale.

Due to the discrepancies found in both the average trip distances and times when compared with official NTS statistics (at regional scale for the distances and national scale for times), an alternative comparison was followed. Instead of comparing aggregated simulated results, individual trips randomly chosen were compared against routes calculated with Google Maps (Google, 2024), where the same origin, destination and departure time were used. The comparisons show convergent results for both routes followed and time spent.

Figure 75 shows some examples, where a trip made by car (left) and another by bicycle (right) are compared. In both cases, Google Maps suggests similar routes as well as similar travel times to those obtained from the model. These verifications, although analysing a small set of random trips, show realistic results that can be found in current mobility, probably being more realistic in the study area than previous statistical datasets used at different geographic scales.

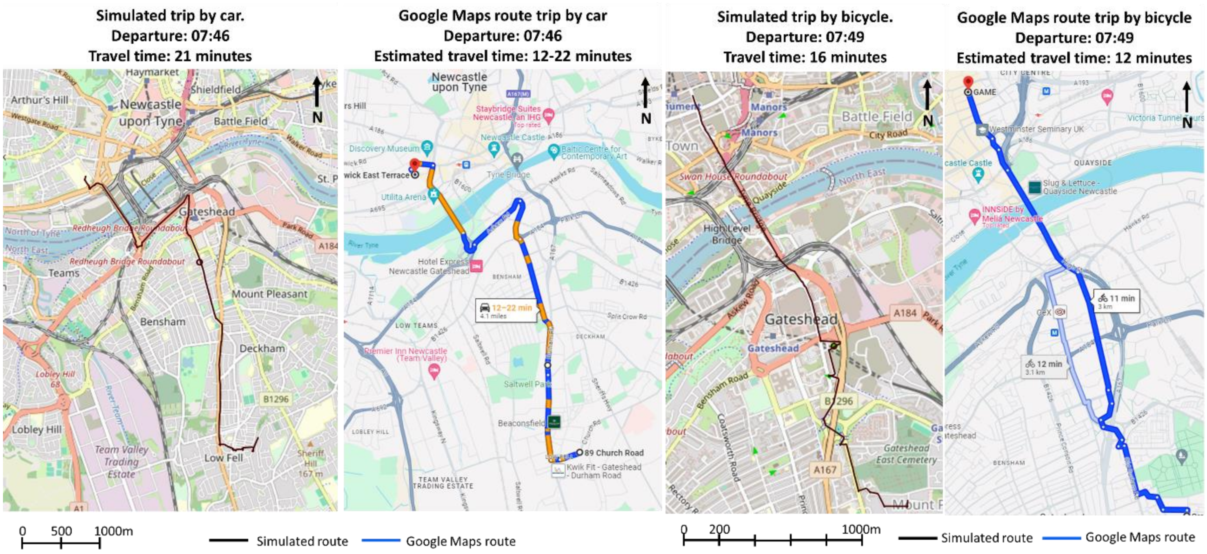


Figure 75 Comparison of chosen routes by car (left) and bike (right) between results obtained from the validated MATSim model (OSM basemap) and Google Maps results.

4.3.4. Percentage of commuting trips per range of distance

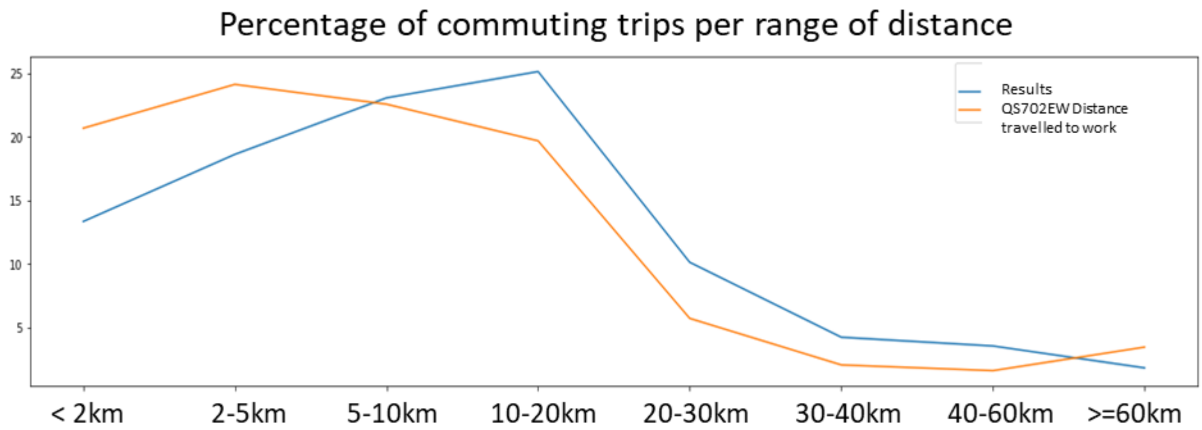


Figure 76 Comparison of the percentage of commuting trips per range of distance, between results obtained from the validated MATSim model (blue) and observed national values (orange).

Figure 76 compares the percentage of commuting trips by range of age. The blue line represents the results obtained from the simulation, while the orange shows the values for the NE region (ONS, 2023b), obtained from the 2011 UK census.

Results show that both have a similar pattern, although discrepancies between them can be observed. Simulated results have fewer short commuting trips than the official data, while for longer distances the results are the opposite, except for the longest trips (60 kilometres and more), where more official trips were found. These differences can be justified by considering that the compared results do not represent the same geospatial extent. While the 2011 UK census data considers all commuting trips of individuals living in the NE of England (i.e., trips within the NE and to other regions), simulated results only take into account those starting, ending or passing through the Tyne and Wear region. Short commuting trips in other areas within the NE of England are not considered (e.g., commuting trip from Darlington to Durham), neither long trips between different regions (e.g., London to Edinburgh). Consequently, a lower percentage of short trips, a higher percentage for longer trips and lower again for the longest were expected.

4.3.5. Bicycle analysis

Analysis of cycling routes was also performed to identify if cyclists were behaving as expected based on the parameters used in the updated MATSim bicycle extension (i.e., gradient and *quietness* attributes). Figure 77 shows the results of a cyclist's route when the updated bicycle contribution is disabled (top) and enabled (bottom). Cycle paths are represented as green lines, while the followed route is in black. Additionally, a route profile generated by Google Maps (Google, 2024) is attached to each route (top right), showing elevation variations in each case.

Differences between both routes are clear, as in the top image travel time is only considered and the shortest route is chosen, while characteristics of the built environment (i.e., *quietness*) and the elevation (i.e., gradient) are considered besides the travel time in the bottom. The latter clearly shows the use of cycle paths (green lines), as a direct consequence of the *quietness* attribute introduced to follow good quality cycle roads, and a smoother route profile in contrast to the former.

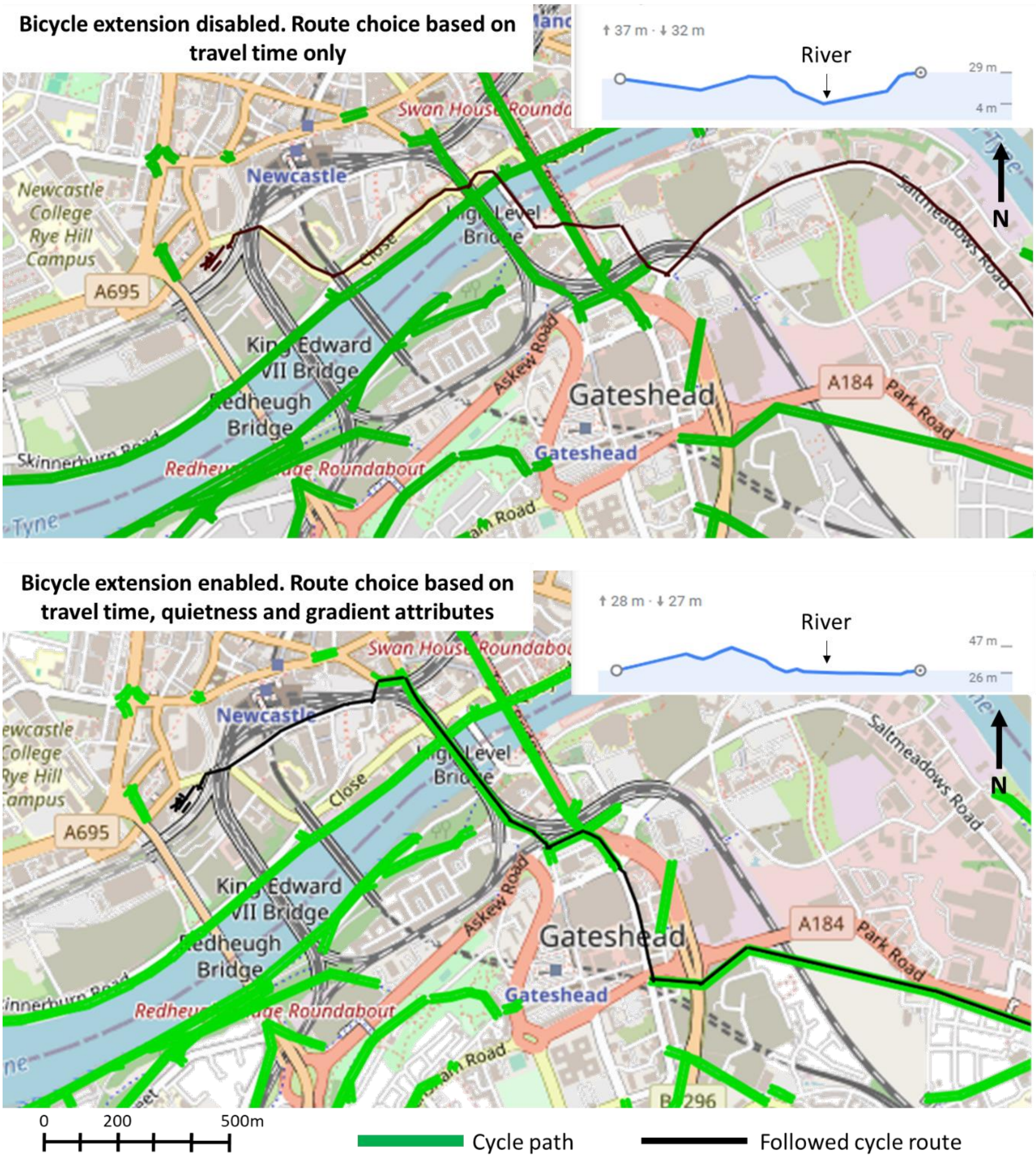


Figure 77 Comparison of the cycle route chosen by a synthetic individual when the updated bicycle contribution is disabled (top) and enabled (bottom) (OSM basemap).

The differences in the followed routes are especially evident in two areas: before and when crossing the river. In the first case, the cyclist chooses the route links based on how good they are for cycling (i.e., based on the *quietness* index), passing through several dedicated cycle paths. In the second case, the agent chooses flat areas in order to cross the river using a high bridge avoiding descending to the river and ascending again on the other side. In aggregated terms, the consideration of the gradient requires ascent and descent of 28 and 27 metres, while when the shortest path is followed, the aggregated slope values are higher (37 and 32, respectively).

Extrapolating this analysis for the whole cycling population, differences flows are also observed when the updated bicycle contribution is enable and disabled. Figures 78-80 show the cycleability rating or *quietness* value of roads (left) and the differences between the number of cyclists using the roads when the updated bicycle extension is enabled and disabled (right). Low values of *quietness* are represented in red and high in green. Similarly, a reduction of cyclists are represented in red and an increase in green, while the lines' width is proportional to the absolute difference in the number of cyclists using each road when the bicycle extension is enabled and disabled.

Figure 78 shows Chillingham Road and surrounding areas (Newcastle upon Tyne). The *quietness* value in this primary road (0.2) is lower than in the vicinity tertiary and residential streets (left figure). Consequently, the number of cyclists using this main road is lower when the bicycle extension is enabled than when disabled (right). This has an impact in the surrounding streets, as more cyclists use alternative routes (e.g., Heaton Rd) where higher *quietness* values are found (0.4), indicating a better cycling experience based on their built environmental characteristics. Similar results are observed in figure 79, where cyclists travelling from west of Newcastle avoid using St. James Boulevards, in favour of roads with higher *quietness* values like Elswick Rd. The former is a primary road with two lanes per direction and maximum speed of 30mph, while the latter is a secondary road with one lane per direction and maximum speed of 20 mph. Lastly, figure 80 shows how agents avoid sharing the road with other vehicles (i.e., A187) when they have the option of using dedicated cycle paths (e.g., Hadrian Wall Path).

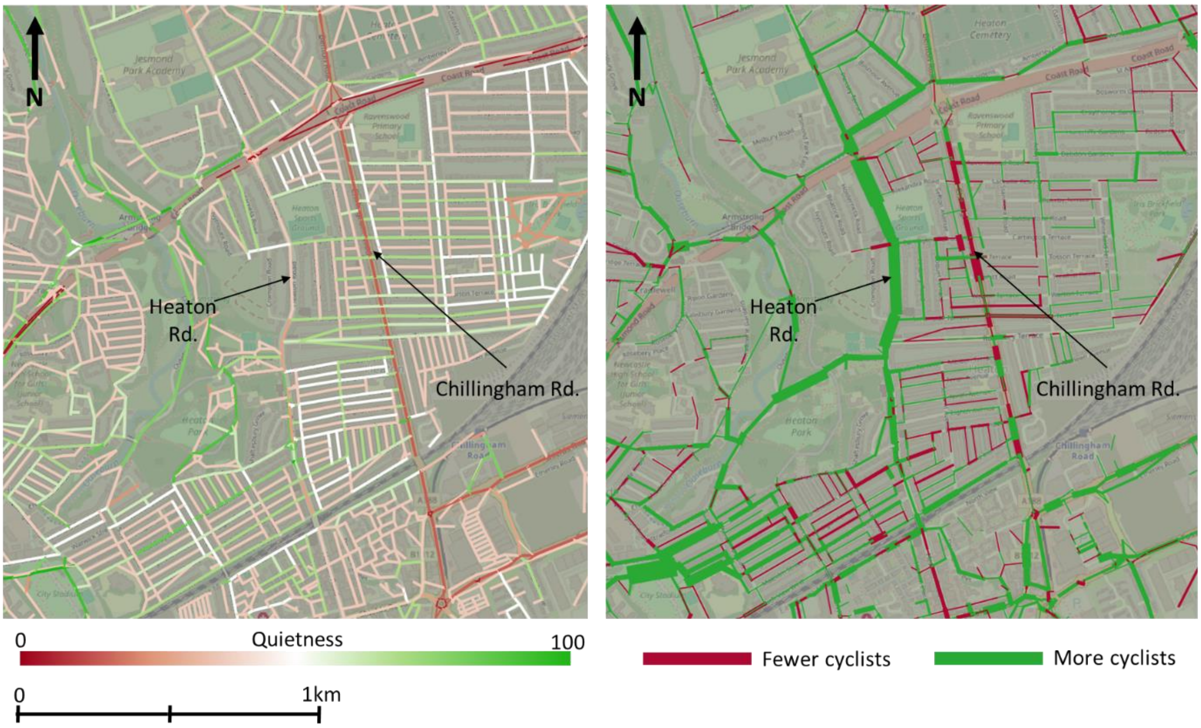


Figure 78 Comparison between the cycleability rating or quietness (left) and the differences between the number of cycling agents when the updated bicycle extension is enabled and disabled (example 1).

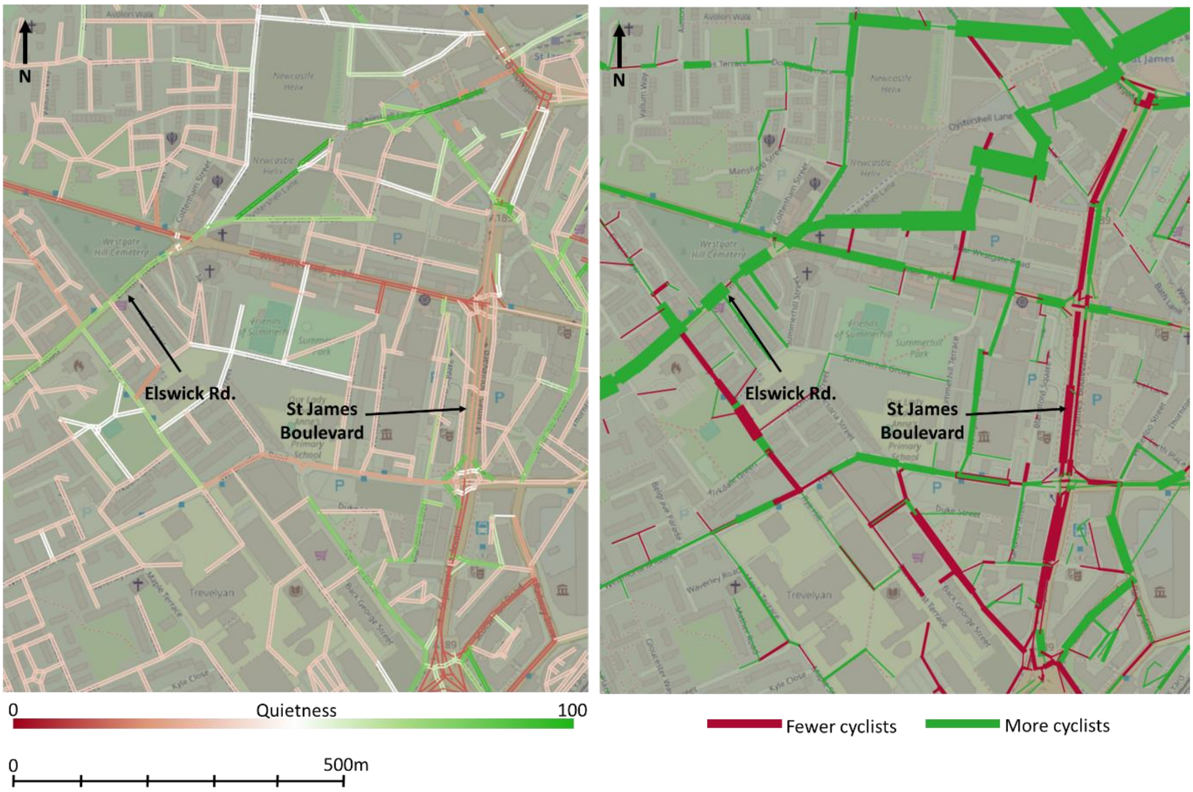


Figure 79 Comparison between the cycleability rating or quietness (left) and the differences between the number of cycling agents when the updated bicycle extension is enabled and disabled (example 2).

Figure 80 Comparison between the cycleability rating or quietness (left) and the differences between the number of cycling agents when the updated bicycle extension is enabled and disabled (example 3).

These examples show the effects on route choice followed by agents to avoid areas with poor cycling quality, based on the built environmental characteristics described in section 3.4.4. The combination of *quietness* and gradient allows simulation of more realistic cycling behaviours as not only the time variable is taken into account but also some fundamental components of the environment that affect cyclists when travelling between two points, such as the characteristics of the roads (i.e., *quietness*) and the ground elevation.

Despite the success in simulating realistic cycling routes, the validation of bicycle counts in different zones of the study area was not accomplished, primarily because of the very low number of cyclists on the roads. As was described before in figure 68, less than 2% of all trips are made by bicycle, which makes it quite difficult to identify the main roads used by cyclists, especially considering that socio-demographic attributes are not taken into account when agents cycle. Currently, this is a limitation that could be solved by introducing sub-populations within the model with different attitudes and behaviours when trying different transport modes based on their characteristics (e.g., age, sex, income, health). Although information about attitudes towards the use of different transport modes based on socio-demographic characteristics in the Tyne and Wear region was obtained (Close *et al.*, 2020), it was not included to avoid an overcomplicated model. Future work could include this information to achieve a more realistic representation of the urban mobility based on socio-demographic attributes.

4.3.6. Active travel trips

Figure 81 shows the percentage of trips below five kilometres made by active modes within the Tyne and Wear region. Simulated results obtained 43.39% of active trips (blue bar), being compared with the national baseline scenario in 2019 calculated by ATE (41%) (orange bar) (ATE, 2023a).

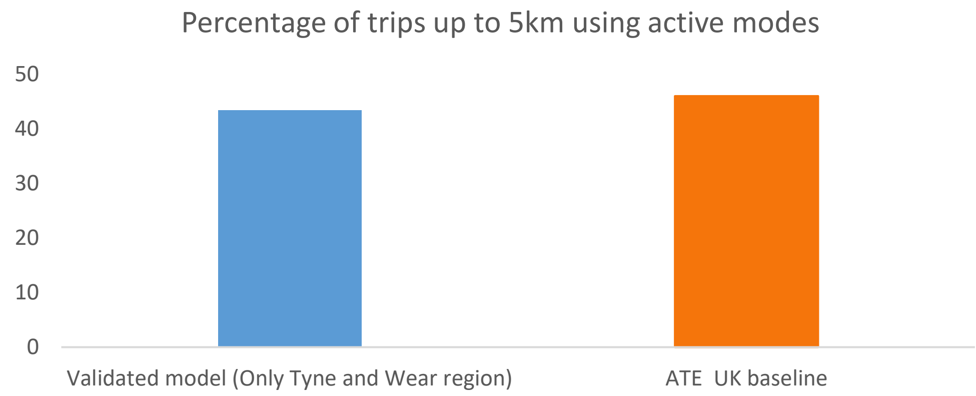


Figure 81 Comparison of the percentage of short trips in urban areas made by active modes, between results achieved in the validated MATSim model (blue) and the ATE baseline (orange).

The difference obtained is below 3%, which makes the developed model an accurate, precise and realistic starting point to test policies to help and support ATE to achieve their goal.

This accuracy achieved can be seen as a common starting point between the established goals in this thesis and ATE's, as both aim to increase the use of active travel modes. Consequently, this validated model could be used to test some of the actions ATE would like to implement to achieve their goal by 2030. Within the actions included in their strategy (DfT, 2000). The following three potential policies to be tested were identified: direct, continuous, physically segregated and safe routes for cycling; the definition of low-traffic neighbourhoods (LTN); and better connectivity between active and public transport modes.

4.4. Scenarios

The defined scenarios in section 3.8.1 were simulated with the validated MATSim model. A definition reminder of each of the scenarios is provided:

- Scenario 1: Fully segregated cycle paths.
- Scenario 2: Low traffic neighbourhoods (LTNs).

- Scenario 3: Active travel reward.
- Scenario 4: Pay when you drive.
- Scenario 5: Cycle hubs next to metro stations.
- Scenario 6.1: Cycle paths – LTN – cycle hubs.
- Scenario 6.2: Cycle paths – LTN – cycle hubs – economic reward.
- Scenario 6.3: Cycle paths – LTN – cycle hubs – economic penalty.
- Scenario 6.4: Full combination.

Results obtained from each scenario were compared against the validated baseline to estimate their efficiency in achieving the shift from private cars to active modes. Aggregated results were compared in the following 11 different groups:

- transport modal share (section 4.4.1).
- Sankey diagrams identifying the changes in transport share modes (section 4.4.2).
- CO_2 emissions (section 4.4.3).
- Geospatial distribution of cars and bicycles (section 4.4.4).
- Walking and cycling statistics (section 4.4.5).
- Active modes trips (section 4.4.6).
- Socio-demographic analysis (section 4.4.7).
- Health benefits (section 4.4.8).
- Built environmental road analysis (section 4.4.9).
- Economic analysis (section 4.4.10).
- Cycle hubs use (section 4.4.11).

4.4.1. Transport modal share

The simulated policies had impact in the use of the different transport modes. Figure 82 compares the percentage of trips made by the different available modes per scenario and the baseline, grouped by transport mode. Figure 83 complements the previous figure showing the differences obtained per scenario when compared directly with the baseline scenario (in percentage-points), while figure 84 shows the ratio of transport modal splits when compared with the baseline (in percentages).

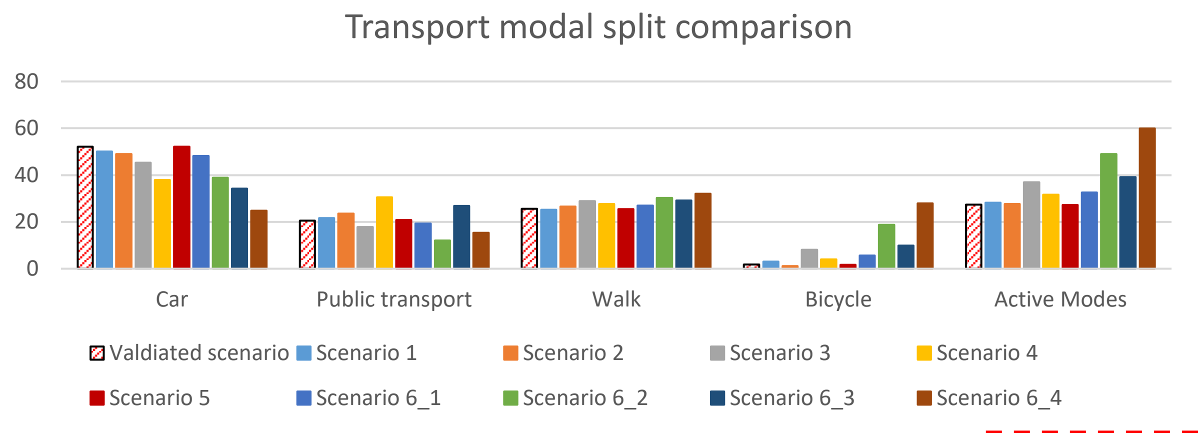


Figure 82 Comparison of the transport modal split between the baseline results and each scenario simulated, by transport mode.

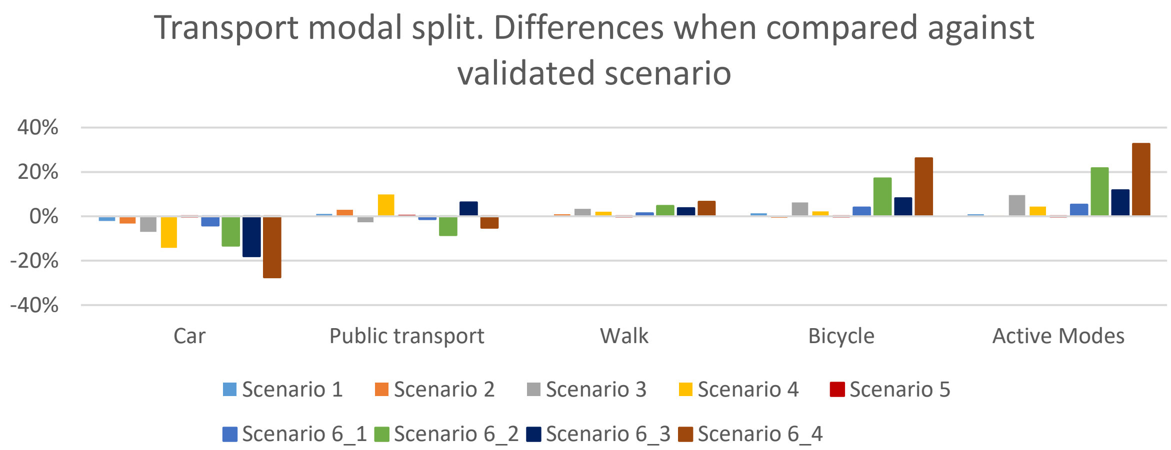


Figure 83 Differences of transport modal split when results achieved in each scenario are subtracted from the baseline scenario.

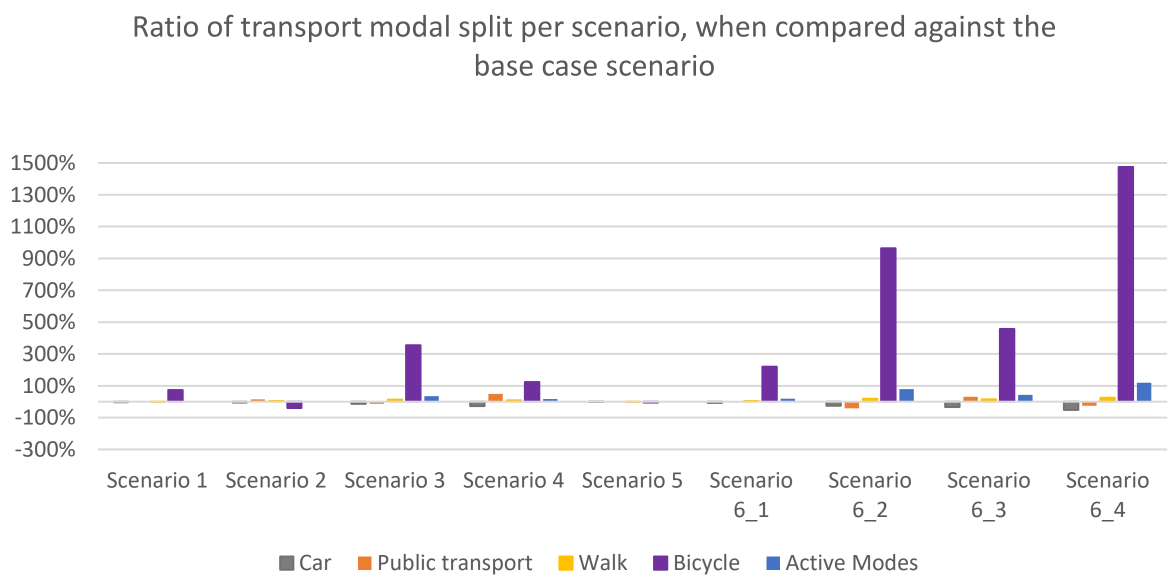


Figure 84 Comparison of the transport modal split ratio of each scenario simulated when compared with the baseline scenario.

Based on the obtained results, scenario 1 has a limited impact in a global human behavioural change, as only a 2.0%-point change reduction in car use is achieved, increasing cycling (1.3%-point) and public transport modes (1.1%-points), with a small reduction of walking trips (0.3%-points) (figures 82, 83). Nevertheless, when results are analysed relatively per transport mode (figure 84), substantial changes can be observed, especially in cycling and public transit modes, where 73% and 5% increases were obtained, respectively, while the use of cars was the most impacted mode, with a 4% reduction. These results show the potential to achieve a shift in transport mobility when improvements for cycling are combined with spatial penalties to private motor vehicles, as the number of cyclists on the roads was almost duplicated.

The results obtained from scenario 2 achieved a greater car use reduction (3.2%-points) than in the previous scenarios (figures 82, 83), although opposite results were obtained for cycling, where a negative 0.7%-point change was obtained. The first outcome was expected, as car users have fewer available roads to be used in urban areas with the potential for increasing congestion, while the second was a consequence of the set up defined in the calibration stage. The reason for the decrease in cycling, even after updating the cycling quality attribute (e.g., *quietness*) in residential roads, was the fact that cyclists continued using the same main roads as cars (i.e., direct routes) and the consequence of car congestion on those roads. As it was explained in section 3.7.1, the method used to overtake vehicles was 'PassingQ', which allows only fast vehicles to overtake slower ones. In this scenario, car users created more congestion zones than in the baseline scenario, impeding cyclists (slower vehicles) to filter through the traffic (as happens in reality), making the use of bicycles slower and, therefore, less attractive. The main winners in this scenario were the public modes (14% increase) (figures 82, 83 and 84) as they were simulated as deterministic modes (e.g., not affected by any congestion). These modes were the best alternative to the use of cars, being faster than any other alternative and consequently, the most attractive modes for the agents.

Scenario 3 achieves an important shift to active modes (10%-points), mainly due to cycling (7%-points), while the use of cars and public modes are decreased by 7%-points and 3%-points, respectively (figures 82 and 83). In relative terms, cycling is increased more than 3.5 times when compared against the baseline scenario, with the use of cars and public transport the most affected modes (13% reduction in both cases), while walking is increased by the same percentage (13%) (figure 84). Even though both active modes were economically rewarded by the same amount, cycling seems to be preferred mainly as it is faster than walking.

Results obtained in scenario 4 show the greatest car use reduction for now, obtaining 14%-point decrease, being mainly absorbed by the public modes (10%-point increase) and lowered by active modes (2%-point increase for each) (figures 82 and 83). In relative terms (figure 84), the use of public modes is increased by almost 50%, while the use of bicycles is duplicated and walking increased 8%, with the use of the car being the most affected mode (27% reduction). The main reason for the massive move to public modes is similar to the argument given in scenario 2, since public modes were simulated as deterministic, with no maximum capacity or cost. Besides this impressive increase of public modes, the duplicated number of cyclists shows the potential of the bicycle in urban areas, even when policies penalising the use of cars economically are implemented, showing the importance of considering both carrots and sticks.

The results obtained in scenario 5 were very similar to those obtained in the baseline scenario. This outcome was expected, as minimum changes were implemented in this scenario. Figures 82 and 83 show insignificant differences in terms of transport share modes (i.e., differences below 0.5%-points) being the consequence of the stochasticity of the model.

The combination of policies in scenario 6.1 (Cycle paths – LTN – cycle hubs) allowed the increase in the use of active modes by 5.3%-points (3.9% and 1.4%-points for the bicycle and walking, respectively), which is almost five-times the use of active modes than when results from individual policies (scenarios 1, 2 and 5) are grouped (1.1%) (figures 82 and 83). These values suggest the potential impact in the use of active modes when more than one policy is combined, as a higher percentage of active mode users are obtained. However, in terms of car use reduction, the sum of individual policies reaches a higher percentage-point change (5.4%-points) than when combined in a single policy (4.1%-points), suggesting that some of the agents using cars could have been affected by more than one of the combined policies (figures 82 and 83). Additionally, public modes were affected negatively by this combination, as the percentage of public modes users was reduced in 1.2%-points when compared with the baseline, while the sum of the individual policies achieved a 4.3%-points increase (figures 82 and 83). These results suggest that the provision of combined advantages for cycling could be more attractive than the public modes. In relative terms (figure 84), cycling was the most benefited mode, duplicating the number of trips, while walking was only increased by 5%. Opposite results were obtained by car and public transport users, as 8% and 6% reductions were obtained, respectively.

Results from scenario 6.2 (Cycle paths – LTN – cycle hubs - economic reward) show very significant increase in the active modes and reductions in the use of cars and public modes (figures 82 and 83). Active travel reached 22%-point increase when compared with the baseline, achieved thanks to 17%-point increase in cycling, multiplying by 10 the number of trips made (figure 84), reaching 49% of total trips made by those modes, almost the ATE goal. In contrast, the use of cars and public modes were reduced 13%-points and 8%-points, respectively (figures 82 and 83), which are 35% and 41% lower than in the baseline scenario (figure 84). When the percentage of cyclists is compared with the combination of the individual scenarios (1, 2, 3 and 5), a significant difference can be observed between them. This scenario reached 17% increase, while the combination of the other four scenarios achieved 6.8%. When analysing the increase of walking, 0.8% higher value was obtained in this scenario than in the combination of the individuals. These values show that the combination of policies in favour of active modes in a single scenario achieves non-linear results and increase its scope in shifting agents towards these modes. When the previous analysis is applied to public modes, it can be observed that these modes were the most affected, as an 8%-point reduction instead of a 1%-point increase was achieved (figures 82 and 83). Similar to the explanation given in the previous scenario, the combination of spatial incentives, now boosted by economic rewards, increased the attractiveness of using active modes.

Results from scenario 6.3 (Cycle paths – LTN – cycle hubs – economic penalty) show a drastic reduction in the use of cars (18%-points change), absorbed by cycling (8%-points), public transport (6%-points) and walking (4%-points) (figures 82 and 83). Cycling has been multiplied by almost five times (figure 84), being the mode with the greatest growth. Public modes were the second winners, increased by 30%, while walking only in by 14% (figure 84). When grouping the results from scenarios 1, 2, 4 and 5 together, the total change in car use almost reaches 20%, which is almost 2% higher than results achieved in this scenario. This indicates that some of the agents could have been affected by more than one policy, similar to the outcome from the previous scenario. Active modes doubled the percentage of trips (12%-

points increase) than when results from individual policies are added together (5.4%-points increase), cycling being the most benefited (8%-points change), as a 5%-points increase more was reached than when individual policies were summed. These results are in line with those obtained in the previous scenarios 6.1 and 6.2 in terms of active modes, showing a similar trend when policies are applied together. Public modes, as in the previous combined scenarios, were the most affected modes when compared against individual policies, as a 6.2%-point increase was obtained instead of a 14.23%-point when results from individual scenarios were added together.

Lastly, results from scenario 6.4 (full combination) show the best achievements in reducing the use of cars and increasing the use of active modes. The use of cars was reduced in 28%-points, while active modes were increased in 33%-points, split in 26% for cycling and the remaining 7% for walking (figures 82 and 83). When analysing the data in relative terms, one in two car users decided to use an alternative mode, cycling was multiplied by 15 times, walking only by 25% and public modes reduced the number of users by 25% (figure 84). This combination of spatial and economic cycling benefits (scenarios 1, 2, 3 and 5) with car usage penalties in spatial and economic terms (scenarios 1, 2 and 4) achieves a similar percentage reduction in car use than when results from individual scenarios are grouped (28%-point reduction in scenario 6.4 and 26%-points when individual scenarios are aggregated). Similar results are achieved for walking (7% and 6%, respectively), although the main winner in this combination is cycling, as it reaches 17%-points more than when results from individual scenarios are aggregated (26% against 9%). Derived from previous values, public transport modes are the most affected when all policies are combined, as a 16%-point decrease is reached (5%-point change reduction in scenario 6.4, while there is an 11%-point change increase when results from individual scenarios are grouped). These results show that the simulated policies are effective in their aims, but producing side effects in the public modes, in the same way as scenarios 6.1 and 6.2.

4.4.2. Sankey diagrams

Sankey diagrams show the transition of transport mode users from the baseline scenario to the urban mobility policy simulated. All scenarios (figures 85 to 92) were compared except scenario 5, as minimum differences were found. Values on the left represent the percentage of trips made by different transport modes in the baseline, while values on the right show the results achieved in each scenario simulated. Four different transport modes are considered: car (blue), public transport modes (orange), bicycle (green) and walking (red).

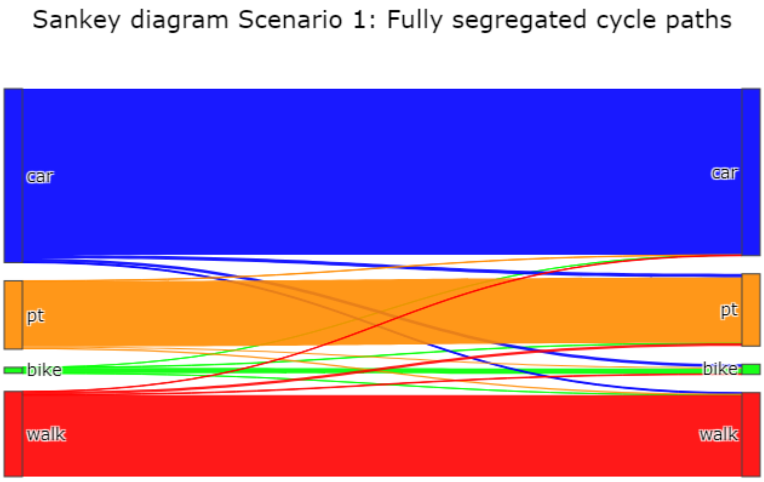


Figure 85 Sankey diagram for scenario 1 (fully segregated cycle paths).

Car users in scenario 1 are the most affected with the implementation of fully segregated cycle paths due to the road space reductions to allocate the cycle paths. Consequently, a proportion of them need to find an alternative transport mode to reach their destinations on time. Figure 85 shows that almost half of the car users who chose another mode used public transport (47%-points), while 39%-points preferred the use of the bicycle and the remaining 14%-points decided to walk. In terms of cycling, most of the new cyclists are coming from cars (63%-points), followed by public transit modes (25%-points) and walkers (12%-points). New cycling users are mainly attracted from car users, which is in line with the applied policy, as the first benefit from safe, direct and comfortable routes, while the second are spatially penalised.

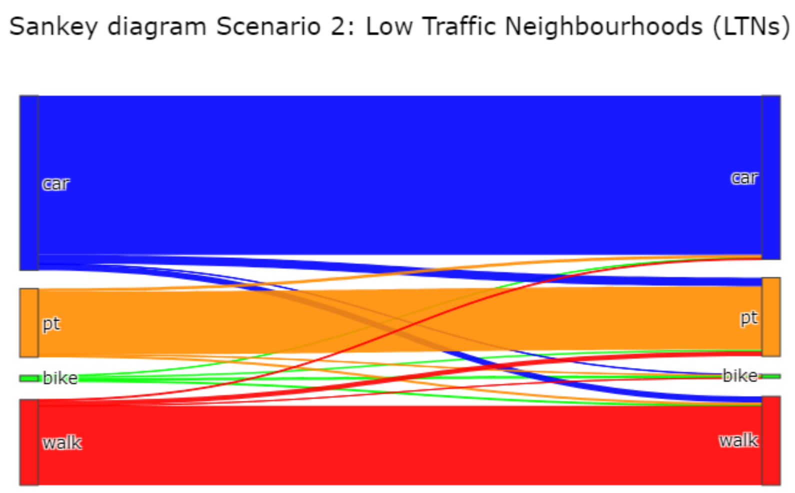


Figure 86 Sankey diagram for scenario 2 (Low Traffic Neighbourhoods).

The Sankey diagram in figure 86 shows the transfer of transport mode users between the baseline and scenario 2 (i.e., LTNs). Almost six in ten car users that decided to use an alternative mode chose public modes (57%-points), followed by walking (40%-points), and an insignificant 2%-points preferred cycling. In terms of cycling, most of former users preferred to use public transports as the best alternatives (56%-points in both), followed by walking (29%-points) and car (15%-points). Overall, the use of public modes attracted the majority of the new users, being almost double the number than walking (the second most attractive).

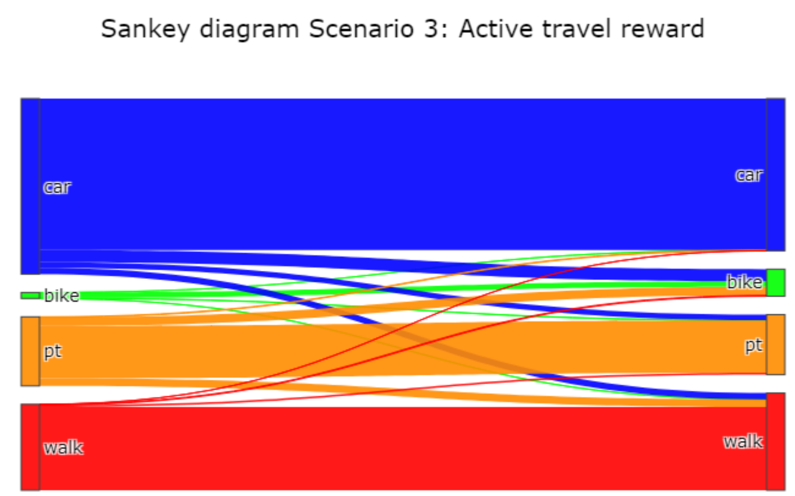


Figure 87 Sankey diagram for scenario 3 (economic active travel reward).

Results obtained in the Sankey diagram from scenario 3 (i.e., active travel economic reward) (figure 87) show that one in two car users that decided to use an alternative mode decided to cycle (51%), followed by walking (26%) and public modes (23%). When results are analysed from the cycling perspective, the new cyclists are principally coming from former car users (56%), public modes (40%) and walking (4%). In the case of new walkers, the agents used to use public transport (54%), followed by the car (45%) and the bicycle (1%). This policy shows the impact of the economic rewards in increasing the attractiveness of active modes in detriment of public transit, as more agents decided to use any type of active modes in greater proportions, although cycling was preferred to walking (1.5 more agents decided to use the first).

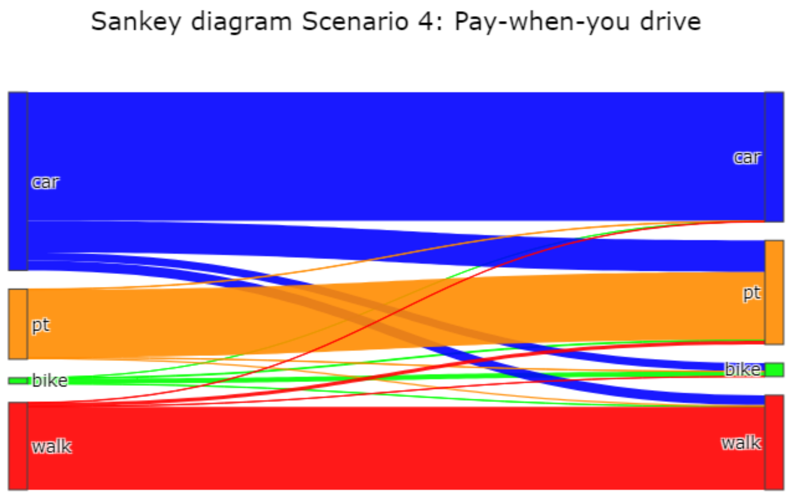


Figure 88 Sankey diagram for scenario 4 (Pay when-you-drive).

The Sankey diagram from scenario 4 (i.e., economic penalty when using cars) (figure 88) confirms that public modes were the most benefited, the number of new users being more than three and four times than those achieved by walking and cycling, respectively. 64% of the car users who decided to use an alternative mode chose public modes, another 20% chose to walk and the remaining 14% to cycle. The new cyclists come mostly from previous car users (95%), the remaining 5% being split between public transport users (3%) and walkers (2%). The new walkers were mainly car users (85%), followed by public transport users (13%) and cyclists (2%). These outcomes show that this policy could be very convenient to reduce the number of private motor vehicles in favour of more sustainable transport modes.

Sankey diagram Scenario 6.1

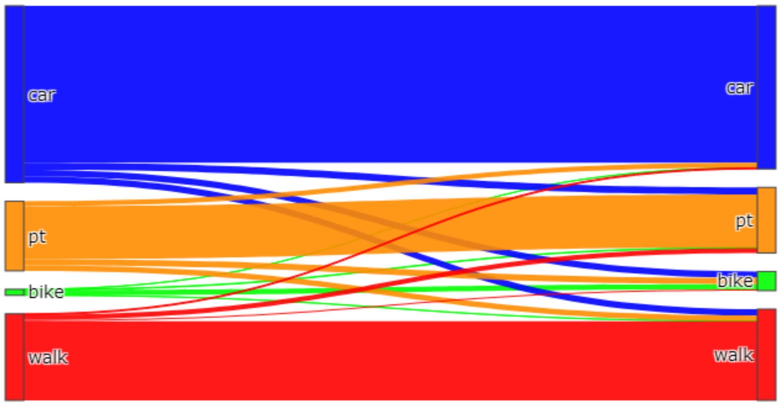


Figure 89 Sankey diagram for scenario 6.1 (cycle paths + LTN + cycle hubs).

When the transition of transport users between the baseline and scenario 6.1 (i.e., Cycle paths – LTN – cycle hubs) (figure 89) are analysed, a great diversity of movements between the modes can be observed, which are a consequence of the simulated policies, the individual behaviours of the agents and their interactions in space and time. Car users that decided to use an alternative mode (8% of the total in the baseline) decided to use the other alternative modes in a very proportional way (36, 32 and 32% for public modes, walking and cycling, respectively). Similar results can be observed from former public modes users (6% of the total), where 38% of them decided to use bicycles, 30% cars and 32% to walk. Conversely, there are modes that increased the number of final users, such as the bicycle and walking. The new bicycle users are mainly obtained from previous car and public mode users (45% in both cases). Most of the new walkers used to use cars (54%), followed by public modes (45%). Considering only those trips made with a different transport mode than in the baseline, the bicycle was the mode that attracted the highest percentage of users (32%), followed by public modes (28%), walking (27%) and car (13%). The mode that lost the highest percentage of users was the car (45%), followed by public modes (37%), walking (16%) and the bicycle (2%). These values show positive balances for cycling (30%) and walking (11%), while negative for public modes (9%) and cars (32%). Overall, these figures show different flows of transport mode movements, but two main winners and losers can be identified directly. The results achieved agree with the simulated policies, as they mainly benefit bicycles and penalise car users, with small increases for walking and reductions for public modes.

Sankey diagram Scenario 6.2

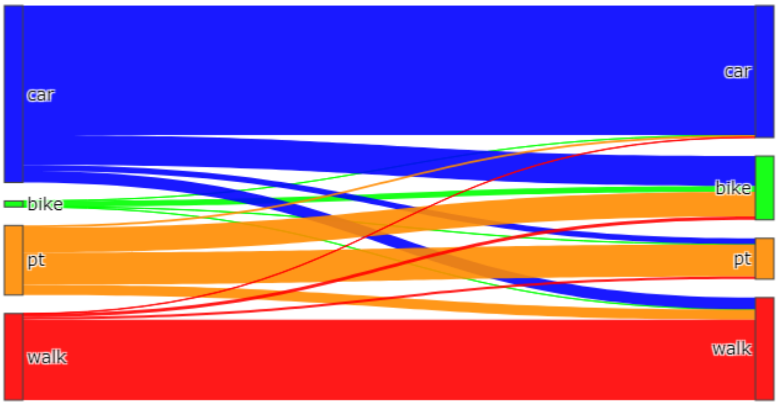


Figure 90 Sankey diagram for scenario 6.2 (cycle paths + LTN + cycle hubs + active travel economic reward).

The Sankey diagram in figure 90 shows the transition of agents from the baseline scenario to the results achieved in scenario 6.2 (i.e., Cycle paths – LTN – cycle hubs – economic reward). Results show a variety of transitions between modes, although two groups can be observed: bicycle and walking as winners and car and public modes as losers. Bicycles were by far the mode that attracted the most of the new users (64%), followed by walking (24%), public modes (9%) and car (3%). The inverse is true when considering the percentage of total users that decided to use an alternative mode. 52% of those agents that decided to change transport mode were using cars, 40% public modes, 7% walk and around 1% the bicycle. Combining previous values, bicycle and walking achieve positives balances (63% and 17%, respectively), while car and public modes got negative balances (49% and 31%, respectively).

Overall, the use of the bicycle is increased by all the other modes, especially from former car and public mode users, which is a similar pattern, although in a lower proportion, to the one observed for walking. When compared with results from scenario 6.1, a stronger transition to active modes is observed, which shows the potential strength of economic rewards to make behavioural changes.

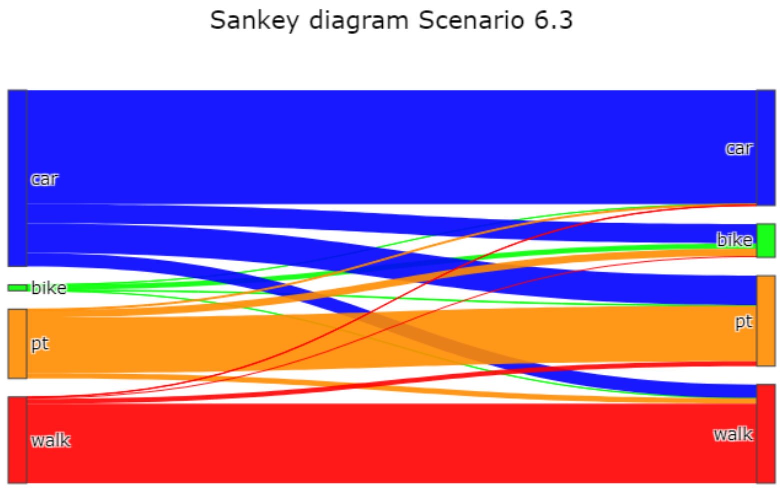


Figure 91 Sankey diagram for scenario 6.3 (cycle paths + LTN + cycle hubs + pay-when-you drive).

The transition of agents between transport modes in scenario 6.3 (i.e., Cycle paths – LTN – cycle hubs – economic penalty) (figure 91) shows main flows from the use of cars to the other three modes. In general, public transit attracted four in 10 agents that decided to use an alternative mode (41%), the bicycle attracted three in ten (34%), walking two in 10 (23%) and the car only one in 50 (2%). In terms of the total percentage of users lost, the car mode was the most affected with almost three in four, followed in the distance by public mode users (17%), walkers (8%) and cyclists (1%). Combining previous values, the main winner is the use of the bicycle, with a positive balance of 32%, followed by public modes (25%) and walking (15%). This outcome is different to the one obtained in scenario 4 (pay-when-you drive), where public modes were the main winners. This shows that when economic penalties for car users are combined with benefits for active modes (especially cycling), more agents prefer to walk or cycle than use public modes.

Overall, the use of the bicycle is the most increased mode, principally due to a minimum loss of users and a gain from former car and public mode users. Public modes are the second most benefited, although losing an important proportion of their users (mainly moving to active modes). Walking is principally benefited from former car users, with minimum loss of users (mainly to public modes). Lastly, the use of the car is the most affected, as 18% of users decided to use an alternative mode, attracting minimum new users from the other modes (probably due to the stochasticity of the model).

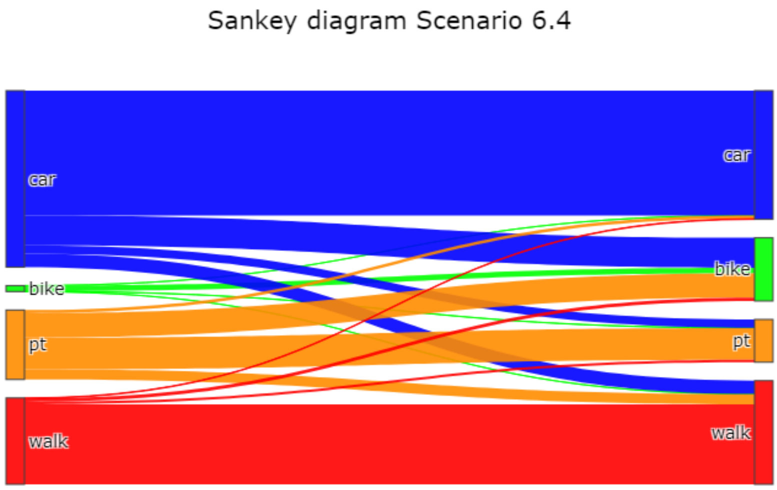


Figure 92 Sankey diagram for scenario 6.4 (fully combination).

The Sankey diagram in figure 92 shows the transition of agents between the results from the baseline and scenario 6.4 (full combination). As in previous cases, it is possible to identify winners and losers. Cycling and walking are found in the first group, with the use of cars and public modes in the second. Globally, the use of the bicycle attracted two in three of the agents that chose an alternative mode (65%), followed by walking ((21%) and public modes (14%). The mode that lost the greatest number of users was the car, with almost seven in ten of the total agents that decided to use an alternative option, with public modes in second position (26%). The combination of the gained and lost users shows the use of the bicycle as the solid winner, with a positive balance of 65%. The other mode that reached a positive balance was walking (16%), while the modes with negative balances were cars and public modes (68% and 13%, respectively). These results are very similar to those obtained in scenario 6.2, where all individual policies in favour of active modes were combined, although achieving less attractiveness to cars as a consequence of the daily toll included in this scenario.

Analysing the results by mode, former car users that decided to use an alternative mode chose the bicycle two in three of the times (65%), while the small amount of new car users came mainly from public modes (82%). Seven out of ten former public transport users that decided to use an alternative mode chose the bicycle (69%), followed by walking (29%), while new users came principally from former car users (85%). Former walkers that decided to use an alternative option chose the use of the bicycle or public modes in similar proportions (55%

and 43%, respectively). New walkers were mainly car users (62%). Cycling was the mode that attracted the greatest number of new users, principally from cars (68%), and public modes (28%). The effect of providing fully segregated, safe and direct cycle paths with an economic reward seems to be a great boost to increase the number of cyclists (as in scenario 6.2), even when combined with economic penalties for car users.

4.4.3. CO_2 emissions

Another factor to analyse is the estimated CO_2 emissions reduction per scenario. DfT provide information about the average CO_2 emissions of newly registered cars in Great Britain (DfT, 2024). The latest value provided in 2015 shows that, on average, each vehicle emits 121.3 grams per kilometre. The European Environment Agency (2024) provide a very similar value for the same year (119.5), although their data reaches up to 2022. In their analysis, an emission decrease is observed from 2000 until 2017, where emissions went from 172.1 to 121.3 grams per kilometre (similar values for DfT). However, a small increase is observed in 2018 and 2019, reaching 122.3 gr/km in 2019, although reduced in 2022 (108.1). These values can be used to quantify the tonnes of CO_2 emitted by cars daily.

In this analysis, the emissions per scenario are calculated based on the total number of kilometres driven and the following assumptions:

- All vehicles are considered new and emit the average value of CO_2 emissions per kilometre provided by the European Environment Agency for the year 2019 (i.e., 122.3 gr/km)
- All vehicles emit the same amount of CO_2 independently of the vehicle type (e.g., car, van, truck)
- All vehicles emit the same amount of CO_2 in time: no variances depending on the vehicle speed are considered.

Figures 93 and 94 show the results obtained for each scenario, in absolute and percentage values respectively. Baseline scenario emits 416 tonnes daily, which is the equivalent to the amount of CO_2 absorbed by 4,326,577 trees in a day (25 tonnes a year absorbed per tree (Ecotree, 2024; Encon, 2024)).

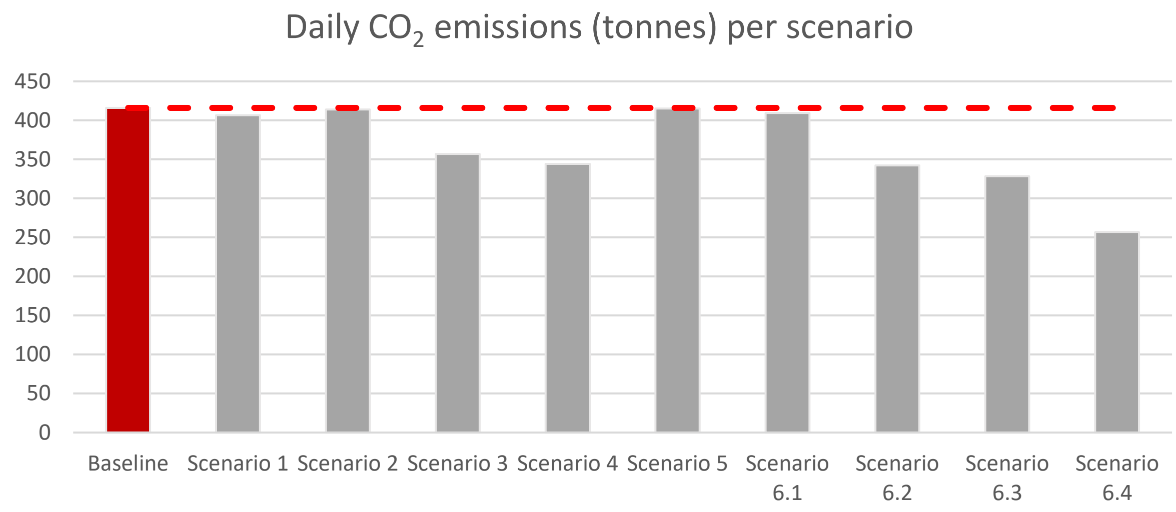


Figure 93 Daily tonnes of CO_2 emissions per scenario simulated

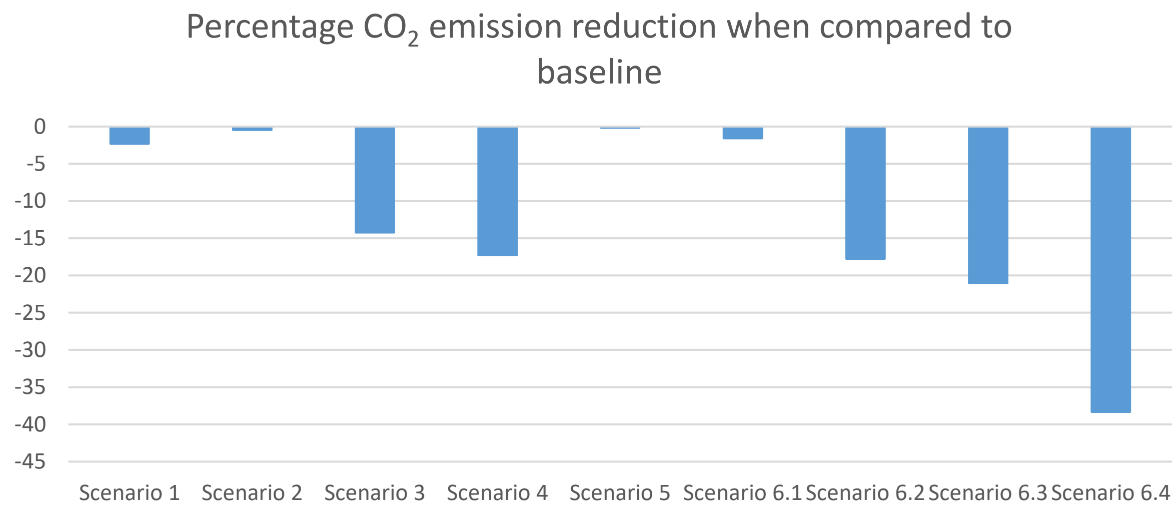


Figure 94 Percentage of CO_2 emissions reductions per scenario

Relative to the individual scenarios simulated (scenarios 1-5), a reduction is observed in all cases, the lowest being achieved in scenarios 2 and 5, with 0.5 and 0.2 tonnes respectively as a consequence of the implementation of LTN's and the possibility of using the bicycle and metro during the same trip, respectively. In the case of the inclusion of cycle paths (scenario 1), there is a reduction of 9.5 tonnes (2.3%), while the highest reductions are achieved in scenarios 3 and 4, where the economic rewards to active modes and penalties to car users reach a reduction of 60 and 70 tonnes (14.2 and 17.3%) respectively.

Similar trends are observed in combined scenarios (scenarios 6.1-6.4), where those with economic policies (rewards and/or penalties) achieve the highest reductions, the penalties to car users being more effective (21.0% reduction) than rewards to active mode users (17.8%).

In the case of scenario 6.4, a combined result between those obtained in scenarios 6.2 and 6.3 is achieved, with a 38.3% reduction, which is equivalent to 159.4 tonnes less CO_2 emitted.

When comparing results between individual and combined scenarios, a higher reduction can also be observed when policies are combined than when results from the individual policies are added together. Scenario 6.2 achieves a further 2.5 tonne reduction than the sum of the individual policies, while scenario 6.3 reaches a 3.4 tonne further reduction. These figures show the extra value that combined policies can achieve rather than the implementation of individual policies, as highlighted in previous sections.

4.4.4. Geospatial distribution of cars and bicycles

It is also interesting to analyse the effects of the urban mobility policies geospatially. Vehicles en-route were counted on each road and compared against the baseline scenario to estimate the areas where the number of vehicles could be reduced or increased. Two different analyses were performed: firstly, number of cars per road segment (figures 95-102); secondly, the number of bicycles (figures 103-110).

Cars

For each scenario, a map showing the number of cars counted per road (left side of the figure) was generated. The brighter the blue, the greater the number of cars counted, as is also shown based on the width of the road. Additionally, the right-hand side map shows the differences when the number of cars per road are compared against the baseline scenario. Green lines represent a reduction in the number of cars, while red represents an increase, the width of the line being proportional to the reduction or increase of cars passing through them. Scenario 5 was not analysed due to the fact the results were almost the same as the baseline scenario.

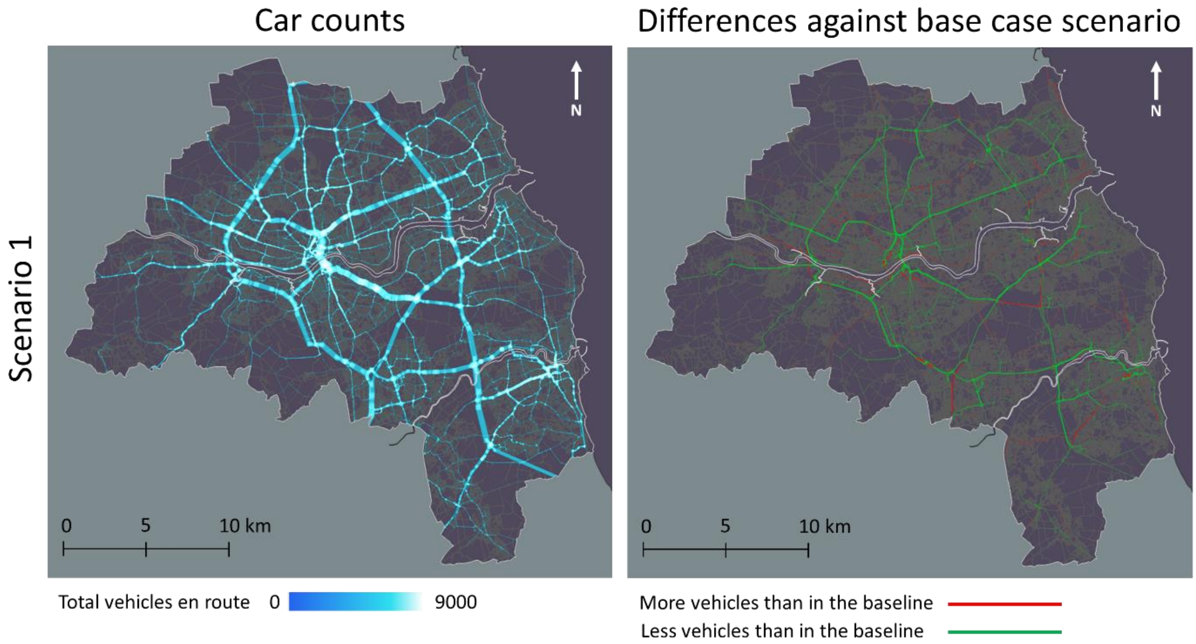


Figure 95 Car counts in scenario 1 (left) and differences when compared with the baseline (right).

The geospatial analysis of cars in scenario 1 (figure 95) shows that motorways and main roads were the most affected ones. In addition, some roads, principally some secondary roads in the city centres of the five LAs increased the number of cars, as well as some connections between motorways. Further investigations are required to have a clear understanding of these outcomes, as simple causes cannot be attributed.

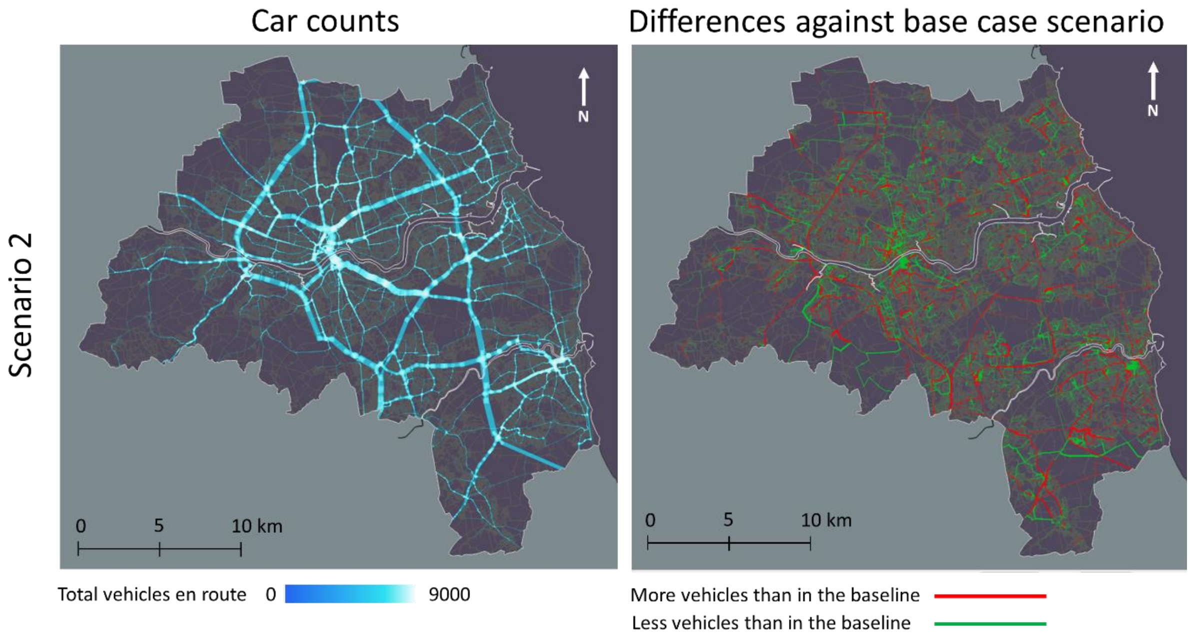


Figure 96 Car counts in scenario 2 (left) and differences when compared with the baseline (right).

The geospatial analysis in scenario 2 shows similar patterns as in scenario 1 (figure 96 left). However, when compared against the baseline (right), it can be observed that the highways and motorways see an increase in the number of cars (e.g., A1, A194, A119). This is also the case on main urban roads (e.g., Westgate, Salters and Osborne Road in Newcastle; Gateshead highway and Durham Road in Gateshead), while a reduction in residential roads in city centres is also observed. The results obtained suggest that car users preferred to use fast and wide roads (e.g., motorways and highways) instead of using very centric urban roads (e.g., the Tyne Bridge between Newcastle and Gateshead) to reduce as much as possible the potential congested areas surrounding residential areas.

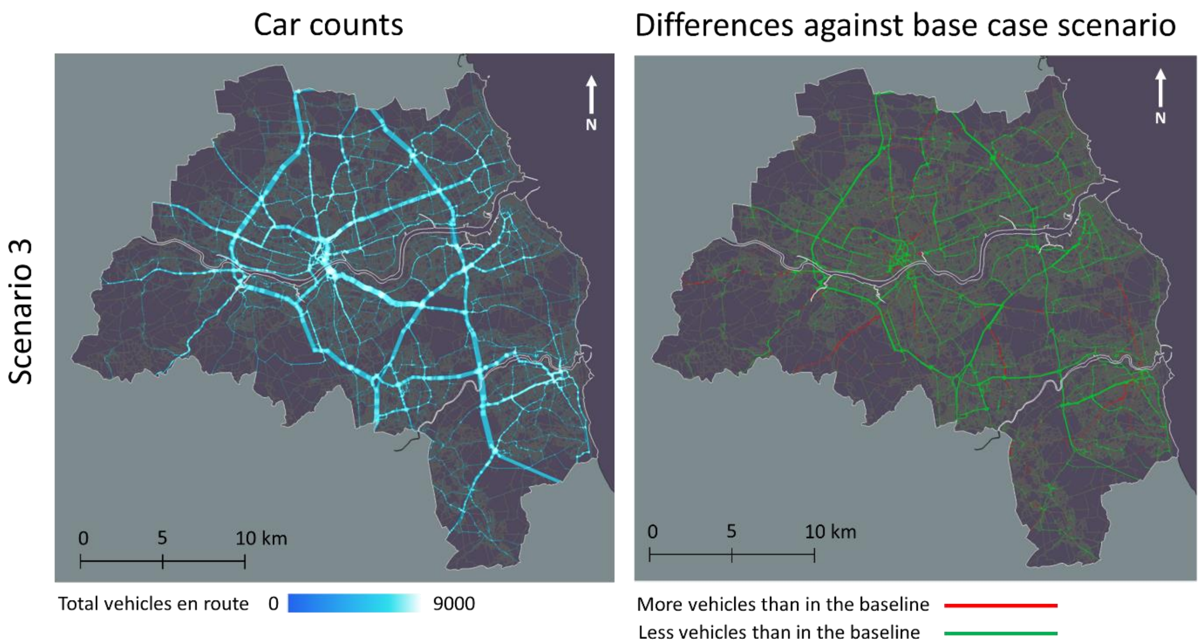


Figure 97 Car counts in scenario 3 (left) and differences when compared with the baseline (right).

The geospatial distribution in scenario 3 (figure 97 left) shows a visual reduction in all types of roads when compared against the baseline, being more prominent in motorways and highways. When results obtained are subtracted from the baseline (right), the majority of main roads have fewer vehicles, although some of them have more (e.g., A695, A692, A195, A1018, A184). Most urban roads achieved a reduction, although some roads experienced an increase as well (e.g., Barrack Road in Newcastle; Durham Road in Gateshead). Although a further and detailed investigation is required to identify the reasons for the increase of vehicles in specific areas, they could be a consequence of the behaviours of other agents. One hypothesis is that these new car users have a better alternative using the car than using the transport mode used in the baseline scenario, as a consequence of the decisions made by other agents. When some agents made the shift from cars to other transport modes (mainly cycling and walking), it allowed these new car users to travel faster, as less congested zones were generated. This is an important effect that shows the importance of AgBMs in transport, as it is possible to visualise this effect in congestion: when car journeys are reduced for some, it just opens more road space for others. Therefore, for a car use reduction, a road space reduction is needed.

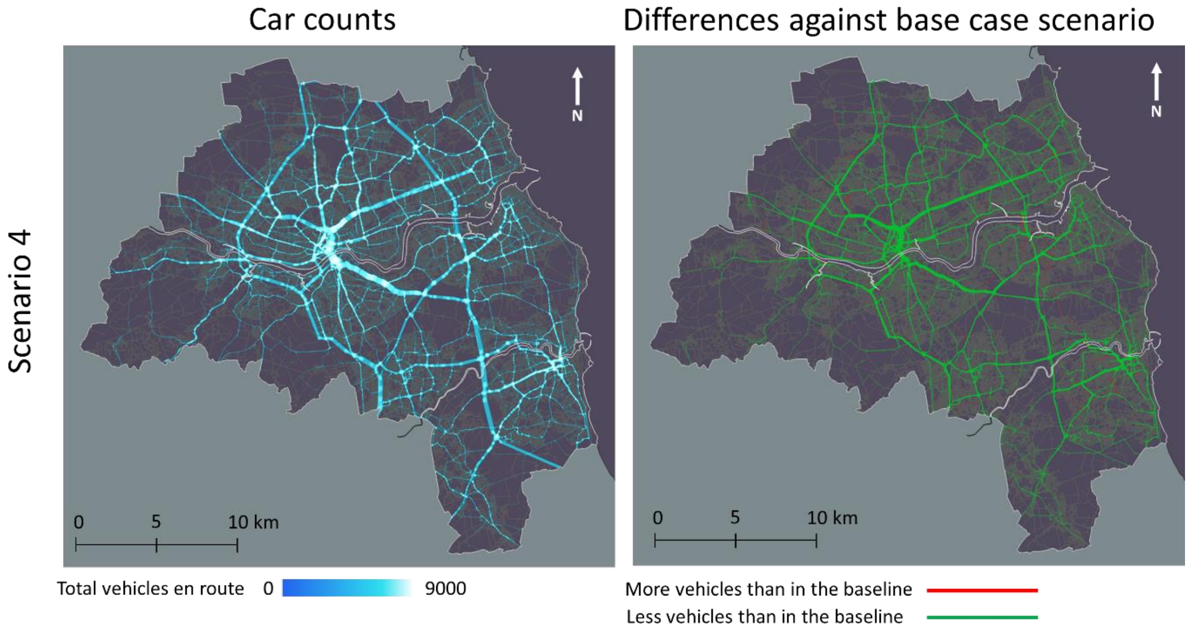


Figure 98 Car counts in scenario 4 (left) and differences when compared with the baseline (right).

The geospatial distribution of cars in scenario 4 (figure 98 left) shows a lower number of vehicles on the roads when compared against the baseline scenario, especially in motorways, as in the city centres these differences are less visual. When differences between this scenario and the baseline are shown (right) a general reduction of cars can be observed in every single road in the study area, which indicates a homogeneous impact of the policy.

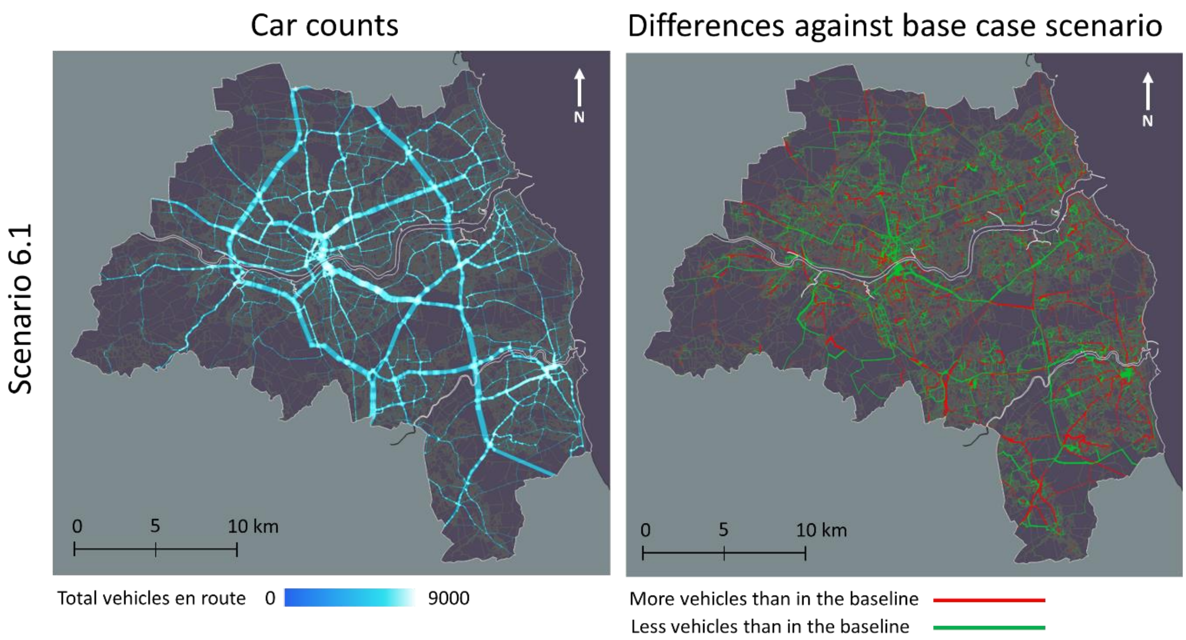


Figure 99 Car counts in scenario 6.1 (left) and differences when compared with the baseline (right).

The geospatial analysis in scenario 6.1 (figure 99 left) shows a reduction in the number of vehicles, as narrower lanes are observed when compared with previous scenarios. When the values are subtracted from the baseline scenario (right), patterns similar to results from scenario 2 can be observed, with an increase of cars (red roads), principally on urban roads, as the main motorways and highways in the area saw a reduction in the number of vehicles (e.g., A1, A1058, A194). In contrast, urban roads with a reduction in cars in scenario 2, reduced the vehicles passing through them even more (e.g., city centres of Newcastle, Gateshead and Sunderland). Primary, secondary and tertiary roads, although showing a similar pattern to scenario 2, achieved a greater car reduction.

The geospatial distribution in scenario 6.2 (figure 100 left) shows a similar pattern as in the previous scenarios, although with narrower lines, indicating a greater car use reduction. When results are subtracted from the baseline scenario (right), a combination of the results obtained in scenarios 1, 2 and 3 is observed (like in scenario 6.1), although with more notable car reductions, especially in motorways and highways (e.g., A1, A1058, A19). In urban areas, some roads with more cars than in the baseline are found (e.g., Westgate Road in Newcastle, Durham Road in Gateshead, B1522 and Tunstall Road in Sunderland), with similar patterns as in scenarios 1, 2, 3 and 6.1. The investigation of the reasons could be considered a specific task to be developed in future analysis.

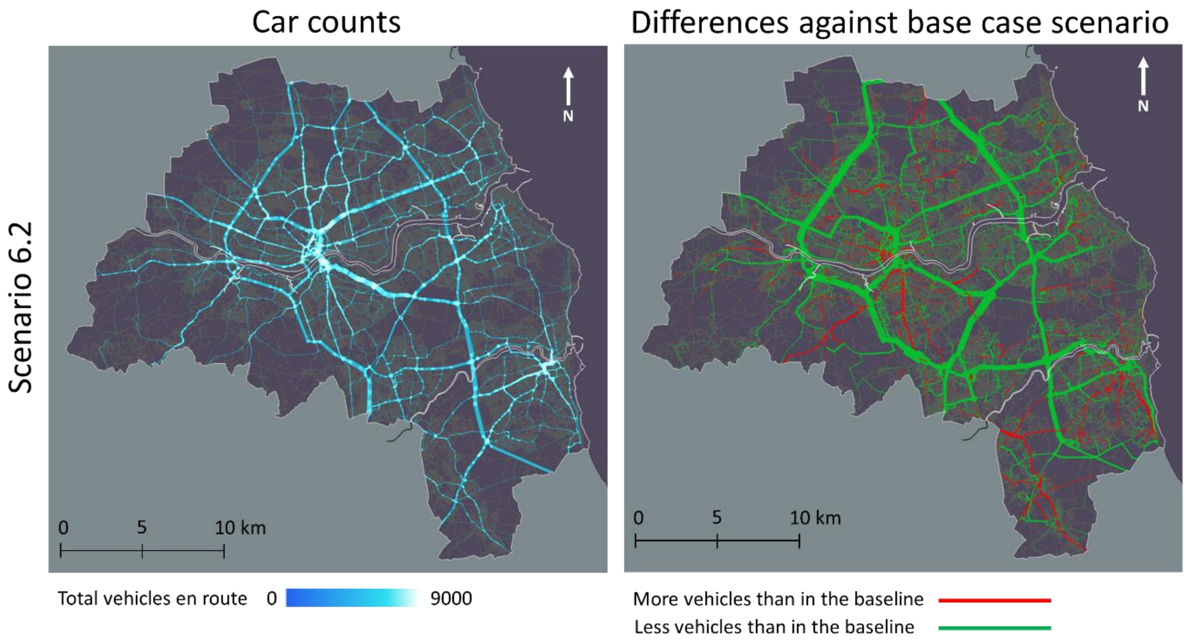


Figure 100 Car counts in scenario 6.2 (left) and differences when compared with the baseline (right).

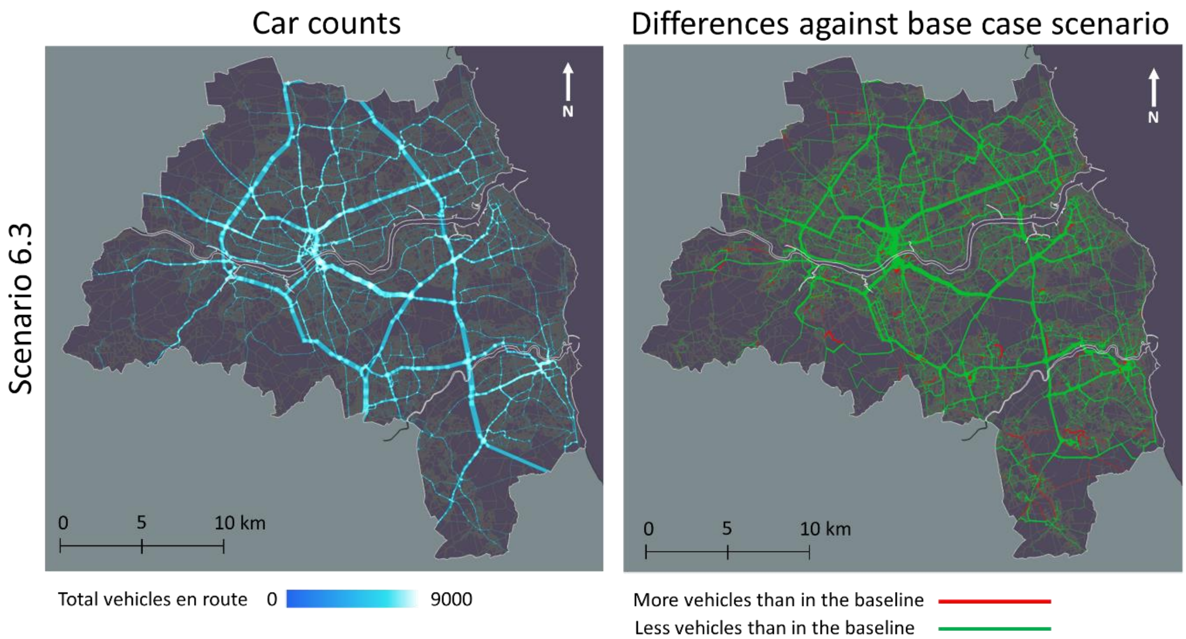


Figure 101 Car counts in scenario 6.3 (left) and differences when compared with the baseline (right).

The geospatial distribution in scenario 6.3 (figure 101 left) shows the same patterns as in the previous scenarios, but with lower levels of cars. When results are subtracted from the baseline (right), main reductions can be observed in the entire region, without distinctions between motorways and urban zones. The reduction in the use of cars seems to be relatively homogeneous in the whole study area, with isolated areas where the number of cars increased (e.g., Suniside in Gateshead, East Herrington in Sunderland, A182), which are similar to those found in scenario 2.

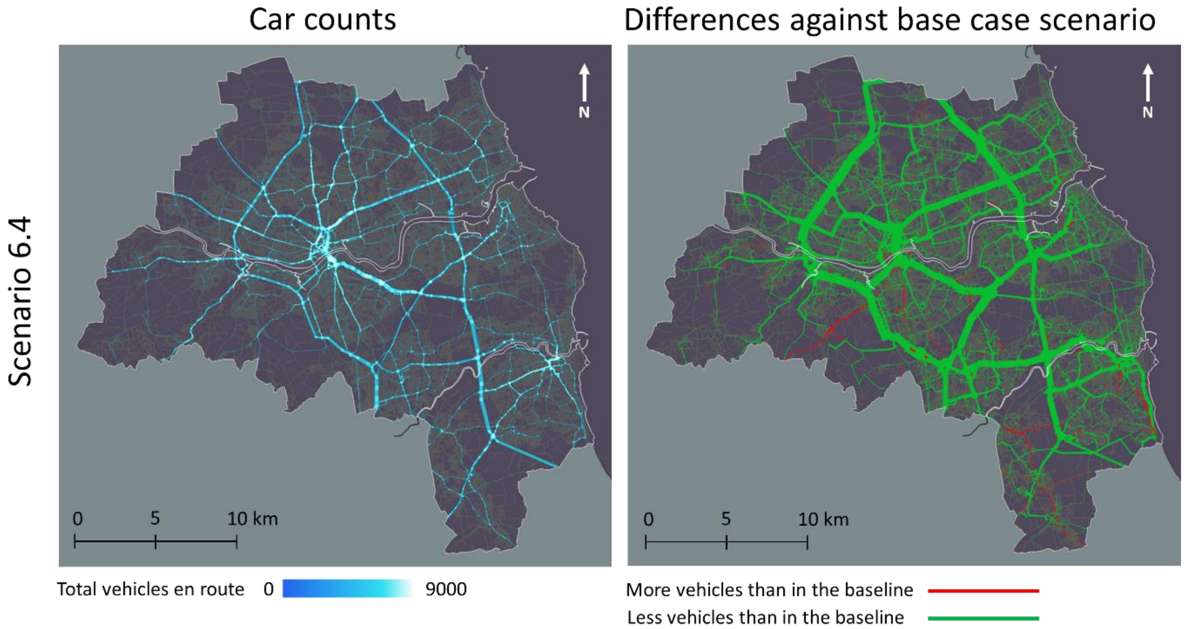


Figure 102 Car counts in scenario 6.4 (left) and differences when compared with the baseline (right).

The geospatial distribution in scenario 6.4 (figure 102) shows a lower car-centric mobility because of the 28% car use decrease, with narrower blue lines in the entire region, especially in highways and motorways (left). When results obtained were subtracted from the baseline (right), previous facts are shown visually. The main motorways (e.g., A1, A19) saw a drastically reduced number of cars, as well as on the main roads in the city centre of Newcastle (e.g., A167, A1058) and Gateshead (e.g., A184). Main urban roads (e.g., primary, secondary and tertiary) also reduced the amount of cars in every LA, although some roads increased the number of them in specific zones, which coincides with results from scenario 6.2 in many cases (e.g., Durham Road and A692 in Gateshead; B286, A182 and B1522 in Sunderland), but in a lower proportion. Further investigation is required to identify the causes that make these zones increase the number of vehicles.

Bicycles

Similar to the case of cars, the number of cyclists per road were analysed. The maps on the left show the number of bicycles counted per road. The brighter the green, the greater number of cyclists counted; it is also shown based on the width of the road. The maps on the right show the differences when the number of bicycles per scenario are compared against the baseline scenario. Green lines represent an increase in the number of cyclists counted, while red represent a reduction, the width of the line being proportional to the increase or reduction of cyclists passing through them. Similarly, scenario 5 was not analysed due to the results being almost the same as the baseline scenario. For visualisation purposes, only roads with differences above or below 100 bicycles when compared with the baseline are shown on the maps on the right.

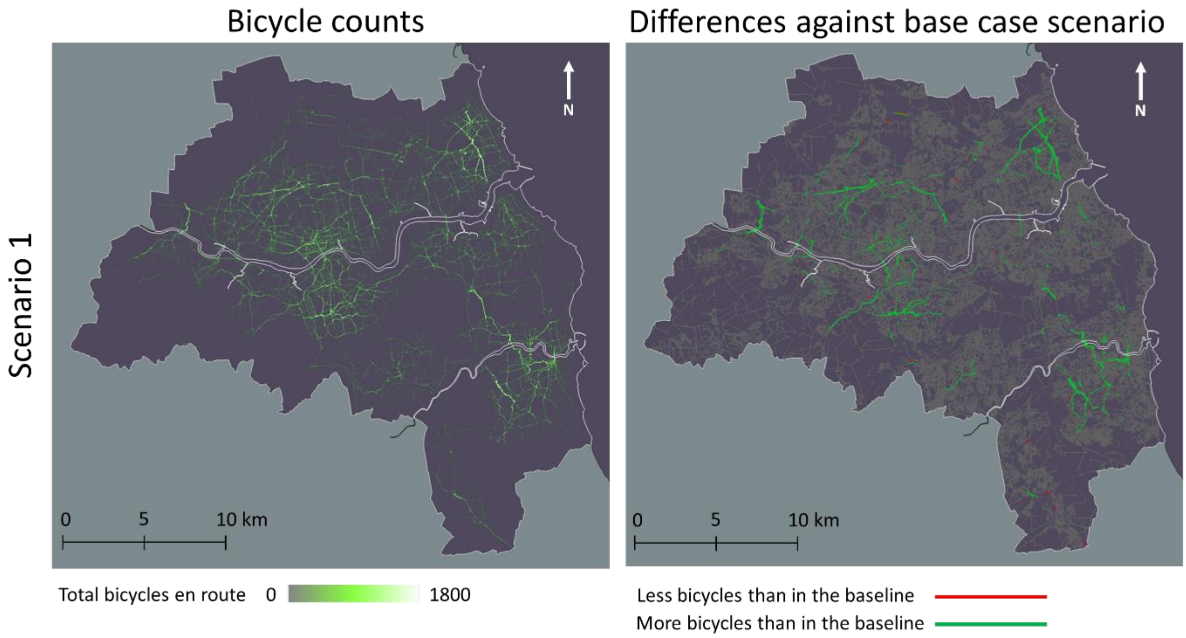


Figure 103 Bicycle counts in scenario 1 (left) and differences when compared with the baseline (right).

Scenario 1 shows a heterogeneous use of the bicycle (figure 103), but with clusters within the main urban areas of the five LAs (left). Differences with the baseline scenario (right) show increases in four of the LAs. In Newcastle, three main cycle path networks are identified: the first connecting the city centre with residential areas (e.g., Elswick Road), the second in the East (Newburn) and the third in the North (e.g., a West-East corridor through Kenton Lane, Red Hall Drive, Benfield Road). In these cases, the networks connect residential areas with shopping, medical and education areas. In Gateshead, there are two main corridors. The first connects residential areas in the SW with the bridges that connect to Newcastle upon Tyne. The second connects residential areas with the Team Valley trading state. In North Shields, there is a main cycle North-South corridor (through Preston North Road) connecting residential areas with education, medical and shopping areas. In Sunderland, two main routes are also identified. The first is found in the SW, connecting residential areas with education and shopping areas. The second connects residential areas in the North of the river Wear and South with the city centre of Sunderland and the Sunderland Royal Hospital. In all cases, the routes chosen are direct, minimising the distances cycled. In South Shields, the results are diffuse, and no specific routes were identified.

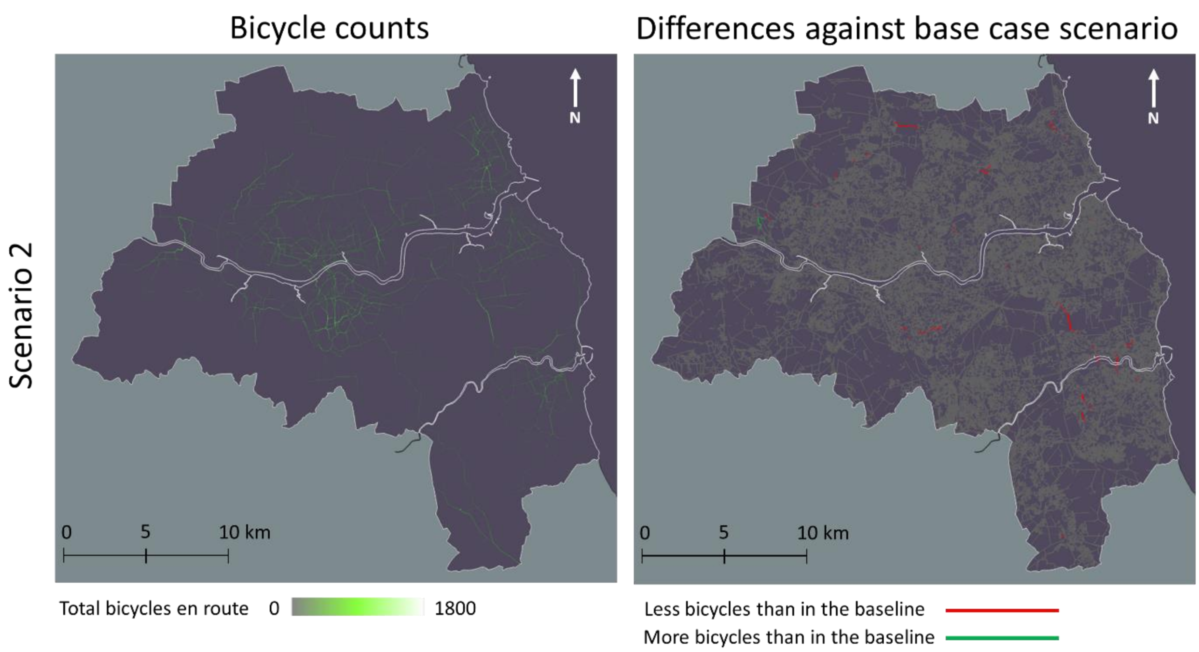


Figure 104 Bicycle counts in scenario 2 (left) and differences when compared with the baseline (right).

Results from scenario 2 show that all roads have a reduction of cyclists. Figure 104 shows in red only those roads with a reduction of more than 100 cyclists. These are the cases of the cycle paths connecting Wide Open and Moorfields in the North of Newcastle; roads in Gateshead connecting to the Team Valley Trading Estate; residential areas between West Boldon and Town End Farm in South Tyneside; and bridges connecting areas from both sides of the river in Sunderland.

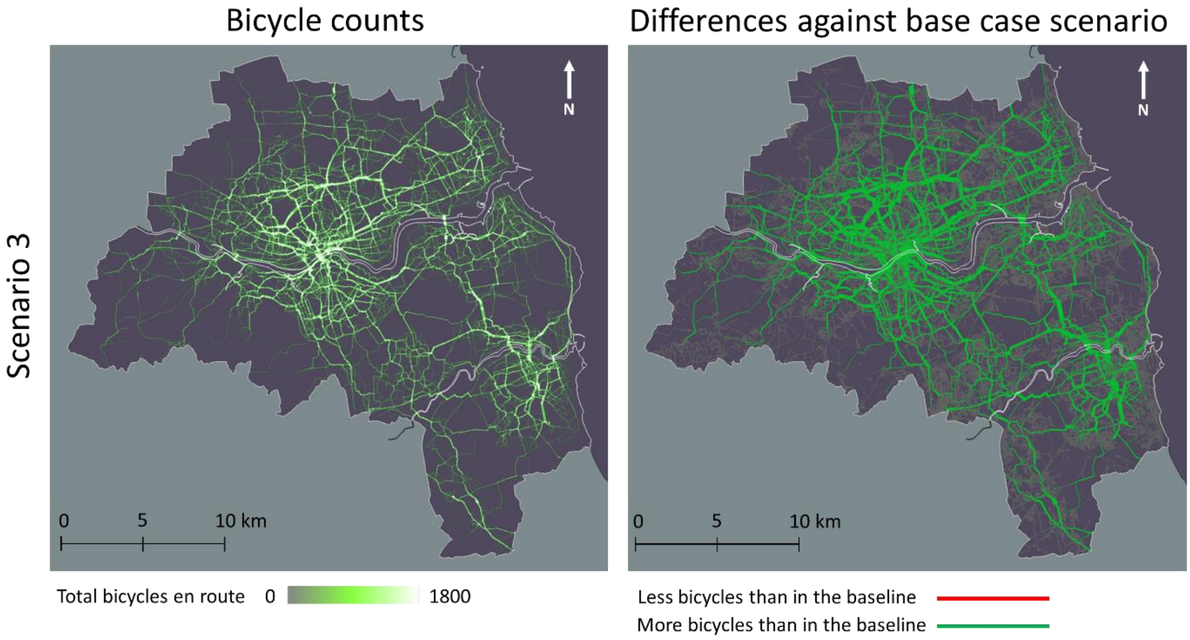


Figure 105 Bicycle counts in scenario 3 (left) and differences when compared with the baseline (right).

Results from scenario 3 (figure 105 left) show a huge boost in almost every urban area, especially in the areas of Newcastle, Gateshead and Sunderland, and the bridges connecting the first two. When compared with the baseline (right), the largest increases can be found in similar areas highlighted in scenario 1. Besides them, the route connecting Jarrow and West Harton, in South Tyneside can also be highlighted. Due to the limited number of options when crossing the rivers, most bridges are highly transited by cyclists (especially those with cycle paths). The most important bridges connect Newcastle and Gateshead, the Tyne pedestrian and cycle tunnel between North and South Tyneside; and the three bridges in Sunderland. As expected, cyclists now use the main roads used by cars, as these roads allow for reaching destinations in a more direct and faster way than the existing cycle paths.

In a similar way as it was shown in the car results, the use of bicycles in scenario 4 obtains an intermediate increase of cyclists when compared with results from scenarios 1 and 3 (figure 106). The most cycled zones are the urban areas and the connections among them (left). When the results are subtracted from the baseline scenario (right), increases in the number of cyclists can be observed. This is especially visible following the main urban roads from the five LAs, with similar patterns as highlighted in scenarios 1 and 3. Additionally, the bridges connecting areas at both sides of the two main rivers saw an increase in the number of cyclists, similar to scenario 3 but in a lower proportion.

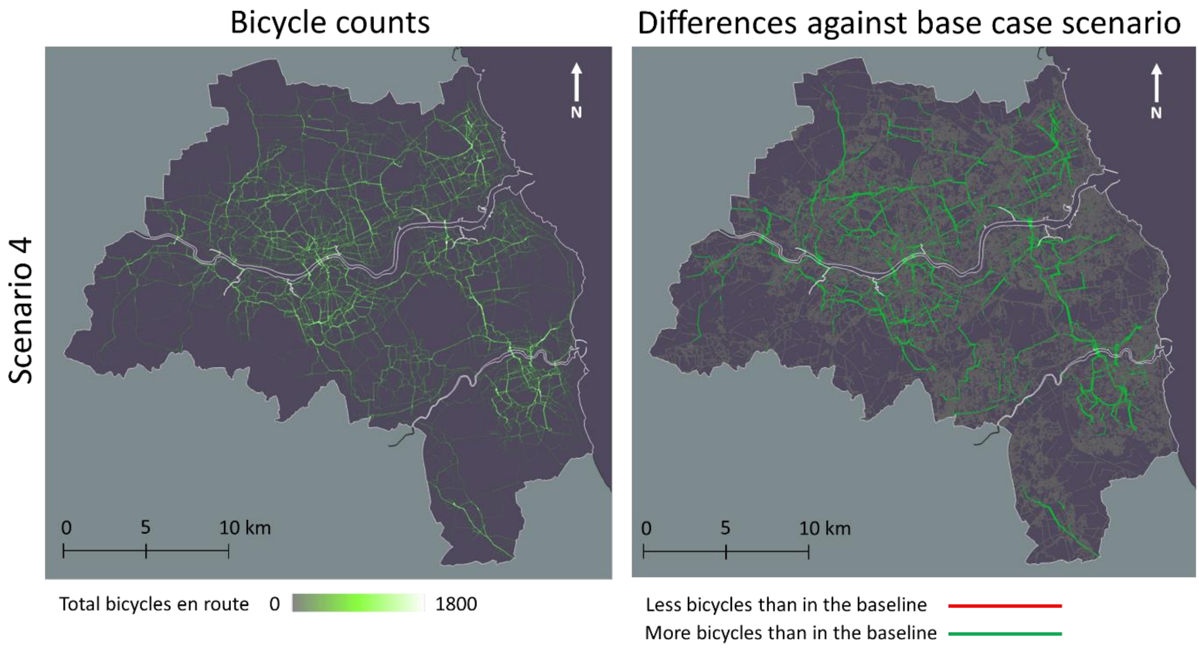


Figure 106 Bicycle counts in scenario 4 (left) and differences when compared with the baseline (right).

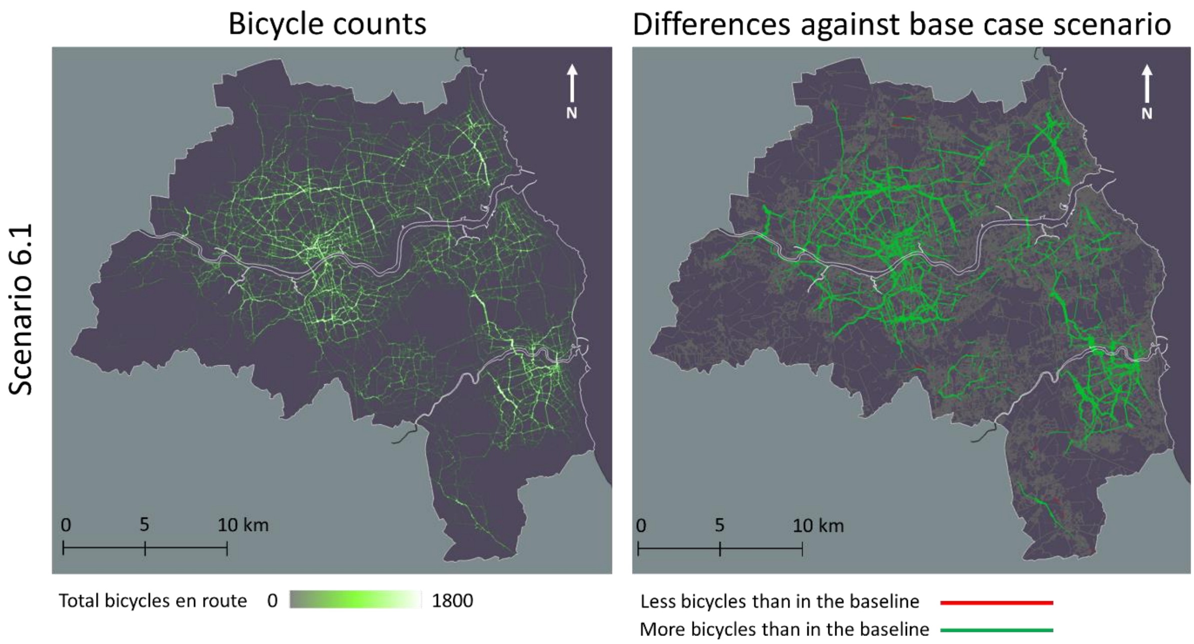


Figure 107 Bicycle counts in scenario 6.1 (left) and differences when compared with the baseline (right).

The analysis in scenario 6.1 shows an increase of cycling with a very similar pattern to results obtained in scenario 4 (figure 107 left). Similar areas as those highlighted in scenarios 1, 3 and 4 can also be identified (e.g., the West-East corridor through Kenton Lane, Red Hall Drive, Benfield Road in Newcastle; the North-South corridor through Preston North Road in North

Tyneside; the routes connecting the Team Valley Trading Estate with residential areas in Gateshead; the South-West route in Sunderland; and every bridge crossing the rivers in urban areas) (right).

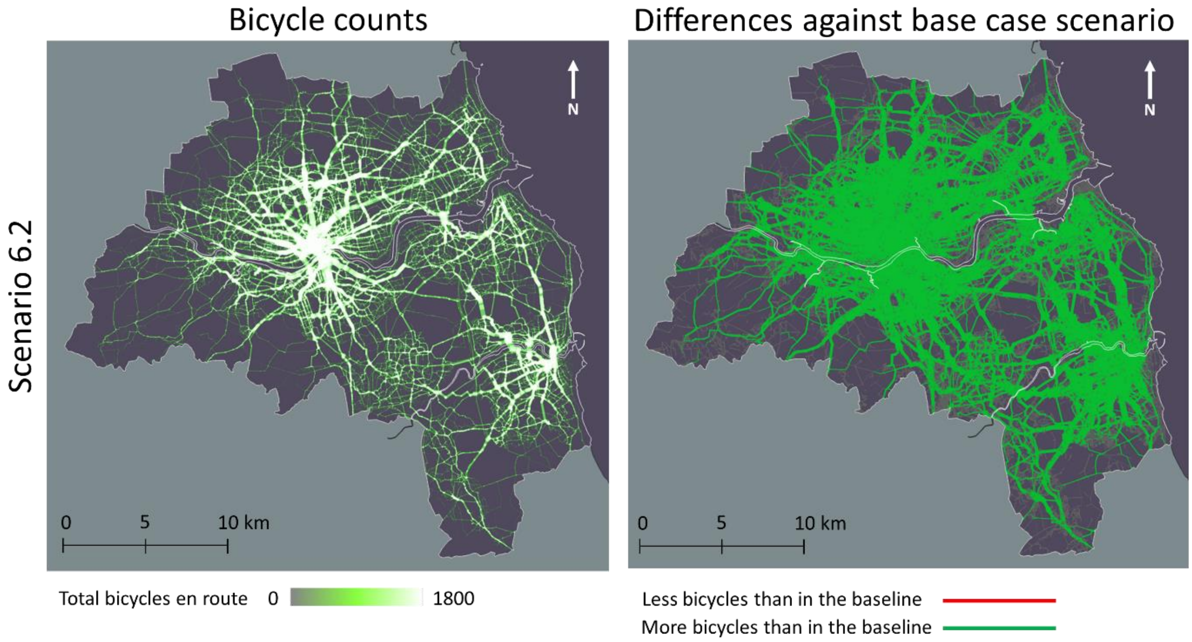


Figure 108 Bicycle counts in scenario 6.2 (left) and differences when compared with the baseline (right).

Results in scenario 6.2 show an impressive boost in the use of cycle paths, especially in urban areas of Newcastle, Gateshead and Sunderland (figure 108 left). When results are subtracted from the baseline scenario (right), a relatively homogeneous increase in almost every urban area of the study area can be observed, as well as in the zones connecting the urban areas of the LAs, highlighting the Newcastle-North Tyneside connection through the A1058, the Hylton Lane and A1018 between Sunderland and South Tyneside. The largest increases of cyclists using the fully segregated cycle paths are allocated in Newcastle, with two routes standing out: the N-S route from Gosforth (Newcastle) to the northern residential areas of Gateshead; and the E-W route connecting the area of Heaton with the city centre of Newcastle. Besides them, areas with bridges crossing the rivers (e.g., Sunderland) are very transited, too. The highlighted routes in the previous scenarios also increased the number of users, indicating their importance in the area.

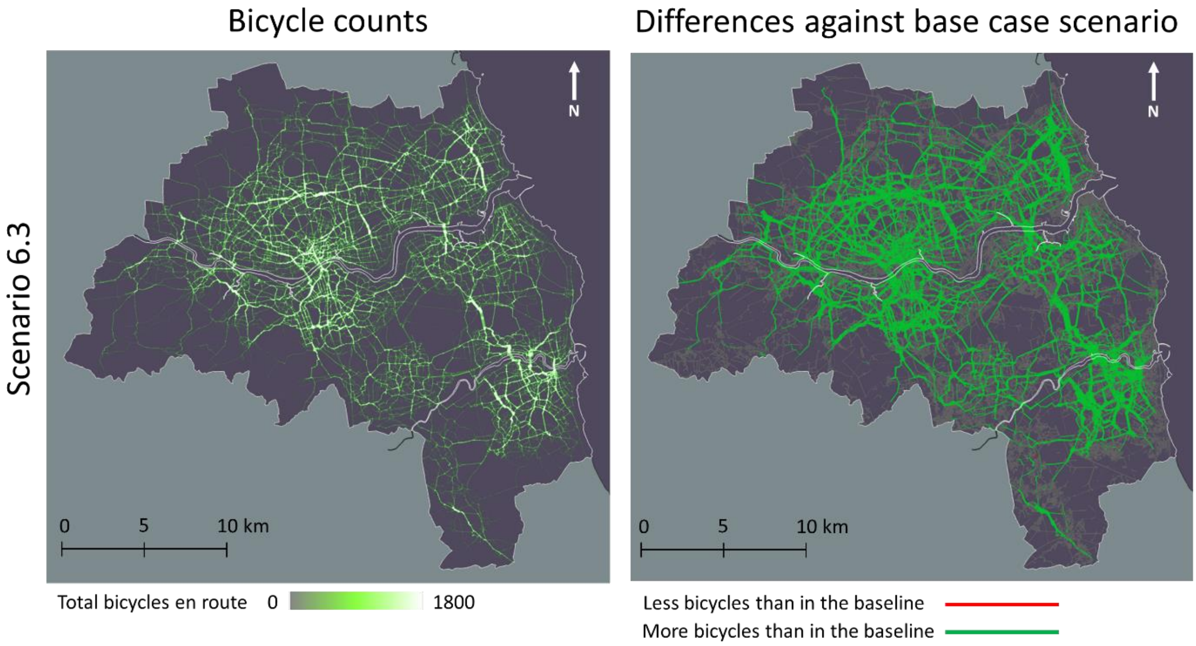


Figure 109 Bicycle counts in scenario 6.3 (left) and differences when compared with the baseline (right).

The distribution of bicycles in scenario 6.3 is very similar to results from scenario 3, as a similar percentage of cycled trips were obtained in both cases (figure 109 left), it being possible to identify the same corridors as in scenarios 1, 3, 4, 6.1 and 6.2. When results are subtracted from the baseline (right), very similar results as in scenario 3 are obtained, although with a general higher increase of cyclists, being principally observed in the corridors highlighted before in each of the LAs. Besides them, a new route stands out. This is the A1058 connecting Newcastle with North Tyneside, being the main cycling route (shortest and relatively smooth and flat) between both LAs.

The analysis of bicycles in scenario 6.4 shows a huge increase (figure 110 left), principally in urban areas of Newcastle, Gateshead and Sunderland, but also in most roads connecting all LAs. When subtracting results from the baseline (right), the outcome is very similar to the results from scenario 6.2, although with a greater volume of cyclists in all roads. This similarity with scenario 6.2 is coherent with the policies simulated in both scenarios, as all possible benefits for cycling were included in both cases. The greater number of cyclists in this scenario is due to the greater percentage of car users that decided to use the bicycle because of the daily toll policy included, showing the importance of both carrot and stick policies combined.

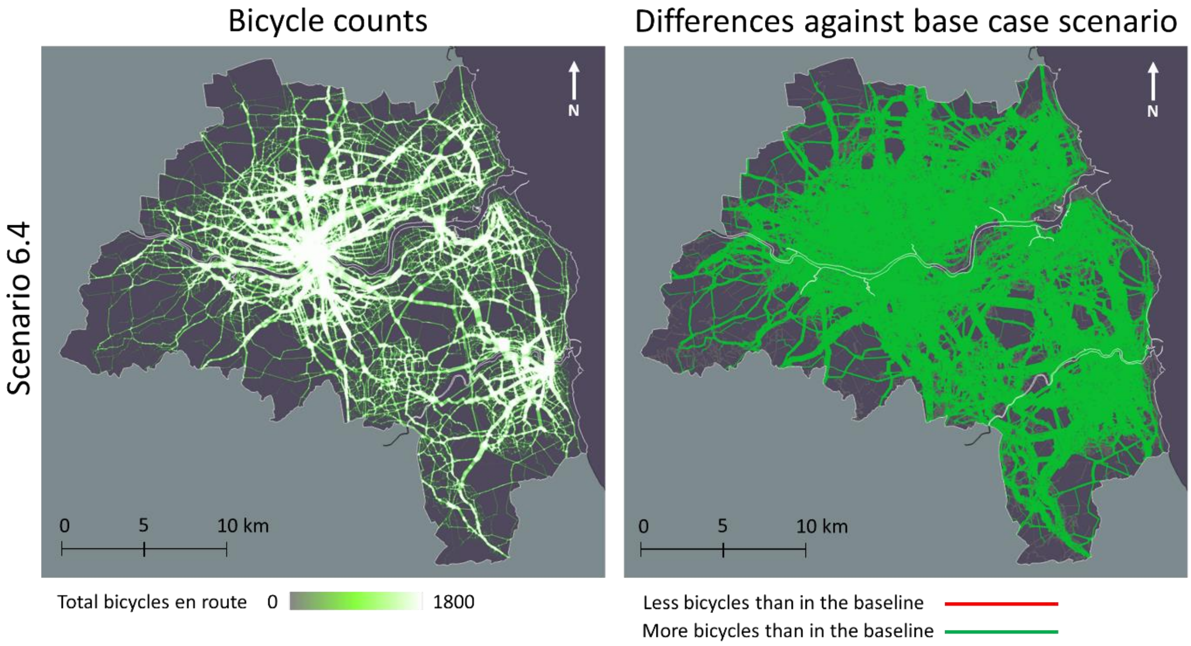


Figure 110 Bicycle counts in scenario 6.4 (left) and differences when compared with the baseline (right).

4.4.5. Walking and cycling statistics

This section identifies the differences in walking (yellow bars) and cycling (purple bars) average trip distance in kilometres (figure 111), trip time in minutes (figure 112) and speed in kilometres per hour (figure 113) when scenarios are compared against the baseline. The goal is to identify how policies influence the use of active modes in terms of distance, time and consequently, the speed. Finally, figure 114 quantifies the total kilometres walked and cycled per scenario, while table 8 identifies the percentage of increase or decrease of walking and cycling per scenario against results obtained in the base case scenario.

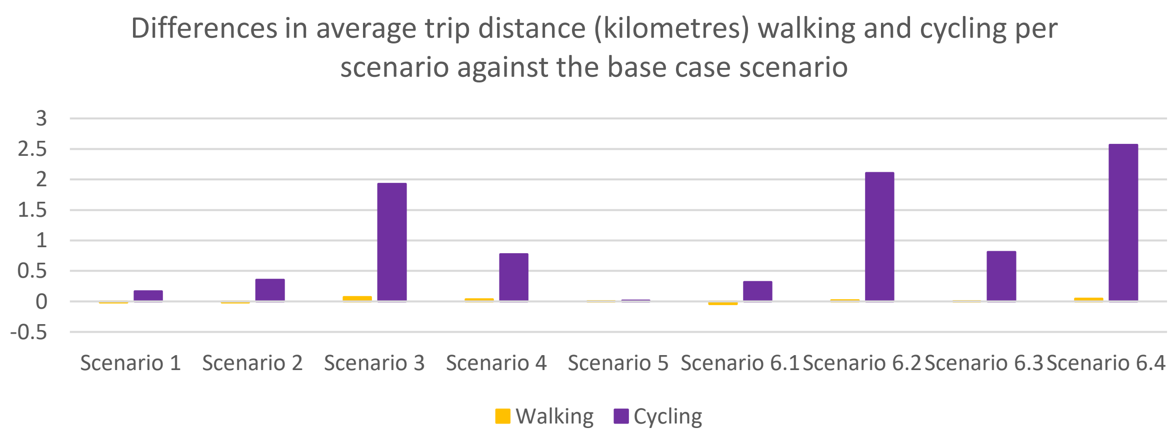


Figure 111 Differences in average trip distances when walking or cycling per scenario against the baseline scenario.

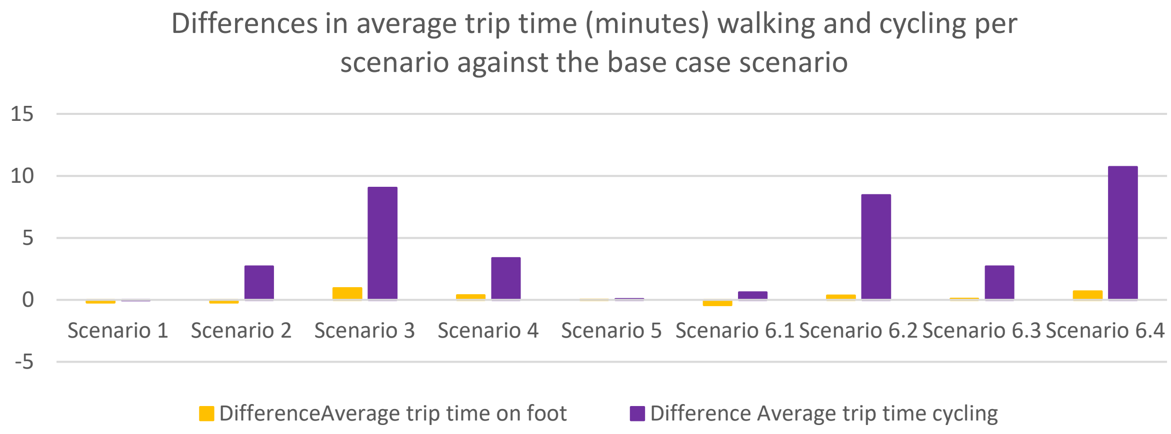


Figure 112 Differences in average trip time when walking or cycling per scenario against the baseline scenario.

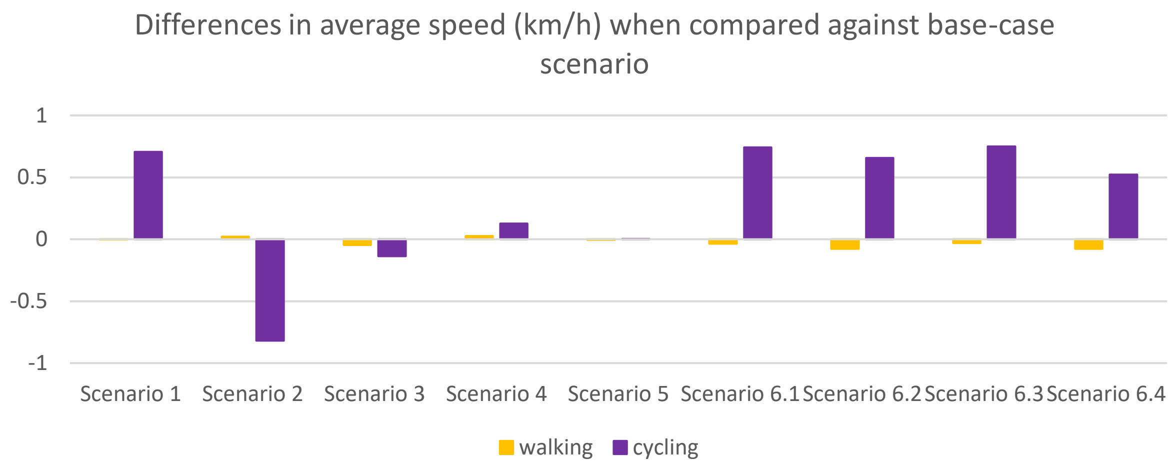


Figure 113 Differences in average speed when walking or cycling per scenario against the baseline scenario.

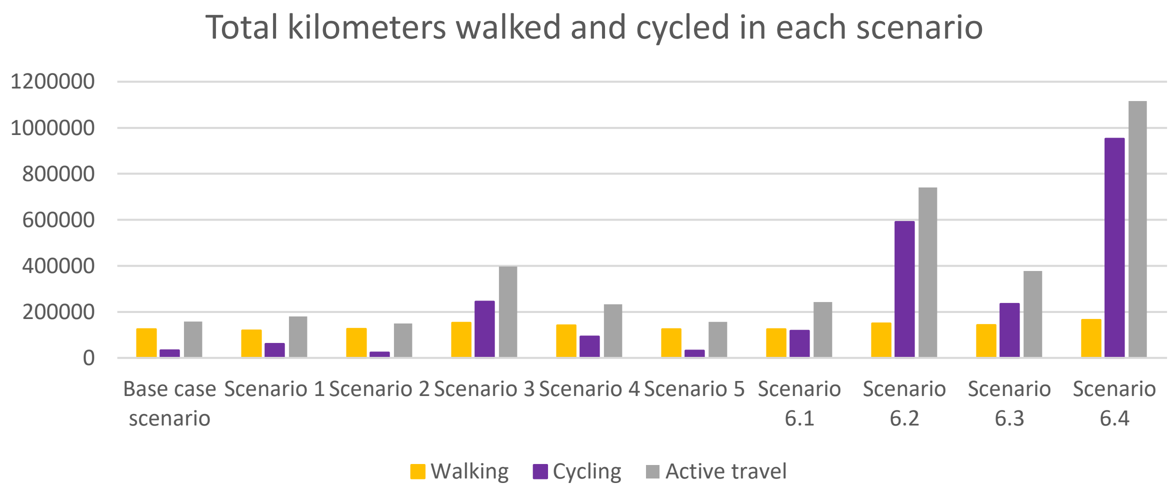


Figure 114 Total kilometres walked, cycled in each scenario simulated.

	Ratio total km walked	Ratio total km cycled
Scenario 1	-4%	82%
Scenario 2	2%	-32%
Scenario 3	23%	628%
Scenario 4	13%	177%
Scenario 5	0%	-5%
Scenario 6.1	0%	252%
Scenario 6.2	21%	1663%
Scenario 6.3	15%	599%
Scenario 6.4	32%	2738%

Table 8 Ratio of total kilometres walked and cycled per scenario simulated when compared with the baseline scenario.

Non-significant differences were observed in scenario 1 in terms of average trip distances (figure 111) and times (figure 112) for active modes when compared with the baseline. Results show a 0.02 kilometres and 0.2 minutes decrease for walking and 0.17 kilometres and 0.1 minutes increase for cycling, although a higher average speed was achieved when cycling (figure 113), thanks to the fully segregated cycle paths that do not interact with cars. These results suggest that cycling was increased by agents travelling longer distances, the increase of the average speed being a crucial factor in attracting more cyclists, with an 82%-points increase in the number of kilometres cycled (figure 114 and table 8).

Results from scenario 2 show slightly shorter average walking time (figure 111) and distance (figure 112) than in the baseline. In contrast, longer average trip distance (0.4 kilometres) and duration (2.7 minutes) were obtained for cycling, as short cycled distances in the baseline scenario were mainly walked or shifted to public modes, as shown in figure 84. In terms of average speed values, figure 113 shows an interesting result related to cycling, as this value was reduced by more than 0.8 km per hour when compared to the baseline, due to the impossibility of overtaking cars when these are in congested areas. Consequently, as shown in figure 114 and table 8, more kilometres were walked (2%) and less cycled (32%).

Average cycling trip distances and times in scenario 3 are also altered when compared with the baseline, where main trip distance and time are increased by almost 2 kilometres and 9 minutes, respectively (figures 111 and 112). These values indicate that more agents were attracted to cycle when economic rewards are provided, even travelling for longer distances than in the baseline scenario. However, the increase of cyclists on the roads made the average speed slower than in the baseline (0.13km/h) (figure 113). This could be a consequence of the amount of cyclists and other vehicles using the same roads at the same time (as in scenario 2). In the case of walking, a slightly longer average trip distance was obtained (figure 111), needing an extra minute to make an average trip (figure 112). Due to the increase of trips made by active modes, almost 400,000 kilometres were made (61% cycled and 39% walked), which is 2.5 times the base case scenario (figure 113). When this value is split by active mode, increases of 23% and 628% for walking and cycling can be observed, respectively. These results show the efficiency of this policy in increasing the number of trips made by active modes.

Results from scenario 4 show increased values for both modes, being greater for cycling (0.8 kilometres and 3.4 minutes more than in the validated scenario) than for walking (0.04 kilometres and 0.4 minutes) (figures 111 and 112). These values indicate that new cyclists are travelling longer distances than in the validated scenario, probably due to less congested routes by cars, allowing them to travel at a higher speed (figure 113), while new walkers are mainly walking the same distances. The number of kilometres walked and cycled were increased as well, mainly cycling (almost three times), while walking increases only a 13% (figure 114 and table 8). These results show the potential benefits that can be achieved for active modes with the solely application of policies that penalise the use of cars. Even though the vast majority of car users preferred public modes, an important proportion of people switched to active modes.

In scenario 5, minimum differences in the average trip distance, time, speed and the total amount of kilometres walked or cycled were observed (figures 111 to 114). However, several differences were found. Firstly, a decrease in the ratio of total number kilometres cycled was identified, with a reduction of a 5%. Secondly, a 5% decrease in the use of bicycles as the main mode used during the trips was observed, while public transport modes increased by 1% (figure 81). These results could be the consequence of allowing the agents to combine the use of the bicycle and the metro, besides acknowledging part of this behaviour to the stochasticity of the model. A small proportion of agents previously using the bicycle as the main mode during the trips decided to combine the use of the bicycle with the metro, the latter becoming the main mode.

In the case of results obtained from scenario 6.1, a small reduction in the average trip distance when walking is observed (figure 111), with more although shorter trips (5%). The average cycled distance is increased (10%), indicating that more and longer trips are made. Accordingly, average trip duration (figure 112) for walking is slightly lower (5%) and higher when cycling (23%). Average cycling values show the improvements achieved in this scenario when compared against scenario 2, as similar average trip distances are made in both (3.5 kilometres), but average trip duration is around 2 minutes shorter, indicating the impact of fully segregated and direct cycle paths on main roads. Differences in average speeds are mainly found in cycling, where a very similar value to scenario 1 is obtained (0.74 km/h faster than the baseline), while walking obtains an insignificant reduction (0.08km/h) (figure 113). This combined policy also increases the number of kilometres using active modes (figure 114), having similar kilometres walked to those of the validated scenario, although a 2.5-fold increase in kilometres cycled is achieved. These values show the potential policy success in terms of cycling, the main beneficiary of the implementation of fully segregated cycle paths, LTNs and cycle hubs, with shorter and slower walking trips, on average.

The combined application of policies in scenario 6.2 made the average cycled trip distance increase by 2.1 kilometres (0.01 kilometres for walkers) (figure 111), spending on average eight more minutes per trip (walkers only 0.3 more) (figure 112). Previous values for cycling can be explained with a speed increase of 0.7 km/h, very similar to the value obtained in scenarios 1 and 6.1, where fully segregated cycle paths were deployed, enabling cyclists to use more direct routes without any potential car congestion. The effect of combining fully segregated cycle paths with economic rewards for cycling can be observed when comparing results against scenario 3, where only economic rewards were given. In the former, the average trip distance and duration were 5.3 kilometres and 23 minutes while, in the latter, the values were 5.1 km and 23.6 minutes. The former allows making longer and faster trips, as it can be observed in figures 111-113. In terms of kilometres walked and cycled, this scenario achieves the highest values so far, multiplying by more than 4.5 times the kilometres using active modes (figure 114), mainly achieved when cycling, as the number of km cycled were multiplied by 16.

The average cycled trip distance in scenario 6.3 was increased in 0.8 kilometres (figure 111), requiring 2.7 more minutes (figure 112) when compared against the baseline (same average trip distance and duration for walking as in the validated scenario). These results are similar to those obtained in the previous scenario 6.2. The effect of combining fully segregated cycle paths and LTNs with economic variations (penalties in this case) achieves longer average cycling trip distances in shorter average times than when the economic policy is applied alone (scenario 4). Similar to previous scenarios, the provision of fully segregated and safe cycle paths increased the average speed (figure 113) in a similar proportion as in scenarios 1, 6.1 and 6.2. In terms of kilometres cycled, the value is increased six times, while walking is only increased by 15% (figure 114 and table 8).

Lastly, scenario 6.4 achieves the longest average cycling distance (5.7 km), which is 80% longer than in the baseline (figure 111), requiring 25.3 minutes, a 73% increase (figure 112). These results indicate that more and longer distances are made by bicycle thanks to the attractiveness gained after the implementation of policies in its favour. Despite this attractiveness, the average cycling speed was not as high as in the previous scenarios where fully segregated cycle paths were implemented. The main reason could be related to the number of cyclists using the same road at the same time and the flow capacity value used (1000), which could result in agents travelling at a slower speed than in free flow conditions. A further investigation of the flow capacity value and the potential use of a more realistic value would help in identifying more accurate results. In terms of walking, the average trip distance and time were increased by 6% (figure 111) and 7% (figure 112), respectively. These results show that new walkers walked longer distances instead of using other modes (principally the car or public modes, as described before). When comparing the number of kilometres walked from this scenario with the sum of the individual scenarios (figure 114 and table 8), a very similar value can be observed for walking (34% increase when individual scenarios are grouped, while 32% in this scenario). In the case of cycling, the sum of the individual scenarios increases the number of kilometres cycled by nine times, while the value obtained in scenario 6.4 is almost 28 times, showing again that the bicycle was the mode that benefited the most from another perspective.

4.4.6. Active Travel England goal

As discussed previously in the thesis, ATE has defined a goal to achieve 50% of trips below 5 kilometres to be walked or cycled in urban areas by 2030. Their baseline identified in 2019 was 41% (ATE, 2023a). This section identifies if the scenarios simulated could achieve the goal established by ATE, from general, trip purpose and geospatial perspectives.

Figure 115 shows the percentage of short trips (e.g., below 5 kilometres) that are made either walking or cycling, per scenario. Blue bars represent the percentages achieved per scenario, while the horizontal dotted red line marks the threshold marked by ATE for the year 2030.

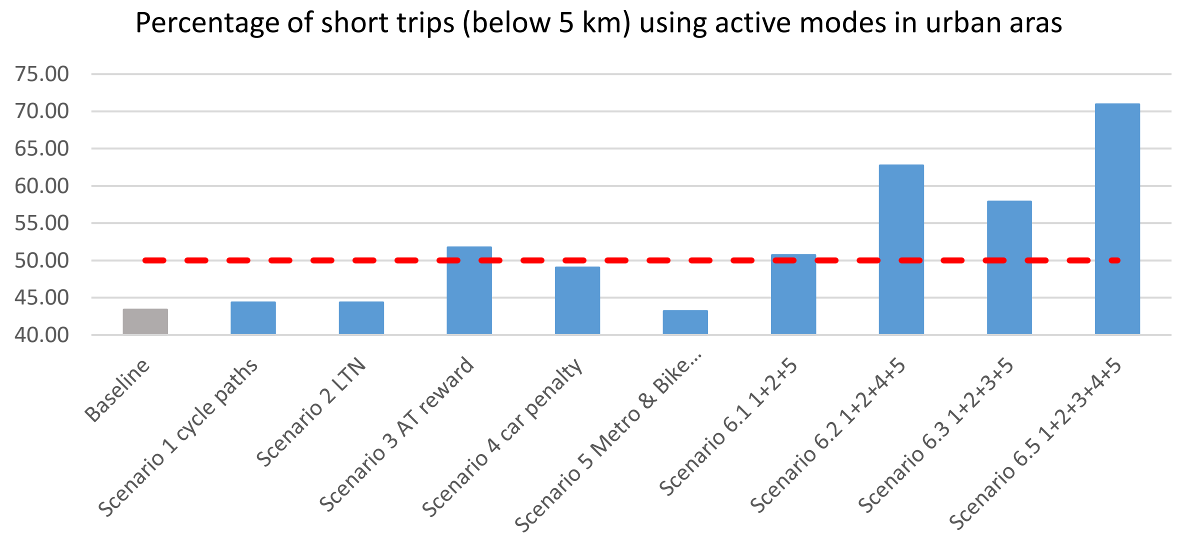


Figure 115 Percentage of short trips made in urban areas in each scenario simulated (blue bars), with the 50% ATE goal (red dotted line).

Tables 14, 15 and 16 quantify the percentage of trips made by active modes per scenario, depending on the purpose of the trip (e.g., education, work, shop, medical, leisure sport and leisure in general). Table 9 estimates only those percentages of trips walked (purple), table 10 only those trips cycled (green), table 11 the combination of both (blue). In the three cases, values highlighted in white represent those that achieve the goal defined by ATE.

WALKING	Education	Work	Shop	Medical	Leisure sport	Leisure act
Base case scenario	46.24	27.92	33.92	28.55	31.04	40.46
Scenario 1	44.89	27.21	33.6	28.02	30.77	40.14
Scenario 2	46.4	27.74	36.81	29.43	34.36	43.21
Scenario 3	49.46	30.18	37.57	31.49	35.2	43.64
Scenario 4	46.13	30.89	38.77	31.82	35.33	43.13
Scenario 5	45.97	28.4	33.8	28.59	30.8	40.43
Scenario 6.1	47.08	27.69	37.16	29.47	34.45	43.43
Scenario 6.2	48.32	28.33	40.7	32.19	39.17	46.28
Scenario 6.3	46.55	30.41	41.25	33.66	38.59	46.06
Scenario 6.4	48.68	29.71	44.08	35.9	41.92	48.57

Table 9 Percentage of trips walked depending on the purpose of the trip, by scenario simulated.

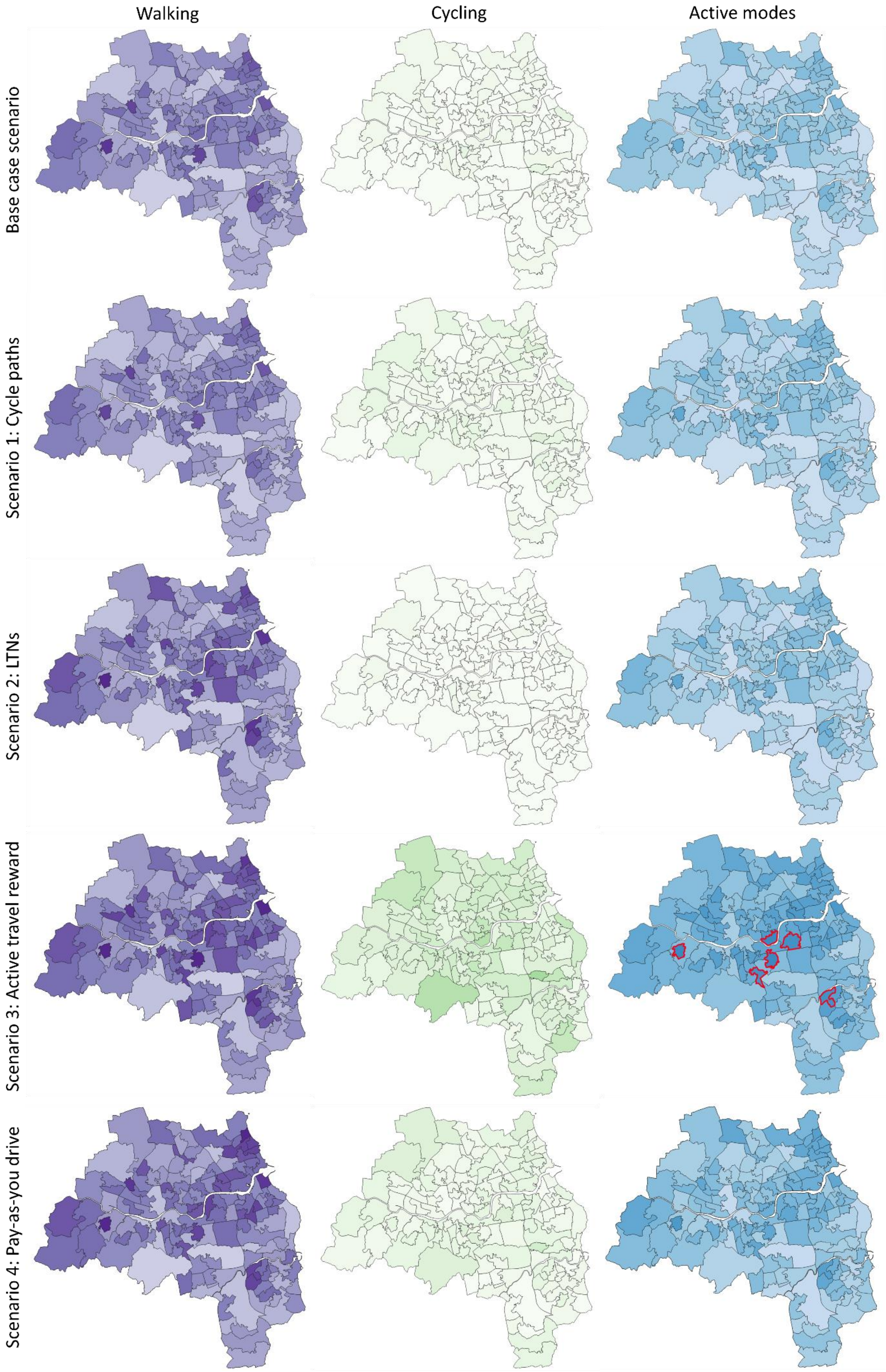
CYCLING	Education	Work	Shop	Medical	Leisure sport	Leisure act
Base case scenario	3.42	2.06	2.03	3.48	3.35	2.45
Scenario 1	6.08	4.44	3.23	5.81	4.57	3.41
Scenario 2	2.03	1.3	1.19	2.43	1.73	1.37
Scenario 3	12.88	11.72	8.65	12.34	8.64	6.97
Scenario 4	6.56	6.22	5.62	7.81	5.97	3.93
Scenario 5	3.14	1.97	1.93	3.36	3.05	2.36
Scenario 6.1	11.02	8.98	6.39	10.13	7.93	5.92
Scenario 6.2	27.2	28.3	15.93	23.56	18.33	14.61
Scenario 6.3	15.16	18.09	11.83	16.68	12.56	8.38
Scenario 6.4	28.95	42.78	25.81	33.25	25.23	19.41

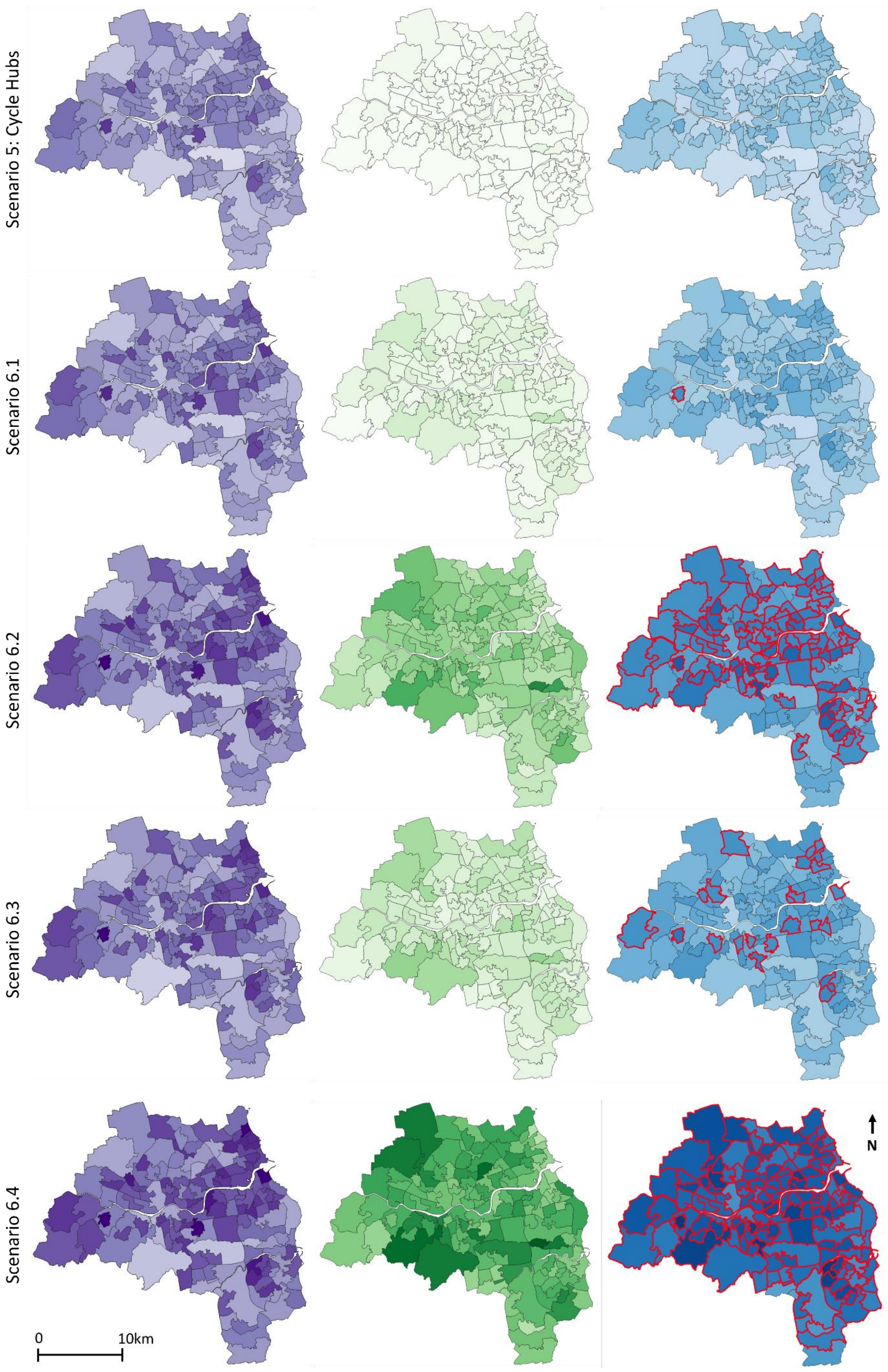
Table 10 Percentage of trips cycled depending on the purpose of the trip, by scenario simulated.

ACTIVE MODES	Education	Work	Shop	Medical	Leisure sport	Leisure act
Base case scenario	49.66	29.98	35.95	32.03	34.39	42.91
Scenario 1	50.97	31.65	36.83	33.83	35.34	43.55
Scenario 2	48.43	29.04	38	31.86	36.09	44.58
Scenario 3	62.34	41.9	46.22	43.83	43.84	50.61
Scenario 4	52.69	37.11	44.39	39.63	41.3	47.06
Scenario 5	49.11	30.37	35.73	31.95	33.85	42.79
Scenario 6.1	58.1	36.67	43.55	39.6	42.38	49.35
Scenario 6.2	75.52	56.63	56.63	55.75	57.5	60.89
Scenario 6.3	61.71	48.5	53.08	50.34	51.15	54.44
Scenario 6.4	77.63	72.49	69.89	69.15	67.15	67.98

Table 11 Percentage of trips walked or cycled depending on the purpose of the trip, by scenario simulated.

In addition to the above analysis, the geospatial component of active travel modes was analysed per MSOA zone in the Tyne and Wear region, per scenario simulated. Figure 116 shows the percentage of short trips walked (first column), cycled (second column) and the combination of both (third column) for each of the scenarios simulated. In all cases, the darker the colour, the greater the percentage of short trips made by the specified mode. Additionally, when a MSOA zone reaches the ATE target, the border of the level is highlighted in red.


Walking
Cycling
Active modes
Base case scenario
Scenario 1: Cycle paths
Scenario 2: LTNs
Scenario 3: Active travel reward
Scenario 4: Pay-as-you drive


Scenario 5: Cycle Hubs
Scenario 6.1
Scenario 6.2
Scenario 6.3
Scenario 6.4
0
10km
N

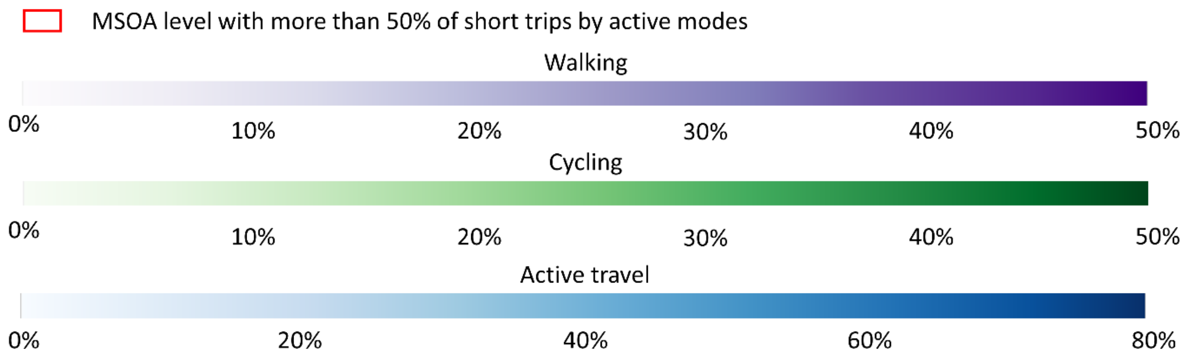


Figure 116 Percentage of short trips made on foot (left), cycling (middle) and the combination of active modes (right) per scenario simulated.

Results from scenario 1 show an increase of almost 1%-point, reaching 44.4%-points of short trips cycled or walked in urban areas (figure 115). When this goal is analysed depending on the active mode and the trip purpose, walking percentages were reduced when compared against the base case scenario (table 9). This was likely in great part in favour of cycling (table 10), where values were increased in all trip purposes analysed, especially when commuting and travelling to school, where values were duplicated and almost duplicated, respectively. When results of both modes are combined (table 11), the ATE goal is achieved when travelling to school (51%), while the other trip purposes increased their percentages, although still being far from the objective. The geospatial analysis of the ATE goal when results are grouped by MSOA area (figure 116) shows minimum differences when compared with the baseline, although a general increase in the use of cycling is observed, especially in residential areas in the outskirts of the main urban areas.

Scenario 2 does not achieve the ATE 2030 goal either, achieving a very similar result as in scenario 1 (44.34%) (figure 115). While in the previous scenario cycling was the most benefited active mode, opposite results were obtained in this one. Walking (table 9) was increased for all trip purposes, except when commuting to work, where a slight reduction (0.18%-points) was obtained, that could be due to the stochasticity of the model or a direct transfer to public modes. The highest increases were found when trip purposes were related to shopping, leisure sport and leisure, with around a 3% increase in each of them. In terms of cycling (table 10), all trip purposes suffered a reduction in the use of the bicycle, trips to leisure sport (1.62%) education (1.39%), leisure in general (1.08%) and medical (1.05%) being those with the greatest reductions. When both modes are grouped (table 11 and compared with the baseline, reductions can be observed when travelling to school (1.23%-points), commuting to work (0.94%-points) and attending medical appointments (0.17%-points), while there are increases in shopping (2.05%-points), leisure sport (1.7%-points) and leisure in general (1.67%-points). Further investigations would be required to identify potential reasons for these values. In terms of the geospatial distribution of active trips, figure 116 shows very similar patterns for walking (left) and a general reduction of cycling trips in all MSOA zones (middle). The combination of both modes (right) has a very similar distribution to the baseline and scenario 1.

Scenario 3 is the first that overcomes the goal, as 51.73% of short trips in urban areas were made using active modes (figure 115). When analysing the results depending on the trip purpose, none reaches the goal when walking, although higher values were obtained for all purposes with an average increase of the 3% (table 9). Cycling did not reach the goal in any of the trip purposes either, although significant increases were obtained, especially when travelling to school, commuting to work and attending medical appointments (around 9% in each case) (table 10). When values are combined (table 11), trips to school and leisure activities overcome the goal, the first being 12%-points higher than the goal. The other trip purposes increased their percentage values, staying close to the target (all above 40%). When active travel trips are analysed from a geospatial perspective at MSOA zone (figure 116), higher values are obtained in the three cases (i.e., walking (left), cycling (middle) and both (right)). Greater percentage values were achieved in the outskirts of the main urban areas of Newcastle, Gateshead and Sunderland. Cycling is mainly increased in the North of Newcastle, South of Gateshead and some areas between South Tyneside and Sunderland. When both modes are combined (figure 116 right), six MSOA areas that reach the ATE 2030 goal are highlighted. All of them are mainly residential areas, where business parks or industrial estates, education buildings and shopping areas can be found. Further investigations about their morphology, transport modes, routes in the area and other transport characteristics would be beneficial to identify the reasons why these areas achieve these percentage values.

Policies simulated in scenario 4 achieve the second-best result when policies are applied individually, even when it is strictly focused on reducing the number of cars on the road, reaching 49.04% of short trips walked or cycled (figure 115). When the trips are grouped by active mode and trip purpose, all trip purposes increase the use of active modes, except for travelling to school where the percentage of walking pupils is slightly lower (0.11%). Shopping, leisure sport activities and medical appointments are the most increased (above 3%-points) when walking (table 9), while commuting to work, attending medical appointments and travelling to school (3%-points increase) are the most increased when cycling (table 10). When the results combine both active modes (table 11), the trips to school reach the ATE goal, especially thanks to the high increase in the use of the bicycle. Commuting to work, shopping and attending medical appointments are the trips that increased the most in percentage terms (above 7%-points). Analysing the number of trips made using active modes per MSOA area (figure 116), similar patterns as in the previous scenarios can be observed, where a general and homogeneous increase is achieved in most of the zones. In this scenario, none of the MSOA zones reached the ATE goal.

In the case of scenario 5, very similar results to the baseline were obtained: global value (figure 115), grouped by active mode and trip purpose (tables 9, 10, 11) and the geospatial distribution of them per MSOA area (figure 116).

This first combined scenario (scenario 6.1) also reaches the ATE 2030 goal (50.7%), although with 1% lower than scenario 3 (figure 115). Analysing this goal by active mode and trip purpose, it is observed that trips to school when walking reach the highest value (47.08%), although the ones that increased the most are shopping and leisure activities (table 9). When cycling, the highest value is achieved travelling to school (11.02%-points), being also the one that increases the most (7.6%-points), followed closely by commuting to work (6.9%-points) and medical appointments (6.7%-points) (table 10). Combining both active modes, the ATE goal is reached travelling to school (58.1%), with leisure activities being close to the goal (table 11). The geospatial analysis (figure 116) shows similar patterns as in the previous scenarios, with one MSOA zone reaching the goal, a residential area of Gateshead. Although this MSOA zone is in an isolated area with the majority of the facilities, further investigation is required to analyse its characteristics and identify the potential causes of its success.

Results obtained in scenario 6.2 reach the 62.74% (figure 115), being 12%-points higher than results from previous scenarios. Similar to scenario 6.1., the greatest percentage of short trips made by active modes was achieved when walking to school (48.32%), followed by leisure activities (46.28%) (table 9). When cycling, a great increase was observed in all trip purposes, especially when commuting to work (28.3%), which was the trip purpose with the lowest percentage obtained in the baseline scenario (2.06%) (table 10). A similar percentage value was obtained when travelling to school (27.2%), followed by medical appointments (23.56%). When both modes are combined, all trip purposes reach the goal, standing out travelling to school, with three in four trips made with active modes (table 11). In all cases, results achieved were higher than in the previous scenario, which shows the potential effect of the economic reward in shifting the use of cars to active modes. The geospatial analysis shows a great increase in cycling, especially in two northern MSOA zones in Sunderland (figure 116 middle), and a majority of MSOA zones reaching the 50% of short trips using active modes, principally located in Newcastle, North Tyneside, the northern parts of South Tyneside and Gateshead, and the urban zones of Sunderland (right). Similar to previous scenarios, further investigations are required to identify potential reasons for these achieved results.

The ATE goal is also achieved in scenario 6.3, with a 57.87% of short trips in urban areas walked or cycled (figure 115). From those trips, walking trips to school and leisure activities reached the highest percentage values (46.55 and 46.06%, respectively) (table 9), while the highest values achieved when cycling were when commuting to work and medical appointments (18.09 and 16.68%, respectively) (table 10). The percentage of agents commuting by bicycle is fewer than in the previous scenario (10%-points), but greater when compared with trips to school (18% and 15%, respectively). Contrary to scenario 4, where the same economic penalty was applied, in this scenario the agents had the possibility of using fully segregated and safe cycle paths using direct routes, which increased its attractiveness to the detriment of public modes (which were the main winners in scenario 4). When both active modes are combined (table 11), all trip purposes except commuting to work (48.5%) reached the ATE goal. The geospatial distributions of the percentages of short trips made on foot and/or cycling per MSOA area (figure 116) show slightly higher percentage values when walking (left), but lower when cycling (middle) than in the previous scenario, although patterns remain similar to those obtained from other scenarios. Similar to previous scenarios, where more than one policy was combined, some MSOA areas where the ATE goal is achieved using active modes (right) are identified. Although dispersed in the study area, most of them are allocated in residential areas with the access to the main daily facilities within them (e.g., educational facilities, shopping areas, leisure). Further investigation is needed to identify the characteristics that made those areas reach the goal.

As can be expected, scenario 6.4 also surpassed the ATE goal, as previous combined scenarios and scenario 3 did. In this case, the highest percentage was achieved (70.96%) (figure 115), which is the normal case as all possible individual benefits and penalties were applied to the use of bicycles and cars, respectively. Walking trips to school again achieved the highest percentage value (48.68%), although the trip purposes that increased the most were shopping (44.08%), leisure sport (41.92%) and other leisure activities (48.57%), with increases of 10%, 11% and 8%, respectively (table 9). In terms of cycling, the trip purpose that reached the highest value and increased the most was commuting to work (42.78% of trips and a 40.72% increase) (table 10). This increase in cycling when commuting was not shown in any of the previous scenarios, being the previous highest value obtained in scenario 6.2 (28.3%), where all policies in favour of cycling were combined. The extra 14.5% achieved could be the consequence of a proportion of former car users finding an alternative mode to avoid the economic toll, besides their possibility of reaching their destination using fully segregated and safe cycle paths, following direct routes. The rest of trip purposes also increased very significantly, being in all cases around 20%. When results of both active modes are combined (table 11), all trip purposes reached the ATE goal. The highest value was obtained in trips to school (77.63%), followed by commuting to work (72.49%) thanks to the boost of cycling, as commuting trips using active modes were in the lowest positions in most of the cases in the previous scenarios. Values achieved for the other four trip purposes were quite close to the 70%. The geospatial analysis of short trips made by active modes per MSOA zone (figure 116) shows the highest values for walking (left), cycling (middle) and their combination (left), although keeping a similar pattern as in the previous scenarios. All MSOA zones except three reached the goal, located in the South-West of Sunderland.

4.4.7. Socio-demographic analysis for cycling

The impact of the simulated policies on different groups in society were also analysed. This is one of the advantages of using AgBMs instead of other alternative modes, as discussed in sections 3.5.1 and 3.5.2.

In this thesis, the different mobility behaviours of the agents were only considered when the activity plans were assigned to them, based on their socio-demographic attributes as explained in section 3.3.6. Unfortunately, health conditions and mobility behaviours that define the attitudes towards the use of different transport modes were not implemented during the simulation stage due to time and data constraints. The inclusion of these behaviours would have made the model more realistic and robust, but at the cost of more complex and difficult calibration and validation stages. This is an acknowledged limitation that could be improved in future work.

However, and always keeping in mind the above limitation, the simulated policy scenarios were analysed in terms of their impact on different population groups. The following sub-sections analyse the impact of policies in favour of cycling depending on the range of age, sex and economic activity.

Range of age

The use of the bicycle is predominant among the youngest agents (i.e., those up to 16 years old), this being a trend observable in all scenarios simulated (figure 117). In the baseline and the scenarios where individual policies are simulated, except in scenario 3, two outcomes can be identified. Firstly, the percentage of the youngest group (orange bars) duplicates the percentage value in respect to the other groups. Secondly, the use of bicycles decreases as agents get older, except when they are over 65 years old, this group being the second that uses the bicycle the most.

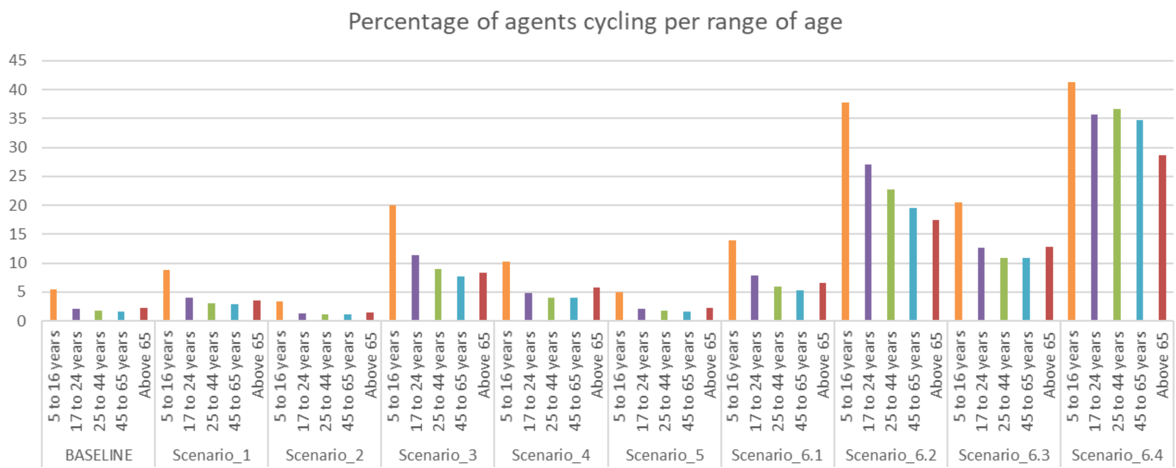


Figure 117 Percentage of agents cycling per range of age.

These results could be consequence of the parameters used during the simulation and the intrinsic characteristics of their trips. The first refers to the ASC values applied to each mode (see section 3.7.1) and the impossibility of the youngest group using cars. The second is related to the average trip distances travelled by each group, as those groups using the bicycle the most travel shorter average distances than those using them less. While agents aged between 5 to 16 and above 65 travel on average 4.0 and 4.6 kilometres per trip respectively, the average distance for the other groups range from 7.2 (group aged 17-24) to 9.9 (group aged 25-44). In contrast, when simulating economic rewards (scenario 3), young adults (17 to 24 years) become the second group in detriment of the oldest group, followed by adults between 25 and 44. This outcome can indicate that economic rewards could be more attractive to these age ranges, as they travel longer distances and can get a higher economic benefit that those travelling shorter distances.

The combinations of policies achieve different results depending on the included policies. A similar pattern as in scenario 3 can be observed when only combined built environmental policies are applied (scenario 6.1), as well as when these policies are combined with economic penalties to car users (scenario 6.3). However the combination of built environment with economic policies rewarding active modes (scenarios 6.2) achieves results inversely proportional to the group ages, relegating the oldest group to the last position (i.e., the younger the agent, the higher the percentage of them using the bicycle). Lastly, when all policies are combined together (scenario 6.4), smaller differences are observed between the age groups, indicating that this combination of policies affects the different groups more evenly, especially adults between 17 and 65 years old.

Sex

When analysing the use of bicycles per sex and scenario (figure 118), females (red bars) use them more than males (blue) in all the cases except in scenario 6.4. The ratio of females and males using bicycles per scenario is around 1.1 (i.e., 1.1 females use the bicycle per male), except in scenario 6.4, where the ratio is reversed (0.9). Although differences between the latter and the others exists, results suggest that simulated policies do not have effects on sex, which is not in line with research publications. Aldred et al. (2016) analysed the diversity of cycling individuals in England and Wales using census data and identified that more men than women cycle, besides highlighting the existence of specific factors limiting the increase of females cycling, even when cycling rates are increased in a specific area.

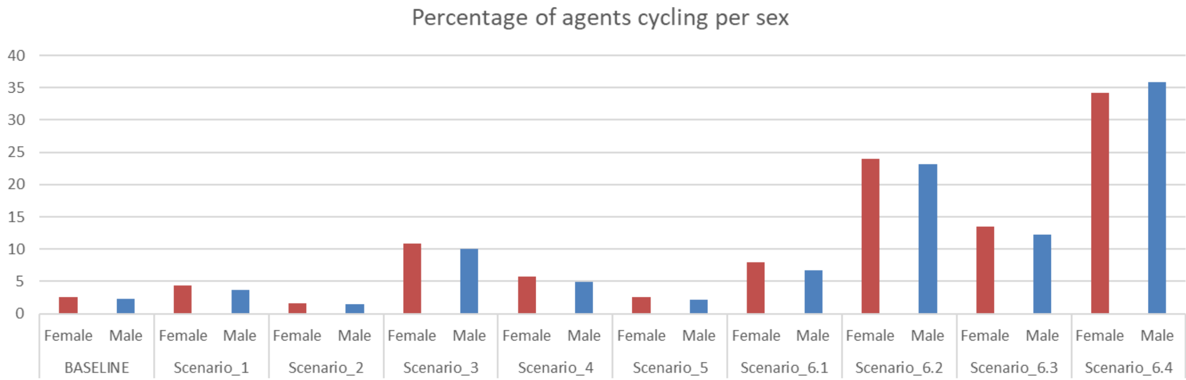


Figure 118 Percentage of agents using the bicycle per sex type

Economic activity

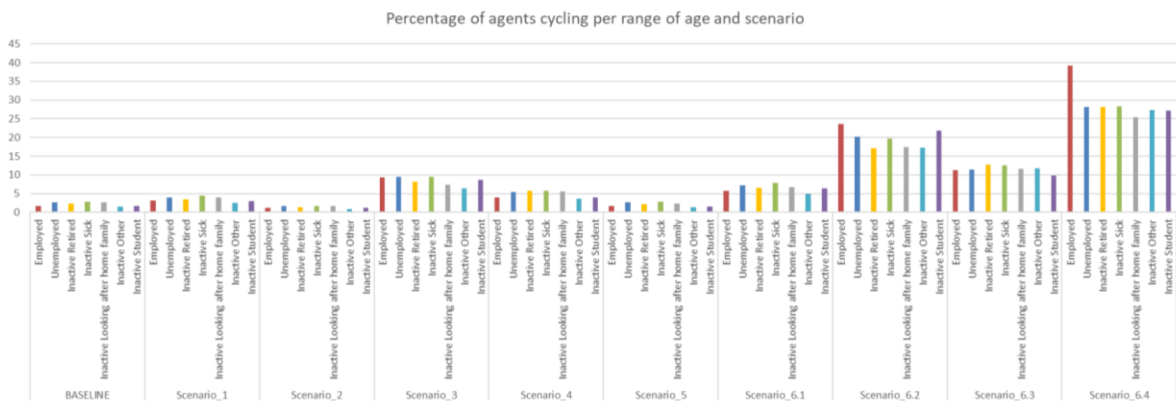


Figure 119 Percentage of agents cycling per range of age and scenario.

In terms of economic activity (figure 119), those agents in the baseline that are sick (green bars), unemployed (blue), retired (yellow) or looking after home/family (grey) are the groups that use the bicycle the most (above 2%). These results do not reflect the reality, as they could be considered less likely to use the bicycle than other groups with a greater potential (e.g., employed, students). This behaviour is entirely a consequence of the type of trips they do, which were assigned to them based on their socio-demographic attributes. One of the effects could be related to average trip distances, as described before in the analysis of the age. In the case of sick, unemployed, retired and looking after home/family groups, their value is between 3.4 and 3.6 kilometres, while the mean for employed and students are 10.7 and 4.3 km, respectively. Shorter distances are more likely to be cycled. These results show the clear need to consider subpopulations with different attitudes towards the use of different transport modes when simulating travel behaviours, otherwise unrealistic behaviours can emerge, as shown above in the use of bicycles between males and females.

Despite the previous, several effects of the simulated policies to the different groups can be observed in figure 119, although taking into account that their effects are entirely based on just the activity plans assigned to them. When an economic policy in favour of active modes is applied (scenario 3), employed agents (red bars) are among the most impacted groups, as well as students (purple), unemployed (grey) and sick (green). When this policy is combined with built environmental improvements for cycling (scenario 6.2), the most benefited groups are employed (almost 25% of them use the bicycle) and students (22%), with greater differences than in the previous case to other groups. Finally, when all policies are combined (scenario 6.4), almost four in 10 employed agents use the bicycle, while the rest of groups are above the 25%. In contrast, when an economic penalty is applied to car users (scenario 4), no differences are shown when compared to scenario 1, where segregated cycle paths are provided. While built environmental and penalty policies have a discrete impact in the economic groups, economic rewards have some more effects, especially in groups travelling long distances (e.g., employed and students).

4.4.8. Health benefits

In addition to decarbonising the transport sector, the increase in the use of active modes also brings health benefits to society, as described in section 2.4.2. The different levels of walking and cycling per scenario can be used to estimate the health impact and its corresponding benefits for society.

Tools such as the Health Economic Assessment Tool (HEAT) estimate the value of reduced mortality risk based on the amount of walking and cycling, depending on the average number of kilometres, trips and/or minutes using different active modes (WHO, 2024). The outcomes combine the benefits from physical activity with the mortality effects of exposure to air pollution and traffic accidents while walking or cycling (WHO, 2024).

Figure 120 shows the differences in premature deaths prevented per year, per active mode (blue bars refer to walking, orange to cycling and grey to their combination) and per scenario when compared with the baseline, using HEAT. The average kilometres walked and cycled per agent simulated were provided as input data, while all default parameters were kept except the value of statistical life, which was updated based on research related to England by Tainio *et al.* (2016).

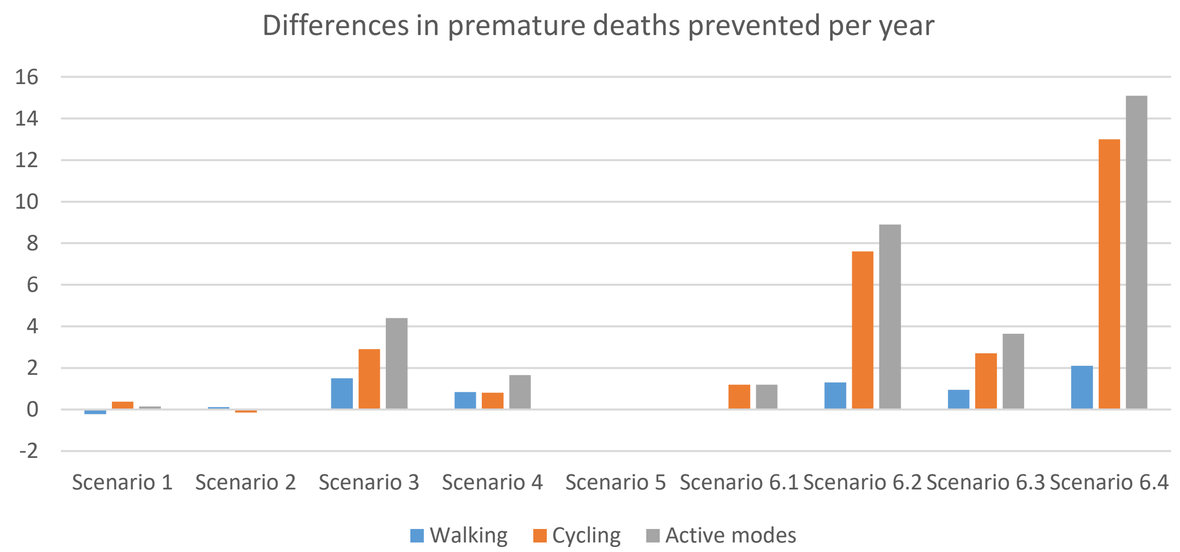


Figure 120 Differences in premature deaths prevented per year and scenario.

As results show, premature deaths are reduced in all scenarios except in those where cycling is affected by the simulated policies (i.e., scenarios 2 and 5), where results are almost the same as in the baseline (0.03 premature deaths increased in both cases). In the rest, cycling achieves better results than walking, except in scenario 4, where similar results are obtained by both modes.

Comparing scenarios where policies are simulated individually (scenarios 1-5), the best results are obtained when economic rewards are provided (scenario 3), reducing 4.4 premature deaths per year, mainly by cycling. Similar results are obtained when policies are combined, scenarios 6.2 and 6.4 being the main winners, preventing up to 8.9 and 15.1 premature deaths per year, respectively.

4.4.9. Analysis of the built environment characteristics for cycling

Built environment features were also analysed to identify the most used roads by cyclists. This analysis could be useful to identify potential zones in the study area to implement new segregated cycle paths, given the increased demand. Figures 121-126 show the number of cyclists per scenario depending on the road type, number of lanes and maximum speed.

Road type

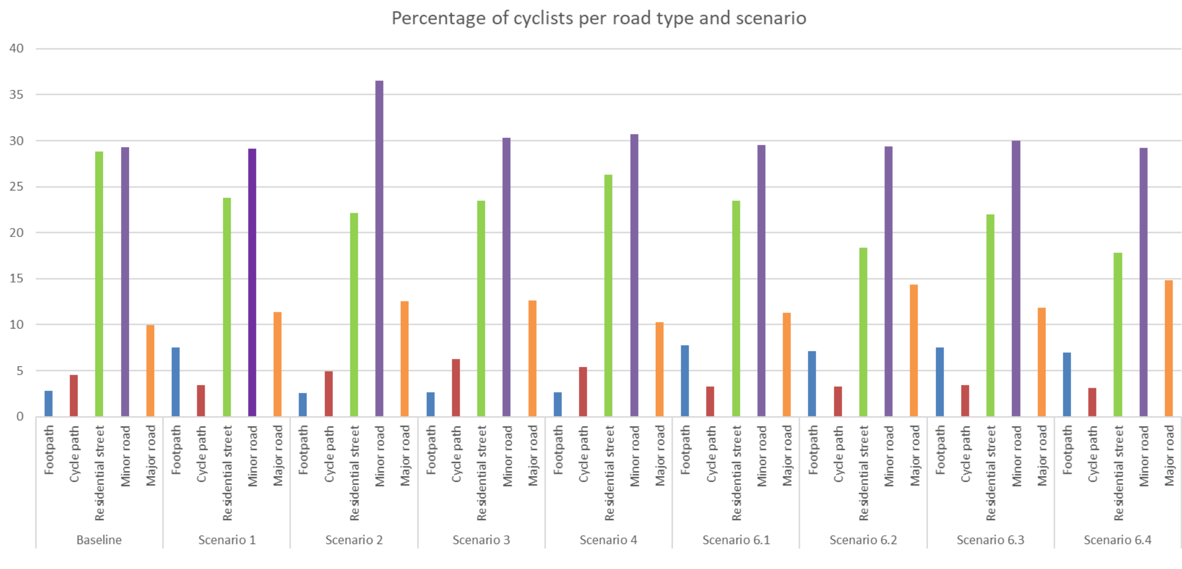


Figure 121 Percentage of cyclists per road type and scenario.

Figure 121 shows the percentage of cyclists using different road types per scenario (footpath in blue; cycle path in red; residential street in green; minor road in purple; and major road in orange). In all the cases, the use of minor roads (i.e., B and C roads in the UK) and residential streets is the trend, the first being used around 30% of the times in all scenarios, with a peak in scenario 2 above 35%, while the second range between 17% and 29%. In contrast, the number of cyclists using footpaths, cycle paths and major roads (i.e., A roads) are the minority in all the cases, ranging between 2.5-7.5%, 3.5-6.3% and 10-14.8%, respectively. In the case of cycle paths, it is worth noticing that in the study area there is a limited amount of them, accounting for less than the 2% of the total roads. Due to visualisation purposes, only five road types were analysed. Consequently, the total percentages do not reach 100%.

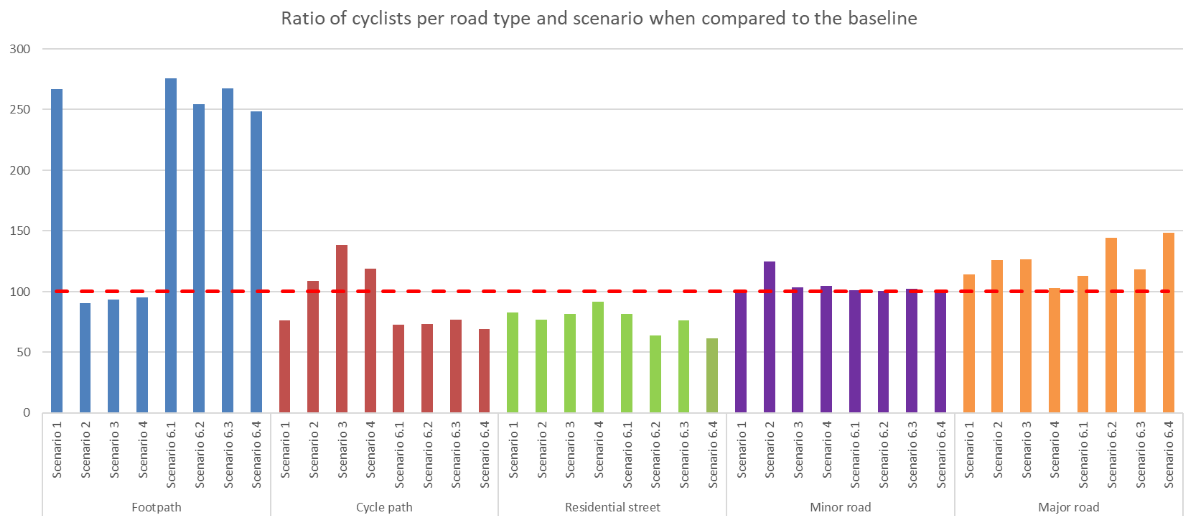


Figure 122 Ratio of cyclists per road type and scenario when compared to the baseline.

Figure 122 compares the ratio of cyclists using the different road types with the baseline (red dotted line). The use of footpaths is multiplied by 1.5 when segregated cycle paths are provided (i.e., scenarios 1, 6.1, 6.2, 6.3 and 6.4 with the maximum *quietness* index), while in the rest of cases their use is slightly reduced. In contrast, the use of cycle paths is only increased in those scenarios where additional cycle paths are not provided (i.e., scenarios 2, 3 and 4). This outcome is indicative of the expected behaviour of cyclists, who tend to use the existing cycle paths on their routes, as defined in the enabled MATSim bicycle extension (see section 3.6), taking into account the *quietness* value of each road (see section 3.4.4). The use of residential streets is reduced in all the cases, while the use of minor roads is kept constant in all of them except in scenario 2, where the percentage of cyclists using them is increased, being the most used road type (as shown previously in figure 121). Lastly, the use of major roads increases in all the cases, being more prominent in scenarios where the use of the bicycle is promoted (i.e., scenarios 1, 2, 3, 6.1, 6.2 and 6.4) rather than in those when policies are applied to penalise the use of cars (i.e., scenarios 4 and 6.3).

Number of lanes

Figure 123 shows the percentage of cyclists using different roads depending on the number of lanes per direction and per scenario (one lane in orange; two in blue; three in red; and four in green). As it can be observed, there is no doubt that cyclists prefer roads with a single lane. In all the cases, the percentage of cyclists using them is above 80%, the use of other roads being residual. Due to the lack of information of the number of lanes from all roads in the study area, the sum of all percentages per scenario are below 100%. Despite this issue, the use of roads with a single lane per direction is overwhelming.

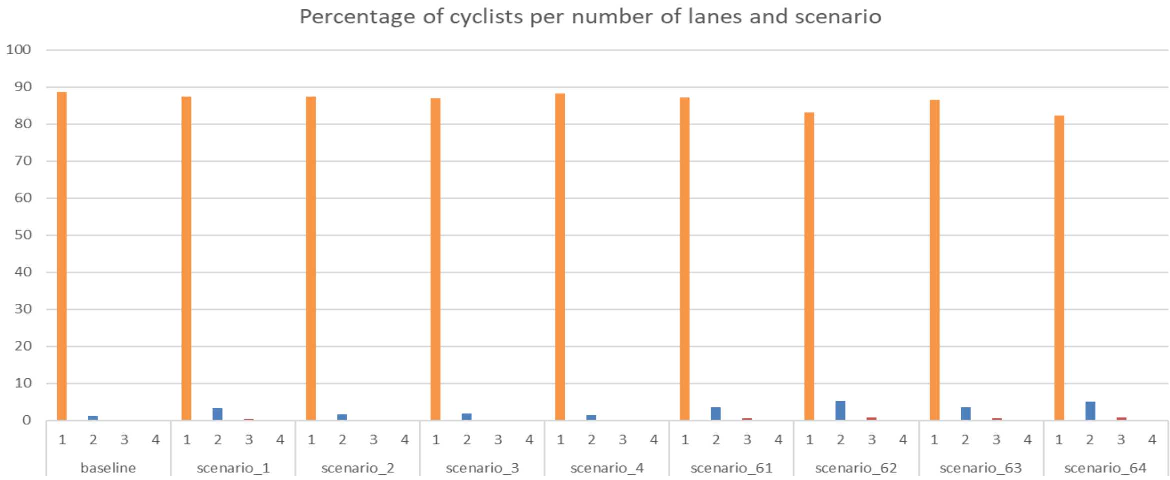


Figure 123 Percentage of cyclists per number of lanes in roads.

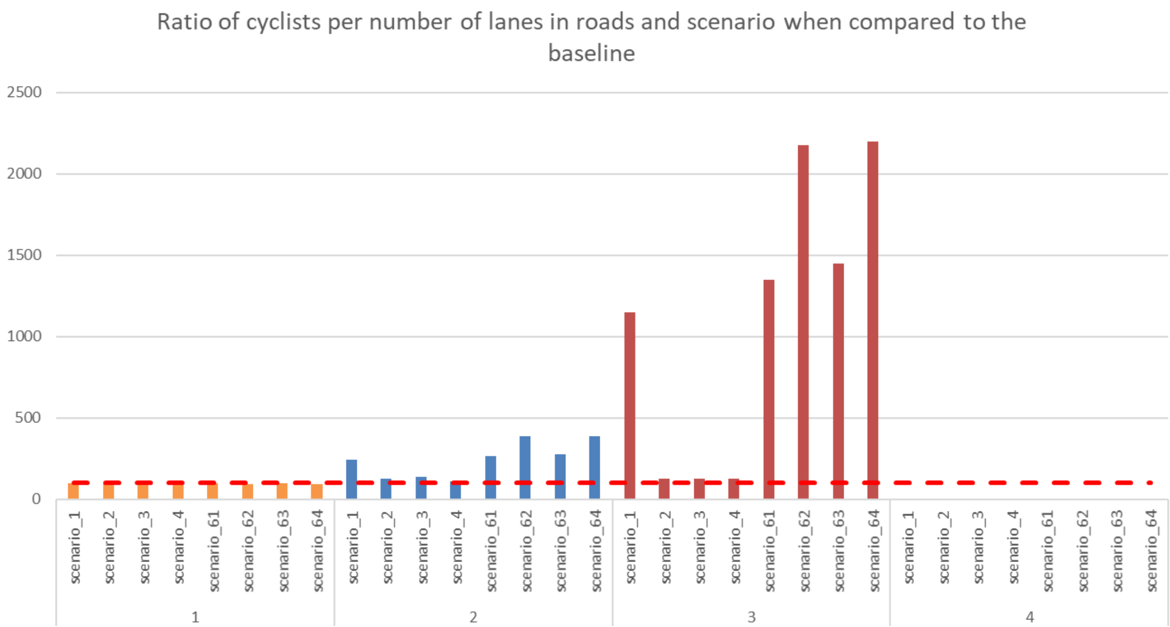


Figure 124 Ratio of cyclists per number of lanes in roads and scenario, when compared to the baseline.

When analysing the ratio of cyclists per number of lanes between scenarios and the baseline (red dotted line) in figure 124, it can be observed that the proportion of cyclists using roads with a single lane is kept constant in all the cases and similar to values from the baseline. Unlike the previous result, differences are observed on two- and three-road lanes. In both cases, the proportion of agents using them is increased when cycle paths are provided, multiplying the users by up to 20 and 300 in roads with two and three lanes, respectively. This outcome could suggest that some agents could have benefited from the inclusion of cycle routes in roads with more than one lane, allowing them to connect areas divided by roads with three lanes, such as motorways.

Road maximum speed

In terms of road maximum speed, figure 125 shows the different percentages of cyclists using them per scenario (purple up to 5 kilometres per hour (km/h); orange between 5 and 20; blue between 20 and 30; red between 30 and 80; and green above 80 km/h). Roads between 5 to 30 km/h are the most used in all scenarios (principally those between 20 and 30 km/h), while those below 5 and above 30 km/h are the least uses. The first group belongs to residential and minor roads. The second group comprises areas shared with pedestrians (below 5 km/h) and major roads or highways (above 30 km/h). These results agree with those shown in figure 121, where the road type was analysed.

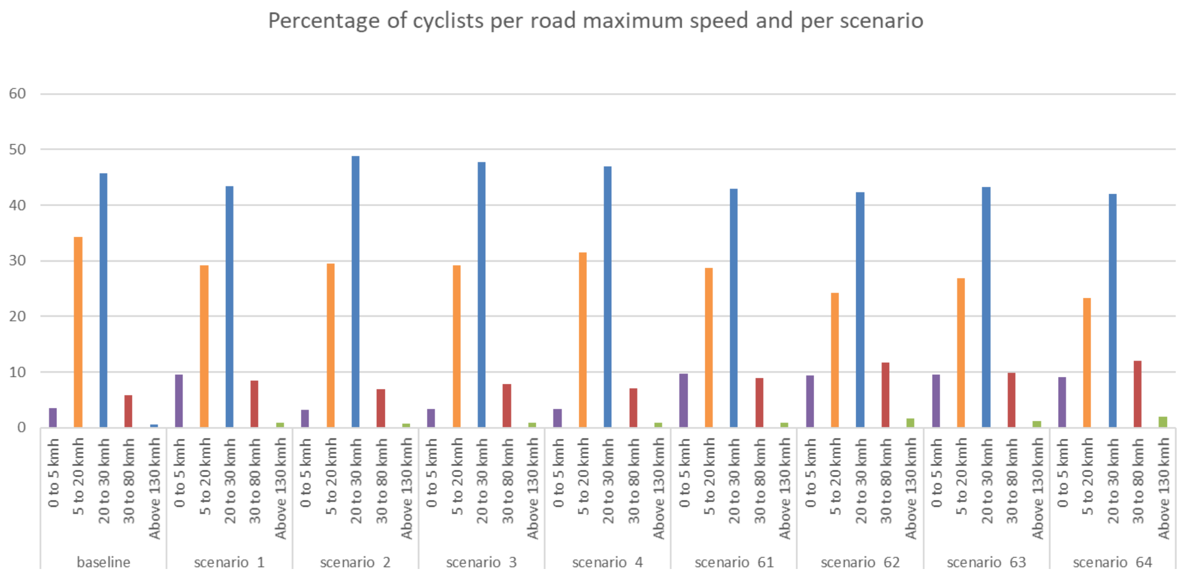


Figure 125 Percentage of cyclists per road maximum speed and scenario.

When analysing the ratio of cyclists between scenarios and the baseline (figure 126), several differences are also observed. The use of roads up to 5 km/h is incremented by more than 1.5 times when cycle paths are implemented (i.e., scenarios 1, 6.1, 6.2, 6.3 and 6.4), in a similar proportion as shown in figure 122 when the road type for footpaths was analysed. For those roads between 5 and 20 km/h, reductions are observed in all the cases, being up to 30% in the worst case (i.e., scenario 6.4). Similar results as in the baseline are observed in roads where speed is between 20 and 30 km/h. However, those scenarios where cycle paths are implemented have a reduction up to 9% (scenario 6.4), while those without them are increased up to 7% (scenario 2).

Results obtained in roads where speed is between 30 and 80 are similar to those obtained in roads above 80 km/h, although in a higher proportion for the latter. These results are in line with the outcomes obtained in the previous road lane analysis, where the use of roads with more than one lane is increased, especially in those scenarios where new segregated infrastructures for cycling are provided. This outcome could also support the case made in the previous road lane analysis, where some agents could have been potentially affected by the lack of cycle routes in roads with more than one lane, which are normally fast routes.

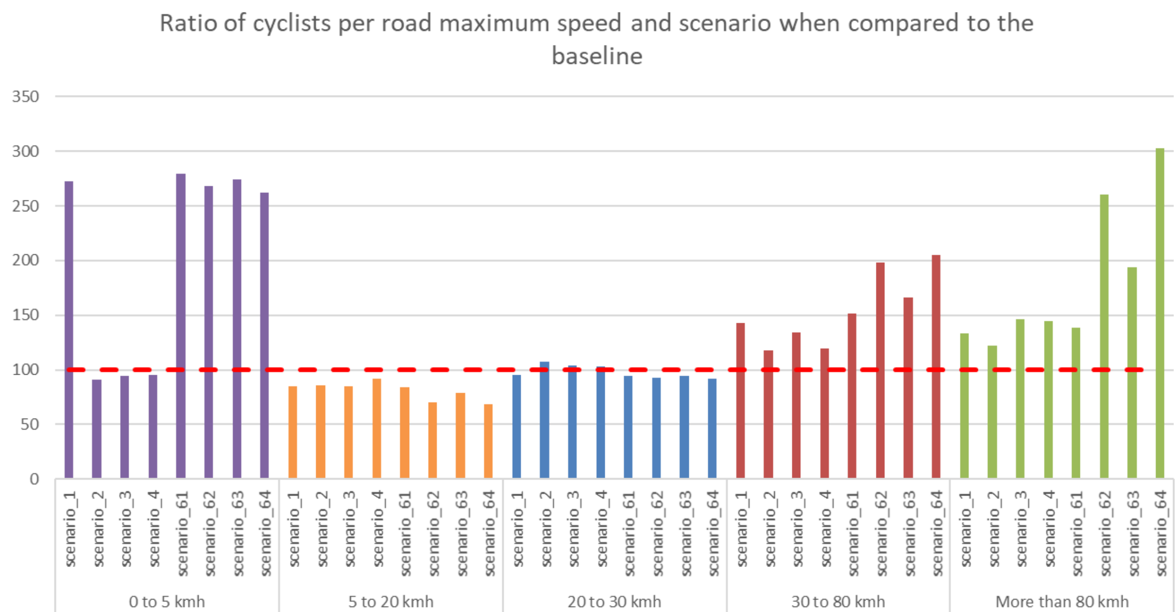


Figure 126 Ratio of cyclists per road maximum speed and scenario.

4.4.10. Economic results

Another factor to take into account relates to the economic consequences of the applied scenarios. In some of them, economic rewards and/or penalties are applied to modify the behaviours of the agents, influencing negatively or positively the economic resources of the LAs. The first type requires LAs to pay each individual using active modes, while the second consists of benefits paid by those using private cars. Additionally, the achieved health benefits (see section 4.4.8) also generate an economic impact, as those avoiding premature deaths continue contributing to society. Table 12 quantifies the daily economic impact of each scenario simulated considering the previous three factors. Economic reward and penalty values were derived from the simulated results (i.e., number of kilometres walked or cycled multiplied by the reward (£0.15), and number of unique agents using private cars multiplied by the toll (£2.5), respectively). Economic health benefits were derived from the HEAT tool (WHO, 2024), using the average kilometres walked and cycled per agent, as described in section 4.4.8.

	Daily economic reward required (£)	**Daily economic penalty collected (£)**	**Daily health impact achieved (£)**	**Total daily economic impact (£)**
Scenario 1			656	656
Scenario 2			-139	-139
Scenario 3	59,599		19,917	-39,682
Scenario 4		191,473	7,556	199,029
Scenario 5			-121	-121
Scenario 6.1			5,253	5,253
Scenario 6.2	111,196		40,778	-70,418
Scenario 6.3		173,142	16,889	190,031
Scenario 6.4	167,482	120,920	66,639	20,077

Table 12 Total economic reward and penalty values per scenario simulated depending on the applied policies

Scenarios applying economic penalties achieve a positive balance (i.e., scenarios 4, 6.3 and 6.4), besides scenarios 1 and 6.1, where economic policies are not simulated. The implementation of economic rewards always has negative balances, except when combined with economic penalties, balancing the total amount and making it positive. Negative values in the economic health column indicate that fewer people use active modes than in the baseline, as shown in table 12.

Furthermore, the number of car and active mode users on the roads has its effects in the balance between the amount of budget required to pay the rewards and the amount collected when applying tolls. When the economic policies are simulated individually (scenarios 3 and 4), a higher economic value is obtained from the penalty (scenario 4) than from the reward (scenario 3). Having fewer cars on the roads and more active users as in scenario 6.4 (where both policies are simulated together) made the potential positive profit become negative. This scenario is only attractive when other positive economic factors, such as the economic health impact is taken into account.

It is worth noting that the economic budgets required to implement each scenario (e.g., the construction of fully segregated cycle paths, the strategies to avoid cars in residential roads, mobile applications to quantify the kilometres walked and cycled, the implantation of tolls for car users, or cycle hubs next to metro stations) are out of the scope of this thesis. Future work could investigate them and identify realistic zones in the study area to be prioritised.

4.4.11. Cycling hubs results

Several scenarios consider the possibility of combining the use of the bicycle and metro when travelling. This is the case of scenarios 5, 6.1, 6.2, 6.3 and 6.4, where the possibility of accessing and egressing metro station with a bicycle is simulated, assuming the agents can leave the bicycle in a secure and safe place (e.g., cycle hub). For these scenarios, the total number of cycle hub users and the percentage ratio per scenario, the most used cycle hubs and their geospatial locations showing the use made by the agents were analysed.

Table 13 shows the number of agents that used the cycle hubs per scenario, besides the percentage increase ratio when compared against the baseline (scenario 5).

	Cycle Hub Users	% Ratio
Scenario 5	352	1 (baseline)
Scenario 6.1	1960	557
Scenario 6.2	1512	430
Scenario 6.3	4312	1225
Scenario 6.4	2644	751

Table 13 Number of cycle hub users and the ratio when results from each scenario are compared with the baseline.

Table 14 shows the 10 metro stations most accessed and/or egressed by bicycle per scenario simulated.

SCENARIO 5	
Station	**Users**
Monument	21
Central Station	16
Haymarket	13
Chichester	12
Gateshead	12
Jesmond	12
South Shields	12
Monkseaton	11
North Shields	11
Brockley Whins	10

SCENARIO 6.1	
Station	**Users**
Monument	139
Haymarket	94
Central Station	81
North Shields	67
Gateshead	60
Felling	56
South Shields	56
Jesmond	54
South Gosforth	54
Jarrow	53

SCENARIO 6.2	
Station	**Users**
Monument	114
Haymarket	81
Central Station	73
Gateshead	54
South Shields	50
Jesmond	47
Monkseaton	47
North Shields	37
Brockley Whins	36
East Boldon	36

SCENARIO 6.3	
Station	**Users**
Monument	265
North Shields	160
Central Station	151
East Boldon	145
Gateshead	128
Felling	115
Haymarket	115
South Shields	115
Hebburn	105
Jarrow	105

SCENARIO 6.4	
Station	**Users**
Monument	187
Central Station	116
South Shields	101
Haymarket	100
Gateshead	99
East Boldon	80
West Monkseaton	79
North Shields	77
Monkseaton	71
Tyne Dock	70

Table 14 Top ten metro stations most used by cyclists per scenario simulated.

Lastly, the results were projected on a map. Figure 127 shows the location of the metro stations and their potential number of users per scenario simulated. Circle size represents the number of users, while colours identify the simulated scenario that could achieve those results (scenario 5 in black, scenario 6.1 in red, scenario 6.2 in green, scenario 6.3 in yellow and scenario 6.4 in blue).

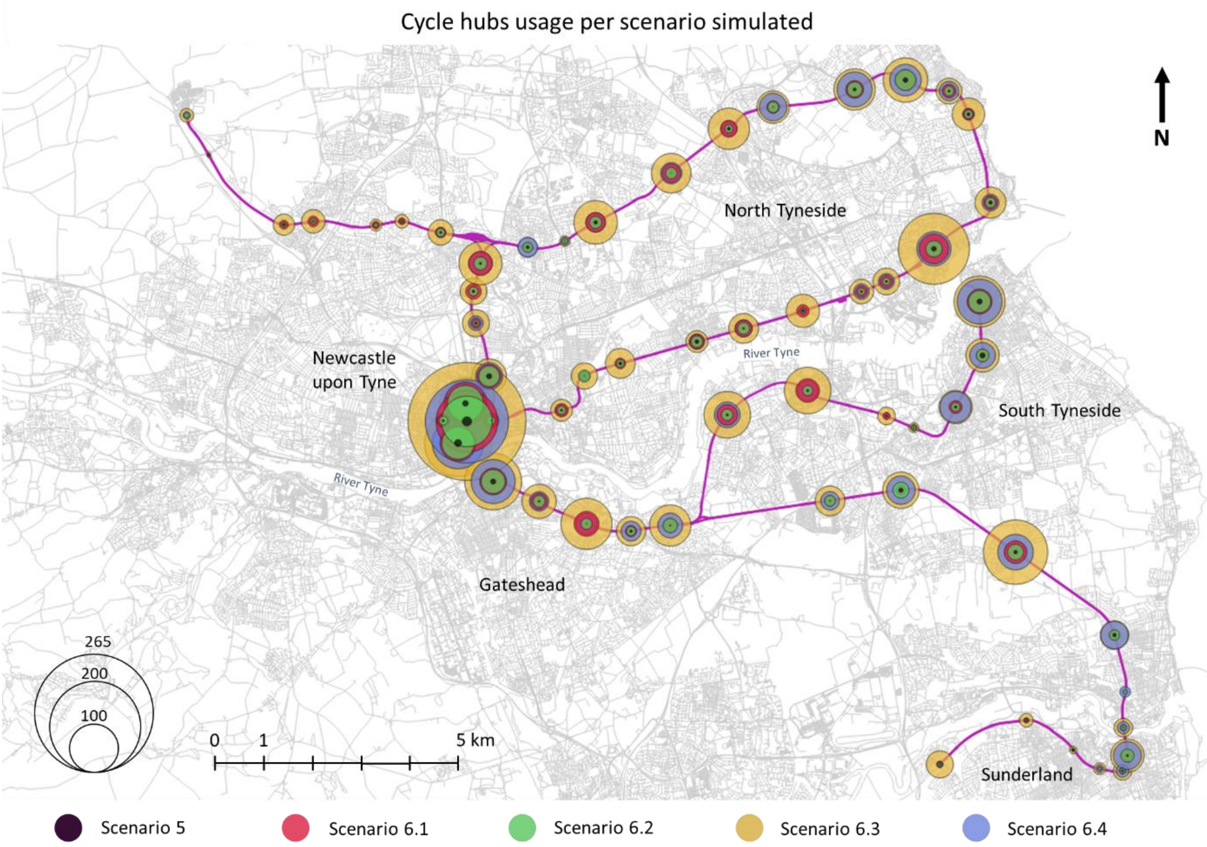


Figure 127 Cycle hub usage per scenario simulated.

Results obtained in scenario 5 show that 352 agents decided to use the bicycle and the metro in the same journey (table 13). The most used metro stations (table 14) are allocated in Newcastle (e.g., Monument (21), Central Station (16), Haymarket (13), Jesmond (12)), North Tyneside (North Shields (11), Monkseaton (11)), South Tyneside (Chichester (12), South Shields (12), Brockley Whins (10)) and Gateshead (Gateshead (12)) (figure 127). No metro stations in Sunderland were found in the top ten used by cyclists. A further analysis of the reasons why these stations were the most used by cyclists could be developed in future research, to identify average trip distances and trip purposes, among others. Due to a limited timeframe, this analysis was discarded to be done during the thesis, although it is encouraged for a future research project. Results obtained show the potential use of these two sustainable transport modes in the same trip, as an alternative to private cars. Following simulated scenarios analysis there is the possibility of combining this scenario with some of the previous ones, to identify if more individuals could be attracted to this combination of modes when fully segregated cycle paths, LTNs, active travel rewards and/or economic penalties when using private cars are implemented together.

In contrast to scenario 5, the agents have full access to the metro stations with fully segregated and safe cycle paths in scenario 6.1, which is a great boost to increase the number of individuals combining these two modes. Based on results achieved, 1,960 agents did this, which represents a 5.5 times increase compared to scenario 5 (table 13). The ten most used cycle hubs were allocated in Newcastle (Monument (139), Haymarket (94), Central station (81), Jesmond (54), South Gosforth (54)), South Tyneside (South Shields (56), Jarrow (53)), North Tyneside (North Shields (67)) and Gateshead (Gateshead (60), Felling (56)), eight of them being the same as in scenario 5 (table 14). No metro stations from Sunderland were found in the 10 most used, similar to scenario 5. In terms of geospatial distribution (figure 127), most of the cycle hubs users were found in the city centre of Newcastle, followed by a relatively homogeneous distribution in the stations allocated in the rest of Newcastle (except the northern link connecting with the airport), Gateshead and North Tyneside. Lower values of use were observed in South Tyneside (with the exceptions of South Shields, Jarrow and Hebburn stations) and Sunderland. East Boldon station, located between South Tyneside and Sunderland also received a substantial amount of users because an industrial estate is found there.

The effects of the cycle hubs in scenario 6.2 were also notable, as the number of agents that combined the use of bicycles and metro was 1,512, which is 4.3 times higher than the baseline (scenario 5) (table 13). However, this achieved value is 23% lower than in the previous scenario, where a total of 1,960 users were counted. This reduction can be explained in line with previous results analysed: the use of the bicycle supported by an economic reward is more attractive than public transport modes. The 10 most used cycle hubs (table 14) were located in Newcastle (Monument (114), Haymarket (81), Central Station (73), Jesmond (47)), North Tyneside (North Shields (37), Monkseaton (47)), South Tyneside (South Shields (50), Brockley Whins (36) and East Boldon (36)) and Gateshead (Gateshead (54)). No metro stations in Sunderland were found in the top 10 most used, as in the previously analysed scenarios. Analysing the results geospatially (figure 127), a similar pattern can be observed as in scenario 6.1 with lower values in general, although higher values are obtained in Sunderland (e.g., Seaburn and Sunderland), South Tyneside (e.g., Brockley Whins) and Newcastle (Chillingham Road, Longbenton, Four Lane Ends and Airport). Further investigation to identify the reasons why some areas reduced the number of users more than others is recommended.

The use of cycle hubs in scenario 6.3 is the highest when compared to any other scenario simulated, as a total of 4,312 agents used them, which is more than 12 times the baseline (scenario 5) (table 13). The main reasons for this increase are that more former car users have the need to find an alternative transport mode (18%) than in the previous scenarios and the lack of any economic reward for the use of active modes, making the use of the metro more attractive. The 10 cycle hubs most used by the agents are located in Newcastle (Monument (265), Central station (151), Haymarket (115)), North Tyneside (North Shields (160)), South Tyneside (East Boldon (145), South Shields (115), Hebburn (105), Jarrow (105)) and Gateshead (Gateshead (128), Felling (115)) (table 14). None was found in Sunderland, as in the previous scenarios. Although similar results were obtained when compared with previous scenarios (i.e., the same six stations were the most used ones in all scenarios (Monument, Central Station, Haymarket, North Shields, South Shields, Gateshead)), a great increment of cycle hub users in South Tyneside was experienced, as three stations were found within the 10 most used (instead of two). The amount of users in North Shields station (North Tyneside) and East Boldon (South Tyneside) is also remarkable, being the second and fourth most used, in contrast with their results in the previous scenarios. The first is located near a shopping area, where the second has an industrial estate in the surrounding area. The geospatial representation (figure 127) shows a similar pattern as in scenario 6.2, where most users are found in Newcastle (except the branch of the network that connects with the airport), followed by Gateshead, North Tyneside (especially in the northerly stations) and South Tyneside (principally East Boldon and those stations close to the river). A general increase is also observed in Sunderland, especially in the city centre, although the level of use is still far from other stations in the network.

The use of the new implemented cycle hubs next to metro stations was also remarkable in scenario 6.4, achieving the second highest value (2,644), which is a seven-time increase when compared against the baseline (table 13). When comparing results with other scenarios, it can be observed that the outcomes are between those from scenarios 6.2 and 6.3, where economic rewards for active modes and economic penalties for cars were simulated, respectively, besides the implementation of fully segregated cycle paths, LTNs and cycle hubs in both. Scenario 6.4 is a combination of the previous two scenarios, as all individual measures from both scenarios were simulated together, achieving intermediate results, something reasonable and expected. More agents were attracted by the combination of cycling and metro than in scenario 6.2 because more agents were forced to find an alternative mode due to the economic penalty implemented for car users. However, fewer agents were attracted than in scenario 6.3 because of the economic reward given when walking or cycling, making these modes more attractive than public modes.

The 10 most used cycle hubs by the agents in scenario 6.4 were very similar to those in the previous scenarios (table 14). The main differences are found in West Monkseaton and Tyne Dock, two stations that were not found in the top 10 in any of the previous scenarios. Both are in residential areas with schools, shopping areas and medical centres in the vicinity. The geospatial distribution of the cycle hubs usage (figure 127) shows a similar pattern as in the previous cases, where most users are located in the city centre of Newcastle, the NE and main urban area of North Tyneside, North of Gateshead, main urban areas of South Tyneside and the station of East Boldon. In the area of Sunderland, results obtained are more similar to those from scenario 6.3, with a similar number of users in the stations allocated in the city centre.

The following chapter provides insight on the principal outcomes achieved in this doctoral thesis, as well as discussing the work presented from the perspective of all stages identified in the methodology, considering the assumptions and limitations acknowledged. The research questions identified in chapter 1 are reviewed, providing a realistic and fair view of the level achieved with respect to the established goal of the thesis. Besides, future work that researchers could consider is identified. Additionally, the implications of research for researchers, practitioners and policy makers are discussed. Lastly, a conclusion of the doctoral thesis is provided.

Chapter 5. Discussion and Conclusion

I would give everything I know for half of what I ignore. René Descartes

This doctoral thesis has brought some insight to a particular challenging and timely topic: the decarbonisation of the transport sector in favour of active modes, applying AgBM techniques. The use of AgBMs is a novel approach within the transport sector. They improve the less-detailed but faster models that have been commonly used in recent decades (e.g., the FSM), providing an understanding of urban transport mobility considering spatio-temporal and socio-demographic characteristics.

Beyond the research done using this incipient methodology in transport modelling, this PhD research project has proposed four novel innovations to simulate transport scenarios within the UK context:

- A new, open-access and very detailed synthetic population methodology that can be applied to any region in England (see section 3.3.3).
- The use of a new network attribute (*quietness*) ranking road links for cycling based on their built characteristics (see section 3.4.4).
- A bicycle contribution update considering the *quietness* attribute when cyclists choose their routes (see section 3.4.4).
- A tailored set of scenarios to test urban mobility policies in Tyne and Wear to enable the agents to use active travel modes (walking and cycling) instead of private motor vehicles (see section 3.8).

The identified research gap was precise, as well as the methodology proposed based on a set of concrete objectives required to achieve the goal. Results obtained provide some interesting outcomes about the potential efficiency of different policies in favour of more sustainable transport, as well as the role of AgBMs in exploring them.

This last chapter concludes the thesis with a global review of the whole document. A summary of the principal outcomes achieved, a discussion regarding the work presented, a review of the research questions defined in chapter 1, a set of future work identified and a description of the implications of the developed work for research and policymakers are provided.

5.1. Principal outcomes

The principal outcomes of the thesis with respect to the original objectives were as follows:

To review the climate change context, the main greenhouse gas sector emitters, the current status of the transport mobility in England and the different urban mobility strategies to tackle the decarbonisation of the transport sector.

Chapter 1 introduces the reader to the climate change context and the role of the transport sector in the UK. Firstly, the climate change concept and its expected worldwide consequences were defined based on official reports and scientific research, pointing out the severity of the situation and the urgency to act. Secondly, comparisons between the GHG emissions by economic sectors were made, with a special interest in the UK context, where the transport sector was identified as the largest GHG emitter and, therefore, one of the most pressing sectors that need to be decarbonised.

Chapter 2 presented the current transport mobility of English society, highlighting a car-centric dependency in contrast to the minimum use of more sustainable transport modes (e.g., bicycle). According to the previously identified car-dependency, several transport strategies for a greener and more sustainable sector were analysed and structured in three main blocks: the decarbonisation of road transport and the modal shift to public and active modes. The first focuses on shifting polluting fossil-fuelled vehicles to zero emission vehicles; the second tries to provide more comfortable and reliable public services; while the third enables the use of active transport modes. Among the three options, scientific analysis suggests the most complete and efficient strategy for the short and medium term is active travel, the others being fundamental for the medium and long-term. Even more, the use of active modes also provides physical and mental health benefits, besides a reduction in transport noise and frees up urban space for better societal interactions.

To review the different models used in transport research and the current use of AgBMs in simulating urban mobility scenarios.

Chapter 2 also reviewed the different transport models to analyse mobility policies. Three models were identified as candidates: FSMs, AcBMs and AgBMs. The first is the easiest but the simplest, without any consideration of socio-demographic attributes and geospatial locations and characteristics. The second is more complex and heterogeneous, as non-aggregated data with information of individuals in space and time are considered. The third has similar characteristics to the second, but also allows the interactions of the agents in space and time, besides the possibility of taking into account characteristics of the built environment (e.g., road type, gradient). The characteristics of the last model, although making it more complex and difficult to implement, made it the most appropriate to analyse policies focusing on active modes.

The use of transport AgBMs in research has been mainly related to emerging transport modes, especially for EVs, the number of publications where active modes are the core of the investigation being low. This is principally due to the heterogeneous nature of active travel behaviours and the lack of granulated data to analyse them (e.g., road characteristics and counts). The small number of publications simulating active modes are mainly related to safety, human behavioural and policy interventions to reduce the number of people using private polluting vehicles and increase active travellers, although considering none or minimum characteristics of the built environment. The literature review finalises comparing different AgBM tools to identify the most appropriate to simulate active modes. Within them, MATSim stood out as an open-source, fully dedicated and well-known transport modelling tool. Individuals are simulated within a microscopic road network during a complete day. Different transport modes are allowed, with the possibility of simulating bicycles considering the characteristics of the roads.

To develop a very detailed synthetic travel demand that represents the individuals living in the area of study based on a set of socio-demographic attributes with a detailed activity plan, using open access tools and datasets, when possible.

Chapter 3 described the development of a very detailed synthetic travel demand methodology, which can be transferred to any other region in England. Firstly, a fully open-source synthetic population methodology was developed, combining the use of SPENSER (Lomax, 2023) and synthPopEng (Alvarez Castro, 2022), being the first contribution developed in this thesis. The outcome was a set of 12 socio-demographic attributes defining each individual (table 1), where individual characteristics (e.g., age, sex), geospatial location (e.g., household location at OA area), family dependencies (e.g., marital status, children dependency), spending power (e.g., economic activity, occupation, annual gross income) and mobility access characteristics (e.g., driving license, car access and bicycle access) were defined. Secondly, the synthetic population was combined with activity plans using NTS datasets to add mobility information to each agent, based on common socio-demographic attributes. Additionally, shared trips among members from the same household were kept, when possible, for a more realistic mobility representation.

Chapter 4 showed the results obtained when the previous methodology was applied to the NE of England. The result was a synthetic travel demand that defines the daily urban mobility of each individual in the study area.

To develop a combined road and public transport network to allow the individuals from the synthetic population to move between activities, with a special interest in characteristics that support the use of active modes (e.g., road network characteristics, elevation and cycleability rating).

Furthermore, chapter 3 presented the followed methodology to develop the network used by the individuals to move between activities. It consisted of the combination of roads and public transport networks, containing all the information required for the use of private cars (e.g., maximum speed, flow capacity, allowed modes) and transit modes (e.g., stops, schedules, routes).

Additionally, elevation information was added to the network using a DEM. Altitude values were assigned to nodes and gradient to the links, providing a third dimension to the network, a fundamental component when simulating active modes. The second innovation developed in the thesis was the inclusion of the *quietness* attribute generated by Cyclestreets (2022a), which ranks the quality of roads for cycling based on their built environmental characteristics. To the best of the author's knowledge, this is the first time this attribute has been used in transport AgBMs. This is an important upgrade, as the knowledge of this characteristic is considered by the cycling agents when choosing their routes, during the simulation stage.

Chapter 4 showed the results achieved when the methodology was applied to the NE of England. This is valuable information to understand the different link hierarchies in the study area, and its potential uses by the different allowed modes when choosing a transport route.

To calibrate and validate a transport AgBM model that simulates the normal transport mobility during a regular day in the study area, where the simulation of cycling routes consider some of the characteristics implemented into the developed network, for a more realistic and accurate understanding of cyclists' behaviours.

Chapter 3 described the steps followed to calibrate and validate the transport model of the Tyne and Wear region, using the previously generated synthetic travel plans and network datasets.

The calibration consisted of identifying the different modules and parameters required to simulate a realistic baseline with active modes. Moreover, the bicycle extension was updated to consider the *quietness* attribute included previously within the network, being the third innovation developed in the thesis. This addition allowed the agents to choose their routes based on the *quietness* and the gradient attributes instead of the other original parameters (i.e., type of road and comfort). This is an improvement, as the new attribute contains more relevant information for cycling than the original parameters, besides its greater geographical extension knowledge with minimum gaps. This updated bicycle extension was developed with the help and support of Dr Ziemke, the main developer of the original bicycle extension. To the best of the author's knowledge, this is the first time the bicycle extension has been updated to consider the *quietness* attribute. A new MATSim version including this update was released (i.e., version 15.0-PR2396) to be used by any other researcher.

The validation phase aimed to verify that results achieved represent normal urban mobility when aggregated values and geospatial representations were compared with official statistical data. Although a global and homogeneous validation method has not been developed yet, the model results were compared with data from different approaches for a more reliable and realistic outcome: transport (e.g., modal split modes), geospatial (e.g., vehicle counts at various locations) and average trip values (e.g., trip times and distances by mode). The outcome was a model that represents, in space and time, regular mobility of the different transport modes allowed in Tyne and Wear. Chapter 4 showed the results of the validated MATSim model of the Tyne Wear region.

To define, code and simulate a set of urban mobility policies to reduce the number of private and polluting vehicles on the roads in favour of active modes.

Chapter 3 defined a set of urban mobility policies to enable the use of active modes instead of private and polluting cars. The first consisted of implementing fully segregated and safe cycle paths on every road of the study area, reducing the flow capacity of cars to accommodate the space for cyclists. The second defined LTNs, restricting the use of residential roads to car users. The third applied economic rewards to those individuals using active modes. The fourth was opposite to the previous, as economic penalties were applied to those agents using private motor vehicles, as a toll to disincentivise their use and encourage more sustainable modes. The fifth combined the use of the bicycle and the metro, allowing the agents to leave the bicycle in a secure and safe place (i.e., cycle hub). Besides them, four different combinations of the previous policies were defined. The main goal was to test if their joint implementations achieve better results than when applied individually, as well as their spatial impact in the study area.

Chapter 4 presented the results achieved when the scenarios were applied to the Tyne and Wear region. Diverse levels of efficiency in reducing the number of cars on the roads were achieved, depending on the policy or policies simulated.

5.2. Discussion of work presented

The body of work in this thesis has been focused on three pillars. Firstly, the development of the two main components required for the use of a MATSim model (i.e., synthetic travel demand and network). Secondly, the model calibration and validation. Thirdly, the simulation of different mobility scenarios to test their efficiency in reducing the number of polluting vehicles for a more sustainable transport sector.

This section reviews a number of decisions that were taken to ensure practical application of the methodology proposed in the available time. Discussion of the results achieved, considering the implication of the assumptions and limitations acknowledged is provided.

5.2.1. Synthetic travel demand

The work presented in this thesis showed the limitations of the existing methods to develop a synthetic population in the UK context. On the one hand, a tool was identified for the UK with a very limited quantity of socio-demographic attributes (i.e., SPENSER). On the other hand, a more detailed tool used for different regions in the world, but never in the UK (i.e., Eqasim). The choice was to use the first and include eight extra socio-demographic attributes, which would provide more detailed results than the latter option considered.

This decision allows simulation of an overly complex and heterogeneous digital representation of the individuals, as a wider variety of characteristics to define a more diverse and integrated society is taken into account. Therefore, the possibility of considering minority groups within society was increased, showing a more realistic view of the world. This is a crucial factor to consider, as some groups in society could have been ignored (e.g., a single person with children dependencies, unemployed and without access to a car).

The provision of attributes focused on family dependencies, spending power and mobility access, makes this developed methodology an unbelievably valuable outcome of this thesis. It was intended to consider as many human realities as possible to minimise the possibility of under-representing sub-groups in society, within the framework of a responsible research and innovation process.

Despite the increased number of attributes, the methodology has two main limitations. Firstly, the attributes are incrementally developed, based on relationships between them (e.g., income depends on economic activity and occupation), as described in section 3.3.3. This means that the accuracy and precision of each new attribute depends on the accuracy and precision achieved in those generated previously. Inaccuracies could be propagated through the process, producing unrealistic representations in the study area (figure 10 shows the interdependencies among the attributes). Future work to improve the validation process and minimise the potential inaccuracies are described in Section 5.4.1. Secondly, the methodology is a purely linear projection of population based on statistical data, without including changes in employment, new construction developments or transport infrastructures, to name just a few. A more complex methodology could be developed or used (e.g., SILO (Moeckel, 2016)) to take into account future projected construction developments that can affect the locations of the synthetic individuals.

The results achieved when the methodology was applied to the NE of England show a very realistic representation of the population. The differences against observed national or regional statistics were relatively low in all cases where data was available (i.e., marital status (<5%), children dependency (< 5%), economic activity (<2%), occupation (< 3.5%), annual gross income (< £1000 per decile), driving license (< 1%)). The impact of these differences in the scenarios simulated was expected to be relatively small, with the potential for underestimating subpopulations of agents that are married or have children dependencies, among others, as these attributes obtained the highest discrepancies (below 5%).

The results achieved show the potential to develop very detailed synthetic populations that could be applied to a great diversity of fields (e.g., transport, land use, social science) in any region of England, as open access and open-source tools were used through the entire process.

The synthetic population was complemented with activity plans. Although there is a possibility of missing short trips when using travel diaries (due to forgetfulness on the part of the interviewees), its use was preferable to data derived from mobile phones. This last option lacks socio-demographic information (due to privacy reasons) and information is provided as aggregated values per geographic areas (MSOA zones).

In the methodology proposed, it was assumed that individuals with similar socio-demographic attributes have similar mobility behaviours, which has been shown to be credible and realistic in research. Every synthetic individual was assigned a set of activities based on their socio-demographic attributes and, in some cases, the interactions with other members from the same household. The results showed that more short trips (principally below 5 miles) than those observed in travel diaries were obtained. Instead of considering this as an error, it was accepted as a potential (and unexpected) correction of the potential forgotten short trips that individuals did not include in their travel survey. Differences in average trip time by mode were within three minutes. More differences were found in the percentage of trip purposes, where more commuting and education trips were obtained (around 10 and 15%, respectively). Although several and combined reasons can be the cause of these differences, it was considered a possibility that the proportion of employed and student individuals who submit the surveys was lower than the proportions included in the synthetic population as the main one.

5.2.2. Network

The outcome achieved with the development of the network was a very detailed road and public transport graph, composed of nodes and lines defining the road, train, metro and ferry networks used by different transport modes. Despite open-source tools being a hallmark within the thesis, it was decided to use an alternative dedicated tool developed by Arup (i.e., PUMA) to merge both networks (road and public transport). Permission was given for the tool to be used in the thesis and a mentoring connection was established in exchange for testing the tool and providing feedback. This collaboration allowed the engagement between academia and industry, where the knowledge and experience of the latter allowed the development of a scientific research project for the former.

Additionally, the inclusion of the *quietness* attribute allows the agents to choose realistic routes when cycling, where the possibility of selecting safe routes would be more likely than dangerous routes (e.g., shared with other vehicles). To complement a realistic network representation, elevation and gradient values were added to the nodes and links, respectively. These factors are then used within the simulation stage, where the cycling agents choose their routes based on the quality of the roads.

Despite following different validation stages to improve the quality of the open access data, errors are still expected because of the potential lack of familiarity of the OSM volunteers that digitised the area. The impact of these potential errors could cause unrealistic mobility patterns in specific zones of the study area. However, it was expected that the consequences would be minimal, since the probability of finding them was greater in non-urban areas than in the principal areas of the study area.

5.2.3. MATSim model

The MATSim model calibration stage defined the modules and parameters used in the simulation, where specific characteristics were assigned to each available transport mode, and therefore, several assumptions and limitations were agreed:

- Car use restrictions were applied to allow only those individuals with car access to drive for a more realistic simulation result.
- Public transport modes were simulated as deterministic, without any maximum capacity and cost to reduce the computational complexity and time. These assumptions could cause a higher attractiveness for these modes, although their attractiveness was compensated with the ASC values applied to each mode.
- Walking was teleported as a consequence of the lack of two main components: a detailed network information and a MATSim extension to simulate it in an analogous manner to cycling. This could alter the attractiveness of walking, as simpler routes were used (i.e., Euclidean distances between origin and destination multiplied by a factor to take into account potential detours), although the ASC values used for the rest of the modes should help in balancing the attractiveness of walking.
- Unfortunately, it was not possible to restrict the use of bicycles to specific individuals based on their socio-demographic attributes (i.e., bicycle access), as was done for car drivers. Consequently, it was assumed that all agents have access to bicycles, since the main barrier for owning a bicycle could be the need to buy one, which should not involve a large financial outlay and be within the reach of almost the entire population.

The validation stage showed a complex procedure, where engagement with stakeholders from academia, industry and policy makers was required. The validation of the transport mode shares was not a simple task, as official sources where the percentages of transport modes for all trip purposes in the NE of England that interact with the Tyne and Wear region were not found. Alternatively, the use of statistical data of specific trip purposes (e.g., commuting and travel to school), the knowledge of the number of vehicles counts per hour at different zones in Tyne and Wear and expert advice, allowed identification of the global transport split modes of the study area. The possibility of interacting with experts in transport mobility was a valuable contribution for the project, as this engagement allowed identification of the followed method to validate the transport mode shares in the study area.

Some discrepancies were found when average trip times and distances by transport mode were compared with NTS statistics. The average simulated trips were shorter in distances and times in general, even after updating the road network (e.g., reducing maximum speed in urban areas) to consider the effects of intersections and traffic lights, also applied in Ziemke (2022). Due to the discrepancies found, probably due to the geographical extensions of the official sources (i.e., the average trip distances were compared with NTS data of the whole NE, while the average trip times with NTS data of the whole of England), individual simulated trips were compared with Google routes. The results were remarkably similar in both, the chosen routes and the estimated times required. This comparison method, although it was applied to a small but random number of trips, helped validate the results achieved and verify that the agents were following a normal behaviour, in space and time.

An important validation stage was the verification of the cycling routes when the updated bicycle extension was enabled. Results showed that the agents choose flatter routes and the use of existing cycle paths, when possible. The main consequences of this implementation were the simulation of longer trips and more realistic behaviours, which were verified by real cyclists from the study area. These results showed the success achieved in the use of the *quietness* attribute and the updated bicycle extension. Although more research and analysis are required to simulate more realistic cycling routes (e.g., the consideration of preferences, differences between cyclists in terms of their socio-demographic attributes, speeds and experiences), this is a contribution that can simulate standard cycling behaviours considering an important set of built environment characteristics.

Another important validation component was the percentage of short trips in urban areas using active modes. This is a crucial component, as it is fundamental to reach a similar baseline as the one identified by ATE. The difference found between both baselines was below 3%-points (43.39% simulated results and 41% ATE estimation). This similarity strengthens the usability of the validated MATSim model, as not only were transport mode shares, average trip distance and times and vehicle counts in space and time realistic, but even the use of active modes reflected the normal mobility of the individuals in the study area. The challenge of shifting car users to active modes has this powerful tool to simulate mobility policies and achieve the shift on a realistic basis.

5.2.4. Scenarios

Different and extreme mobility policies were simulated to estimate their efficiency in reducing the number of cars on the roads, besides other co-benefits thanks to the use of active modes, such as CO_2 emission reductions and health benefits. Although these scenarios could rarely be fully implemented in the real word, they can provide a detailed overview of their potential.

Transport mode shares

A reduction of cars on the roads was achieved in all scenarios, although with various levels of impact depending on the scenario simulated. The ones with the highest effect were those where an economic penalty was included (i.e., scenarios 4, 6.3 and 6.4). The other two combined scenarios where economic penalties were not applied (i.e., 6.1 and 6.2) reached lower percentage-points reductions than in the single scenario including it (i.e., scenario 4). These results could indicate a stronger impact of the toll by itself than when car space reduction and road restrictions are applied (i.e., scenarios 1 and 2). Another notable fact was the lack of extra benefits when policies were combined to reduce the number of cars on the roads in the same scenario, since reductions in percentage-points were similar to those obtained when the results of the individual policies were combined.

	Car	Public transport	Walk	Bicycle
Scenario 1 Fully segregated cycle paths	-2.1%	1.1%	-0.3%	1.3%
Scenario 2 Low Traffic Neighbourhoods	-3.2%	3.0%	1.0%	-0.7%
Scenario 3 Active travel reward	-6.9%	-2.7%	3.3%	6.3%
Scenario 4 Pay-when-you drive	-14.2%	9.9%	2.1%	2.2%
Scenario 5 Cycle hubs	-0.1%	0.2%	0.0%	-0.1%
Scenario 6.1 Cycle paths + LTN + cycle hubs	-4.1%	-1.2%	1.4%	3.9%
Scenario 6.2 Cycle paths + LTN + cycle hubs + active travel reward	-13.2%	-8.5%	4.7%	17.0%
Scenario 6.3 Cycle paths + LTN + cycle hubs + pay-when-you drive	-18.0%	6.2%	3.7%	8.1%
Scenario 6.4 Fully combination	-27.5%	-5.1%	6.5%	26.1%

Table 15 Summary of the percentage-point differences achieved in each simulated scenario when compared with the baseline scenario, by transport modes.

Similar to previous results but considering active modes, the highest increases in percentage-points were obtained when economic policies were applied. The best results are observed when economic rewards are implemented (i.e., scenarios 3, 6.2 and 6.4). The combination of policies to increase the use of active modes achieved extra benefits than when the results of the individual policies were added together. Higher percentage-points increases were obtained, unlike the case of car reductions explained in the previous paragraph. This effect was almost five (scenario 6.1), three (scenario 6.4) and two times (scenarios 6.2 and 6.3) higher in the combined scenarios than when results from the individual policies were added together, suggesting that the effects of implementing multiple policies in favour of active modes could influence a greater shift to these modes. This is a particularly important outcome, showing an extra potential impact of the combined policies in favour of walking and cycling.

Within the active modes, the use of the bicycle was the most benefited, although walking reached higher percentage-point increases in two single scenarios where cycling was penalised (i.e., as a consequence of not being able to overtake cars in congested areas (scenario 2), and when cycling was combined with the use of metro in the same trip (scenario 5)). In the remaining scenarios, the bicycle was the clear winner, especially in combined policies, where the percentage-points increased by two or even by two significant figures, while walking reached 25%-point increase in the best case. The fundamental reasons for the differences between the modes are two: firstly, most policies are focused on cycling; secondly, cycling is faster than walking, making the former more attractive than the latter.

Despite public transport modes not being the focus of this doctoral thesis, interesting outcomes from the scenarios were found, as they were benefited or penalised depending on the policy or policies simulated. In policies simulated individually (i.e., scenarios 1 to 5), the use of public transport was penalised only when economic rewards to active modes users were applied (i.e., scenario 3). In the remaining cases, the use of public modes increased, especially when economic penalties were applied to car users (i.e., scenario 4). In combined scenarios, the use of public modes is reduced in all of them, except the one that penalised economically car users without economic rewards to active modes (i.e., scenario 6.3). These results show the dispute between the active and public modes, as both compete for the former car users that decided to use an alternative mode, as well as between their usual users (as shown in the Sankey diagrams in section 4.4.2). The shift of public transport users towards active modes could be an issue for policy makers as these types of modes are intended to complement each other rather than compete. If fewer people use public modes, fewer investments could be approved, with the potential to increase prices. This would particularly affect those people who are unable to use active modes (i.e. people with mobility issues) or do not have the possibility of using any other mode (e.g., vulnerable people without access to a car). Further investigation is required to identify potential policies in benefit of both modes.

Table 15 summarises on a coloured-scale (i.e., reductions in red, increases in green) the percentage-point differences achieved in each simulated scenario when compared with the baseline scenario, by transport modes.

CO_2 emission reduction

Estimates of CO_2 emission reductions per scenario were also analysed to understand the potential impact of the simulated policies on the environment.

Baseline results showed that 416 tonnes of CO_2 are emitted daily, equivalent to 4,326,577 trees required to absorb them daily. Although all scenarios achieved emission reductions, the most successful were those including economic policies, either rewarding the use of active modes (scenarios 3, 6.2 and 6.4) or penalising car users (scenarios 4, 6.3 and 6.4), reaching reductions up to 17 and 38%, when applied individually and combined, respectively. Those scenarios only simulating policies varying the built environment characteristics (e.g., scenarios 1, 2, 5 and 6.1) achieved very limited improvements, reducing emissions up to 2.3% in the best case.

Furthermore, combined polices reached better outcomes than when results from individual policies are added together. This implies a stronger effect for the environment when policies are applied at once, multiplying their effect by a factor greater than one.

Geospatial representation

All scenarios reduced the number of cars on the roads, although they were geographically uneven. Single scenarios reduced the number of private vehicles on motorways, highways and main urban road, except in the implementation of LTNs. Within them, the number of cars in the first two types was greater except in the city centres of main urban areas, as car users avoided the use of slow urban areas (due to congestion) in favour of faster motorways. Combined scenarios reduced even more the number of cars in all areas.

Furthermore, the general reduction of cars on the roads had consequences in the behaviour of some other agents previously using other modes in specific areas. New users occupied the free space left by former car users, as a response to less congested roads. The new users used this freed space into their benefit, as a better alternative in the use of cars was identified. This behaviour was observed in minor areas in some of the scenarios simulated (e.g., scenarios 1, 2, 3, 6.1., 6.2, 6.3 and 6.4), as shown in figures 95-110. This is an important effect that shows the importance of AgBMs in transport, as it is possible to visualise mobility geographically: when car journeys are reduced for some, it just opens more road space for others.

In the case of cycling, the same specific cycling routes were identified in the majority of the scenarios (e.g., the W-E corridor in the north of Newcastle, the N-S corridor in North Tyneside, the routes in Gateshead connecting with the Team Valley trading estate), the amount of cyclists being proportional to the increase of bicycle users in each scenario. These areas could be analysed in detail to understand the mobility patterns that make them that attractive. Additionally, these spatial patterns could be useful in cycle network planning. Future infrastructure investments in favour of cycling could be prioritised in these zones, as it could be argued that they are an indication of latent demand, where people might shift to cycling if enabled.

Statistical analysis

Statistical analysis of active modes showed relatively constant values in average trip time, distance and speed when walking, while values differ for cycling depending on the scenario. Cycling was used for longer distances and time when segregated cycle paths, economic rewards for active mode or economic penalties for car users were applied individually or in combination.

The average cycling speed is very dependent of the existence of fully segregated cycle paths (figure 113), being almost 1km/h faster than in those scenarios where this policy was not implemented. This is an important outcome achieved, which shows the need to provide fully segregated cycle paths that connect origins and destinations with direct routes, since not only longer routes are taken, but higher speeds can also be reached, therefore increasing the attractiveness of cycling. The logical consequences of the increase in bicycle use are a healthier lifestyle, a less congested transport system, and, as described above, a more sustainable and less polluted and noisy environment.

Achievement of the ATE 2030 goal

The implementation of several policies together and the single effect of economic rewards for active modes exceeded the ATE goal of reaching 50% of short trips walked or cycled. In terms of trip purposes, travelling to school on foot always achieved the highest percentage value, although its increase was limited within the scenarios (up to 2.5%-points in the best case). In contrast, the percentages of trips made by bicycle were increased for all kinds of purposes, especially when all policies were combined (i.e., scenario 6.4). This was a consequence of the provision of fully segregated and safe cycle paths, the economic reward and the need to avoid a car toll (in the case of former car users).

The results achieved in all scenarios were shared with the ATE team, where discussions in the development of more detailed and specific scenarios were considered for their purposes. This engagement allowed the understanding of the strategies and methodologies that ATE set for their goals in 2050.

Socio-demographic analysis

The impact of policies on the agents based on their socio-demographic attributes is another advantage that AgBMs offer compared to other alternative models.

The obtained results, apart from the interactions of the agents in space and time, are predominately based on the intrinsic characteristics of their activity plans (e.g., locations, trip distances and duration). An example is the impact of economic rewards (e.g., scenario 3) to agents travelling long distances, based on their age range. This type of policy makes young adults increase the use of bicycles the most, as this group travels longer distances on average and can get a higher economic benefit than those travelling shorter distances in urban areas.

Unfortunately, different attitudes towards the use of different transport modes and health conditions among the agents were not considered, due to time and data constraints. This is a huge simplification of the agents' normal behaviour, as a homogeneous behaviour is assumed during the simulation stage (e.g., when choosing their transport modes and routes). Consequently, results obtained do not reflect real actions. Examples of these unrealistic results are observed in the analysis of the use of bicycle per sex and economic activity. In the first, it was observed that women use the bicycle more than men, both in the baseline and the scenarios. This behaviour is opposite to that observed in real life as described by Aldred et al., (2016), where men use the bicycle the most and are less affected by factors that can limit their use. In terms of economic activity, it was observed that agents initially considered less favourable to cycling (e.g., retired, sick) were among the groups that used this mode the most. This is an effect in which agents only take into account the characteristics of the trips, since those who use the bicycle the most are those who travel short distances. A further model development is required if socio-demographic analysis is needed to identify the impact of the policies to the agents based on their characteristics. This is a future work that researchers can contribute to make the model more realistic and robust, as indicated in section 5.4.4.

Health benefits

Mobility policies in favour of active modes can also influence health conditions, as people increase their physical activity when walking and cycling, and emit less CO_2 to the environment for a cleaner environment, as described in section 2.4.2.

Results obtained showed that several premature deaths can be avoided in each scenario, depending on the type of mobility policies applied. The highest reductions were observed, as was expected, in scenarios where more people use active modes (i.e., scenarios 3, 6.2 and 6.4). The common factor between them is the economic reward per kilometre walked or cycled. Prevented annual deaths range between 4.4 (scenario 3) and 15.1 (scenario 6.4). This reflects the powerful effect that economics can have in modifying people's mobility behaviours.

These health benefits go beyond preventing premature deaths, as they also impact the economy. These prevented premature deaths require fewer medical services and can continue to contribute economically to society. Therefore, this co-benefit is twofold: improves human health and helps the economy.

Built environmental analysis

The use of AgBMs also allows the analysis of the transport network used by the agents, being a valuable source of information that cannot be collected with traditional models (i.e., FSMs). In this case, an analysis was applied to identify the roads most used by cyclists per scenario. The outcome showed that minor roads (B and C roads), residential streets, roads with a single lane per direction and between 5 and 20 km per hour were the most used in all case scenarios, independently of the policies simulated, although with variations depending on them.

The biggest changes were observed in the use of footpaths and three-lane roads, where their use increased by 2.5 and 300 times respectively, but only when fully segregated cycle paths were implemented. These two cases show the use of new types of roads previously not allowed for cyclists. The first related to areas only used by pedestrians in urban areas, while the second to roads such as motorways that divide areas where bicycle use is permitted and prevent connections between them.

These outcomes could help identify and prioritise future cycle path implementations in the study area. Priority routes could be defined to provide the agents with safe ways to travel, removing barriers that could affect potential new cycling users.

Economic results

Mobility policies that attempt to influence a behavioural change in society towards the use of more sustainable modes also have an economic impact. Some of them require financial compensation to individuals to encourage the use of active modes (e.g., scenarios 3, 6.2 and 6.3), while others demand sanctions to discourage the use of polluting cars (e.g., scenarios 4, 6.3 and 6.4). Additionally, all policies have a health impact in the population, and therefore, in the economy, as described in section 4.4.10.

Results obtained show that policies applying economic rewards to active mode users require a substantial economic investment. This outcome makes this type of policy difficult to implement in the real world, due to the limited budgets that the majority of cities could use to cover these expenses, with exceptions such as cities in the Netherlands, Belgium and France, as described in section 3.8.1. Those policies that impose penalties on car users could raise significant revenue that could be reinvested in policies that support a sustainable transport future (e.g., fully segregated cycle paths, public transport services improvements), strengthening commitment to a decarbonised and more resilient transport sector.

When these types of policies are combined in the same scenario, different results are obtained than when applied individually. While tolls for car users collect higher economic benefits (scenario 4) than the amount required when providing economic rewards to active users (scenario 3), the opposite occurs when both policies are combined (scenario 6.4). This is a consequence of having fewer cars on the roads (i.e., fewer benefits collected) and more people using active modes (i.e., more investment required to pay them per kilometre walked/cycled). This is an important concern, as potential clashes and side effects between different policies combined need to be taken into account. When adding the potential economic benefits derived from the health benefits, a positive balance is achieved in this type of scenario.

It is also worth saying that, although the values used to reward active users and penalise car users are not based on any research or proposal by any official entity, they can show a global picture of the economic consequences they can produce. Further research is required into using more realistic values, as well as defining either with more specific constraints (e.g., trip purpose, maximum distance).

Cycle hubs results

Lastly, the use of cycle hubs to allow the use of the bicycle and metro during the same trip achieved different results depending on the simulated policies. The number of users was multiplied by 5 when the cycle hubs were reachable via fully segregated paths (scenario 6.1), by 4 when economic rewards for active modes and fully segregated cycle paths were allowed (scenario 6.2), by 12 when economic penalties were applied to car users and cycle paths were allowed (scenario 6.3), and by 7 when all single policies were combined (scenario 6.4). These results show the previous acknowledged dispute between active and public modes, as a lower number of cycle hub users were counted when economic rewards to active mode users were applied than when economic penalties were applied to car users. In terms of the most used cycle hubs, six of them were always within the 10 most used, being principally located in urban, shopping, residential or working areas of Newcastle, North Tyneside, South Tyneside and Gateshead.

5.2.5. Feasibility of implementing simulated scenarios in the real world

Despite the decarbonisation, health, economic and environmental benefits that previous mobility policies can provide, some objections are found when trying to implement them in the real world. The following paragraphs analyse three of them to understand some of the main difficulties faced.

The first difficulty relates to the population acceptance, as not every individual is interested in modifying their mobility behaviours in favour of a decarbonised and resilient mobility. Groups in society have been found against sharing the roads or giving part of them to cyclists, the implementation of LTNs or road tolls, to name just a few. According to research, about a third of drivers consider that cyclists should not be on the road but only on cycle paths (Bilton, 2022; GB Road Safety, 2022). Furthermore, Prati *et al.* (2017) argue that cyclists have been relegated to a secondary place, facing discriminatory treatments and disproportionate safety outcomes. Related to LTNs, the freedom to use the car, the potential benefits for privileged people, the blockage of roads, an undemocratic situation, the potential impact to emergency services, the increase of pollution in other roads and the potential impact to local businesses are the main objections provided by those against them (The Guardian, 2022). Lastly, opposition to road tolls is mainly related to attitudes against climate change and the environment, which are closely related to right-wing populism, based on a Norwegian survey and analysis performed by Aasen and Sælen (2022).

In addition to the public acceptance, attitudes towards the shift to more sustainable transport modes play an important role as well. As discussed previously in section 2.4.2, a great majority of the population (circa 70%) is concern about the need to use less polluting transport modes, but a similar proportion considers indispensable the use of cars (Ipsos, 2022). This reasoning shows the differences between what people think would be good for the environment and society, and their personal convictions (and/or needs) to make the shift.

The third is about the economic costs, which vary depending on the interventions. In the case of segregated cycle paths, investments range from £0.24m to £1.45m per kilometre, based on typical costs of cycling interventions (Taylor and Hiblin, 2017). Although the implementation of a cycle lane in every road is an extreme case (as in some of the previous scenarios), the results obtained in this thesis could be used to prioritise areas and benefit a potential latent demand that could make the shift first. Then, more areas could be benefited gradually, based on the demand and satisfaction achieved. LTNs requires cheaper interventions, where roads could be blocked with simple elements (e.g., planters) that could be moved in the case of emergencies. In the case of systems to quantify the kilometres walked/cycled per individual and road tolls, a substantial investment would be required (economic, infrastructure and technological). Detailed research would be needed to take into account the specific characteristics of the population and the environment in each study area. Lastly, cycle facilities to park bicycles in a secure place are also defined economically by Taylor and Hiblin (2017), estimating a cost between £0.12m and £0.20m per facility. The Greater Manchester area is an example where these facilities have been implemented at 15 busy destinations, providing 1,206 parking spaces with secure card access and CCTV.

All in all, a balance between benefits and objections is required when considering the implementation of mobility policies to achieve a decarbonised transport sector. However, an important consensus should be reached to acknowledge the importance of facing the climate emergency and the need to modify the normal mobility behaviours of the population. Awareness campaigns will be required to show the public the benefits in decarbonisation and co-benefits in health, economic and environmental terms that can be achieved. Additionally, the combination of policies could help reduce the costs if revenues (e.g., road tolls) are combined with incentives for active users (e.g., cycle paths), as shown previously in section 4.4.10, where the economic benefits derived from health improvements play a fundamental role.

The outcomes obtained in this thesis could be an excellent starting point to define specific and delimited strategies in the study area.

5.3. Reviewing research questions

This doctoral thesis has contributed to achieving a more decarbonised transport sector, applying cutting-edge tools, datasets and methods with a clear trend towards the use of open-source tools and open access datasets for reliable and robust research. Based on the knowledge and experience gained during the development of this thesis, the research questions defined in chapter 1 can now be answered with a greater appreciation and understanding of both the global context and the required procedures to achieve them.

How can open-access data and open-source tools support the development of spatio-temporal scenarios to assess the effectiveness of policy portfolios to increase active travel uptake, taking into account socio-demographic attributes and built environment characteristics?

The use and development of open-access data and open-source tools to simulate active travel mobility policies is an emerging and growing activity, not only in academia but also in industry (e.g., Arup CML, Connected Places Catapult). They contribute to helping democratise and expand the use of models, since more researchers and practitioners have the opportunity to access, use and replicate them in other regions.

Open-access data and open-source tools play a key role in the development of spatio-temporal scenarios to assess the effectiveness of policies to increase active travel uptake. They are particularly important when socio-demographic attributes and built environment characteristics need to be taken into account, as the majority of these types of data do not exist, have access restrictions or are proprietary and, therefore, not accessible.

Socio-demographic attributes and built environment characteristics are fundamental components for estimating the effectiveness of policies in favour of active modes, since these modes require physical effort and control from the individual on a continuous basis, unlike public and private modes. Therefore, greater detail is required to define them as they condition the attraction and satisfaction of the individuals when using active modes, as well as the followed routes.

Fortunately, open-source AgBM tools have been developed to combine both factors at the individual level. Tools such as MATSim and SimMobility, among others, allow the spatio-temporal interactions of agents, behaving differently depending on the characteristics of the transport network, used modes and their own socio-demographic characteristics. Access to these tools allows researchers, practitioners and the public the ability to define and test numerous scenarios considering active modes, making the process more transparent and accessible, although a high level of understanding is required to use them. Additionally, new open datasets and tools have been created to improve the simulation results. Some examples are the development of detailed and heterogeneous synthetic populations and transport networks with a focus on active modes (e.g., the methodologies presented in this thesis); the definition of indexes to rank built environment characteristics for cycling (e.g., Cyclestreets (2022a)); and the possibility of simulating cycling as an independent and fully defined mode taking into account characteristics of the environment (e.g., Ziemke et.al., (2017)).

Unfortunately, all required inputs to simulate and test scenarios to increase active travel are not open access. This is the case for travel diaries, as this information is considered sensitive and explicit permits are required. Additionally, more efforts from the open-source community are required to define walking in a greater level of detail, as this mode is usually discarded from simulations due to lack of data or interest in considering it as part of the dynamic flow, as described by Batty (2001).

This thesis aligns with the premise of using and developing open-access data and open-source tools, where possible, to contribute to reproducible, open and transparent research. A strong commitment in the definition of socio-demographic attributes and built environment characteristics was taken, as shown in the four novel innovations generated. These improvements enabled the possibility of simulating more realistic scenarios in favour of active modes, predominantly for cycling based on the available resources used and developed.

What synthetic population attributes are required to capture the behavioural responses of transport users to active travel policies, and how can these attributes be produced using open-source demographic tools?

As Garrido *et al* (2020) state, synthetic populations are the basis to define travel demand. They describe with a great level of detail the inhabitants of the study area. This level of detail depends on the number of attributes considered and their heterogeneity, as they are directly related to the number of subpopulations that can be identified within a society. Consequently, the greater the number and diversity of attributes considered, the more inclusive and equitable representation of society and its mobility patterns.

As described in section 3.3.3, research has found that different mobility behaviours can be identified depending on the characteristics of the individuals (e.g., age, sex, ethnic), the relationships with other household members (e.g., marital status, children in the dwelling), economic level (e.g., economic activity, occupation and income) and mobility options (e.g., driving license, car access, bicycle access, public transport pass). Besides them, attributes considering health conditions would help to better describe the normal mobility of the synthetic agents. Therefore, a certain diversity among them provides a descriptive vision of society with different mobility behaviours and needs.

In this thesis, a novel and heterogeneous open-source synthetic population methodology combining open-source tools (SPENSER (Lomax *et al.*, 2022) and synthPopEng (Alvarez Castro, 2022)) was generated. This methodology uses open-access data from the 2011 UK census, ONS and NTS, which enables researchers to apply it in any region of England. This allows for more transparent, replicable and reliable research, as described in previous research question. A detailed description of the tools and datasets considered can be found in section 3.3.3. The outcome is a synthetic population with 12 socio-demographic attributes, where individual characteristics, family dependencies, spending power and mobility access attributes are taken into account. Unfortunately, due to lack of time, attributes about health conditions were not included. This limitation has been identified as future work to improve the quality and diversity of the outcome. Section 3.3.4 describes the generated attributes in detail.

When these socio-demographic attributes are considered to estimate the acceptance of active travel policies with AgBMs, different behaviours are observed among the agents, as shown in section 4.4.7. Unfortunately, lack of time prevented the possibility of considering different attitudes and levels of attraction towards active modes from different sub-groups in society. Consequently, the results obtained cannot be considered reliable, as they are mainly conditioned by the activity plans assigned to the agents. Although these activity plans were assigned based on socio-demographic attributes (see section 3.3.6), more conditions affect agents' decisions, such as their awareness of climate change and interest in more sustainable transport, to name just a few. This implementation has been highlighted as future work to achieve more realistic and reliable outcomes, as described in section 5.4.

Which characteristics of urban infrastructure are important in shaping travel choices, and particularly the use of active travel?

Road infrastructures and their condition are fundamental for a normal and comfortable mobility for all kind of transport modes.

Particularly, active travel requires a set of conditions to make it attractive and usable, as it requires some physical effort by the individuals when moving between locations. The mobility has to be safe, direct and comfortable. As highlighted in section 3.6, research has found that slopes (Menghini *et al.*, 2010; Hood *et al.,* 2011; Li *et al.*, 2012), pavement surface conditions and smoothness (Landis *et al.*, 1997; Hölzel *et al.*, 2012; Milakis and Athanasopoulos, 2014) are fundamental factors that influence the use of bicycles.

This thesis analysed the characteristics of the roads for cycling, based on the *quietness* attribute developed by Cyclestreets (2022a). Road and surface type, number of lanes per direction, allowed modes, maximum speed and cycle paths' width were considered. The outcome shows that those residential and minor roads with cycle paths of at least 2.5 metres, regular and compacted surfaces (e.g., sett, compacted, concrete, asphalt and paved), with one lane per direction and up to 20 km per hour are the ones that obtain the highest values in ranking, and therefore, the most attractive for cycling.

This outcome was confirmed when we allowed the agents to try different routes when cycling during the simulation stage. The validates scenario (i.e., baseline) showed that agents prefer to use residential and minor roads, with a single lane per direction, as well as direct routes to minimise the time spent but taking into account road gradients, as demonstrated in section 4.3.5. These results are aligned with the updated MATSim bicycle contribution, where both the *quietness* and gradient attributes are considered when choosing the route.

Additionally, some of the scenarios simulated in this thesis show the importance of providing safe cycling infrastructures (i.e., scenarios 1, 6.1, 6.2, 6.3 and 6.4). As a result, more agents decided to cycle. In all cases, more direct routes and faster travelling speeds were identified, indicating that cycle paths are a fundamental component to increase the use of active modes.

Unfortunately, a similar analysis for walking was not developed mainly due to the lack of datasets and tools. This drawback has been highlighted in the thesis, as well as identified as future work for a more cohesive and complete research of the human mobility.

5.4. Future work

At the end of the writing up of this doctoral thesis, it is believed that the aim has been accomplished at a very high level. However, new and exciting challenges have been identified to improve and expand the outcomes obtained in this 3.5-year doctoral thesis, which surely will lead to more thrilling approaches. The following sections collect all the derived and new questions identified during the development of the thesis that could make both the methodology and results more accurate, precise and robust.

5.4.1. Synthetic travel demand

The development of a very detailed synthetic travel demand consists of the use of a vast amount and diverse datasets that are rarely in the same format, structure or spatio-temporal scale. This implies that the results cannot be fully validated and, therefore, the achieved precision and accuracy are not totally guaranteed.

This is the case when developing a synthetic population, as open access regional and national datasets from various sources and timeframes were used to develop eight new socio-demographic attributes. Although the results were internally validated (when data was available) using aggregated values of a small number of combined attributes (e.g., age and sex in most of the cases), the accuracy of the results cannot be guaranteed. More aggregated socio-demographic attributes should be considered when validating the results obtained (e.g., validate the economic activity considering aggregated values based on age, sex, income and marital status), as well as using external datasets from diverse official sources. The application of a more robust and constrained validation method will improve the precision and accuracy of the results achieved. Further investigations in available datasets, tools and other resources are required to accomplish this highlighted challenge.

Besides the improvement of the obtained results, there is also the possibility of developing new attributes for individuals, such as health status, and increase their heterogeneity. To simulate more realistic mobility behaviours, extending the synthetic population with an attribute that can categorise the level of mobility of the agents (e.g., very bad, bad, good, very good) is encouraged. While good mobility for all the individuals was assumed in this thesis (which is not an accurate representation of the population), knowledge about the health could provide insights in terms of potential users of active modes and discard their use for those with mobility difficulties or disability. This could help simulate a more representative mobility of society, as well as limit the distances walked.

Within the activity plans, it was assumed that individuals with similar socio-demographic attributes behave and have similar mobility patterns. This assumption was used to transfer activity plans from the NTS travel surveys from the whole England except London between 2011 and 2019 to the synthetic population' agents. Although this argument is held by scientific research as indicated in the section 3.3.3, the development of massive and detailed travel diaries only within the area of study (i.e., Tyne and Wear or the NE region) would reduce the inclusion of outliers and patterns that do not belong to the area of study and occur in some other areas. The possibility of obtaining or developing travel diary surveys covering the whole study area only would be encouraged, although this task could be time consuming and underrepresent specific groups of society (Franco *et al.*, 2020), or the use of additional data sources (e.g., mobile phone data) combined with socio-demographic information.

5.4.2. Network

During the development of the network, challenges and future work that could increase the precision and accuracy of the urban environment were also identified.

Firstly, it would be beneficial to include characteristics for walking (e.g., width, surface type, conditions), similar to the *quietness* attribute for cycling. A similar attribute ranking the pavements would be useful to simulate, instead of teleport, walkers during the simulation stage. Unfortunately, the acquisition of this information and its inclusion in the network would not be enough, as a MATSim extension to simulate walking would be required, similar to the one generated for cycling.

Although the *quietness* attribute developed by Cyclestreets is a very valuable information for cycling purposes, an authoritative dataset for cycle network quality in the UK would be required to consider more attributes and more precise values that condition the use of the bicycle. It would be ideal if Ordnance Survey could survey this information (e.g., surface quality, segregated cycle paths, width of the road) and make it available for research purpose.

For both active modes, it would also be interesting to consider traffic accidents when routes are chosen. This information is open access and can be added to the network. The main issue is about how the data is used during the simulation stage. A new or updated MATSim extension for cycling and/or walking would be required to allow the agents to avoid roads where the number of accidents is high.

Beyond the inclusion of more information into the network, there is also the need to improve the network validation stage. Despite checking the results from several and complementary perspectives (e.g., analytic checks of public transport routes with PUMA (Arup, 2022b), and visual network checks identifying anomalies when visualising the results in space and time using Simunto Via (Senozon AG, 2018)), it is believed that errors in the network are still included. While open access OSM data is extremely useful and valuable, there is a high probability of it containing errors due to the potential lack of knowledge of the volunteer who digitised the roads and their characteristics, as a result of not being familiar with the area. A further investigation would be required to spot unrealistic network structures as well as incorrect attribute assignments. Development of a tool to minimise this potential issues as much as possible would be encouraged.

5.4.3. MATSim model

Beyond the validated model, there is room for more improvements to make it more realistic and accurate, reducing the limitations and assumptions made, but also including new features that could bring new insights about the daily transport mobility.

A set of parameters could be updated for a more realistic mobility representation. Firstly, buses could be simulated as stochastic modes, which would allow their interactions with other vehicles on the road and be part of potential congestion. This would generate a more realistic representation of their movements and reduce the artificial attractiveness for the agents assumed in the model. Secondly, public transport modes could consider their maximum capacities to simulate a realistic number of passengers per vehicle, which could also reduce their artificial attractiveness in case agents are forced to wait for the next available vehicle. Thirdly, the inclusion of a payment when using public transit modes, incorporating a new economic variable at the calibration and validation stages could be considered. Fourthly, walking trips could be simulated within the model instead of being teleported, although more information about the built environment characteristics and a dedicated walking extension would be necessary to consider this option, as highlighted earlier.

Attitudes towards the use of different transport modes were not considered, either different environmental concern or behaviours. These limitations assume that all the agents behave similarly, as their performances are conditioned only by the time spent, spatio-temporal interactions and, sometimes, by the economic impact of the implemented policy. The only differences between the agents in terms of their mobility are their activity plans, which were assigned based on their socio-demographic attributes. To increase the agents' heterogeneity and personal behaviours, different sub-populations with different mobility approaches could be considered within the model (e.g., different levels of concern about the climate change and the willingness to use more sustainable modes based on their characteristics). Franco *et al.* (2020) developed a survey in 2019, where 1,500 residents in Tyne and Wear were asked about their current travel behaviours, attitudes towards the use of different transport modes and socio-demographic attributes. This information could help in identifying diverse groups within the population with different interests and concerns in terms of transport mobility and apply them to the model. Although this implementation could improve the model precision and accuracy, it would be at the cost of a higher complexity, as more parameters would need to be calibrated.

Despite knowing the total percentage of cyclists in the area (below 2%), it was difficult to match their geospatial routes with real journeys, especially due to the low percentage of them and the lack of knowledge about where the majority of real cyclists live. The possibility of identifying distinct groups in society with different propensities in the use of bicycles (based on their characteristics and/or statistical datasets per MSOA or OA area) and applying them to the model could improve this approach and achieve more realistic results. This task would require the acquisition of official datasets of real cyclists with their socio-demographic attributes and a trial and error calibration procedure. Similarly, as in the previous paragraph, this more realistic outcome would be obtained at the cost of a more complex model.

Further investigations could involve the possibility of allowing the use of more and diverse transport options such as micro-mobility modes (e.g., e-bikes and e-scooters). These modes could alter the behaviour of the agents, as their use might increase the willingness of the agents to use sustainable modes, make longer distances and minimise the negative effect of road gradients.

Different strategies could be also enabled, such as the possibility of allowing the agents to change the activity location, which could provide a land use analysis. The fact that agents cannot alter locations of activities in response to policies is a limitation, as individuals travelling long distances are very unlikely to use active modes. The possibility of enabling them to choose their destinations could modify their behaviour and, therefore, achieve a higher level of use of the active modes.

Another possibility could be the addition of more modules, such as the emission contribution (Hülsmann *et al.*, 2011; Horni *et al.,* 2016) for exhaust emission calculation, to estimate polluting particles produced by the vehicles. This implementation could help estimate the level of pollution generated in each scenario using a more detailed methodology than the one used in this thesis.

5.4.4. Scenarios simulated

Beyond the scenarios simulated, the following challenges and future work were identified.

There is the need to identify the geospatial morphologies and any other urban characteristics of those routes, areas or regions where the highest reductions or increases in the use of the different transport modes were estimated in each of the simulated scenarios. Results achieved in this thesis have estimated the efficiency of the simulated policies in reducing the number of private and polluting vehicles in favour of active modes and their geospatial locations. Future work could focus on the identification of common geospatial characteristics between those areas benefited or penalised by the implementation of the policies, with the possibility of extrapolating the results to other regions with similar characteristics. Moreover, there is the need to use more accurate or more realistic economic penalty and reward values for the study area in those scenarios where the economic factor is applied. Although the applied values are similar to those found in regions where a similar policy was applied (e.g., economic rewards in the Netherland, and the ULEZ in London), the values were just representative of potential policies to be applied. The results achieved cannot be considered as correct, but the obtained trends show the potential effects in the individuals, and therefore, on the transport mobility.

The developed baseline scenario, despite the improvements suggested, could be used to simulate more scenarios in a range of different contexts. Firstly, more detailed (both in space and time) scenarios could be defined. The goal of the simulated scenarios in this thesis was to have a first approach of the potential efficiencies that could be reached, while future scenarios could be built from results achieved in this. One example is the simulation of fully segregated cycle paths (scenario 1) applied to designated areas. ATE is working on the development of specific cycle paths in Tyne and Wear, so the simulation of this scenario could help them to estimate the expected impact on the number of users, routes and kilometres cycled. Besides, different economic measures, with more realistic values, could be applied to specific groups in society, trip purposes, zones and/or periods of time in the study area. More examples could include the implantation of specific active travel rewards when travelling for specific purposes (e.g., commuting, travel to school), the application of different economic penalties depending on the time of the day when using cars, as well as the application of access restrictions to car users in the vicinities of school areas to promote active modes.

In a similar way as described before, new scenarios where agents have different attitudes and behavioural responses towards the use of transport modes could be considered. This approach could be useful to take into account different transport modes' attractiveness within the different subgroups in the population, which could lead to simulation of tailored policy scenarios and checking how they would affect the diverse groups.

Lastly, the model could be used to address resilience and adaptation to extreme weather conditions as a consequence of the climate emergency. Different climate extreme events (e.g., floods, the failure of infrastructures) could be simulated in specific areas and time. The goal would be to estimate the agents' mobility changes derived from the extreme event, identifying the most affected zones, the potential expected delays and the identification of isolated areas that could not be reached.

5.5. Implications of research

This section identifies the implication that the research conducted in this thesis could have for fellow academic researchers, practitioners and policymakers.

5.5.1. Implications for researchers

The research undertaken in this doctoral thesis provides new tools and methodologies to generate the two main input datasets for MATSim model, applicable to any region in England, thanks to the use of open-source tools and open access datasets. In cases where it was impossible to use them, alternatives were provided.

The development of a very detailed and heterogeneous synthetic population has been explained with a high level of detail. This methodology can be applied not only to transport mobility scenarios in England, but for any other purpose where the knowledge and understanding of the different socio-demographic attributes of the individuals in a specific region are required (e.g., demography, epidemiology and politics). The developed methodology to assign activity plans to the agents is also open access and accessible by any researcher. Although the NTS dataset used is restricted and requires approval from the data-owner, any researcher could obtain it when proving the need for the data for a research purpose.

Additionally, the MATSim bicycle extension developed by Ziemke *et al.* (2017) was updated to consider the *quietness* attribute generated by Cyclestreets (2022a). This update allows the possibility of considering more built environment characteristics than the original version and simulates realistic cycle routes. The extension has been released in MATSim version 15.0-PR2396 and could be used by any researcher worldwide.

Lastly, section 5.4 identified and described some of the future work that the academic community could pursue for a more accurate and precise science. Several ideas to improve and/or expand the knowledge in each of the methodology steps followed in this thesis were mentioned.

5.5.2. Implications for practitioners

Former transport models, such as FSMs, are not enough to represent the variety of new transport modes (e.g., micro-mobility, car sharing, EVs), and the different human mobility behaviours and attitudes to decarbonise the transport sector. The use of AgBMs could help in tackling these issues as more detailed, disaggregated, multi-modal and spatio-temporal models could be generated to test the efficiency of different policies, taking into account different human transport behaviours and attitudes.

Although some companies (e.g., Arup, Catapult Connected Places) develop and apply these models, the current trend in transport modelling is to use models developed decades ago, due to the expert knowledge, complex datasets and computational resources required to make the change. Practitioners must be prepared to open their work to new and different tools, such as AgBMs, to consider more complex and current mobility patterns that are far from those modelled in past decades. Interactions between the individuals and the environment are now particularly important components in transport mobility, as well as the possibility of interrogating disaggregated results in space and time, both being key components to estimate the satisfaction of different mobility policies considering different groups of society.

Although AgBMs are not a *panacea* and many challenges need to be overcome, they provide a new perspective in transport modelling aligned with the need to decarbonise the transport sector. It is expected that more companies, institutions and government departments will take a step forward to apply and develop transport AgBMs for a sustainable and decarbonised transport future.

5.5.3. Implications for policy makers

Currently, the implementation of transport policies in favour of sustainable modes, such as walking and cycling, is controversial in the UK and many other countries, as shown in sections 2.4.2 and 5.2.5.

Policy makers are under pressure to apply policies to reduce the GHG emissions, but also afraid of applying them and upsetting citizens (Shah *et al.*, 2021; Huseyin, 2023). One case is the implementation of LTNs, a very controversial policy for car drivers, as some consider it an attack and limitation to their freedom in the use of cars, without seeing the bigger picture of the current climate crisis and the need to reduce GHG emissions.

Another drawback faced by policymakers is the fear of not obtaining any benefit after the implementation of policies in favour of sustainable modes (Aldred, 2019). Cultural barriers (e.g., weather conditions, a car-centric society) could make the applied measures unsuccessful, although positive results can be found in areas with minimum cycling culture (e.g., Seville (Marqués *et al.*, 2015)).

As shown in this thesis, the use of AgBMs could enable policymakers to make more informed decisions, from transport to geospatial and statistical approaches. More robust decisions could be taken, informing the citizens about the potential benefits to be achieved (e.g., emissions reduction, health benefits, economic impacts) at the individual and local level, as well as the possibility of identifying potential areas where the policies could be accepted at a higher level by the population, reducing the possibility of failure. These more detailed and comprehensive analyses could be seen as a potential improvement in decision-making.

It is expected that governmental transport departments at national, regional or local levels will take into consideration the use of these tools, in line with Switzerland (Scherr *et al.*, 2020) and Germany (German Center for Aviation and Space Flight (DLR), 2024), among other countries.

5.6. Conclusion

The work presented in this thesis aimed to contribute to a more sustainable transport future as a response to the climate crisis.

The MATSim model built for the Tyne and Wear region is crucial to understanding current (2019) urban mobility in space and time, as well as the potential efficiencies of the simulated policies to achieve the project goal. This model, in contrast to former transport models, provides insights into the spatio-temporal interactions of very detailed synthetic individuals among themselves and with the built environment, fundamental components for active modes. Therefore, a more complex and detailed analysis is achieved from the transport and geospatial points of view.

The methodology proposed is open-source and uses open access datasets, when available, for robust and reliable research that could be replicable by any other researcher. In the event that open-source tools or open access datasets were not applied, alternatives were provided to achieve a similar outcome. Besides the methodology developed, four novel contributions were generated: a very detailed synthetic population methodology fully applicable to any region in England, the addition of the cycleability rating (i.e., *quietness*) to networks, the updated MATSim bicycle extension to consider the previous attribute, and tailored scenarios to reduce GHG emissions in the Tyne and Wear region.

This research forms the first steps towards the definition of more precise and accurate policy scenarios to be applied to the Tyne and Wear region or any other area in England, although international scenarios could be developed when updating the tools to those geographical contexts. It is expected that the methodologies and results achieved in this thesis could bring knowledge and support to fellow researchers in the use of transport AgBMs to simulate mobility scenarios to decarbonise the transport sector.

The challenge of a decarbonised transport sector is huge, where diverse perspectives, knowledge and methodologies are required to identify the best solutions and achieve a more sustainable environment and healthier life. I hope that my contribution with this doctoral thesis can help achieve this goal.

List of acronyms

AcBM: activity-based modelling

AgBM: agent-based modelling

AI: artificial intelligence

ASC: alternative specific constant

ATE: Active Travel England

CA: cellular automata

CDT: Centre for doctoral training

CML: City Modelling Lab

DEM: digital elevation model

DfT: Department for Transport

DRT: demand response transit

EDA: exploratory data analysis

EPSRC: Engineering and Physical Sciences Research Council

EU: European Union

EV: electric vehicle

FSM: four-step model

GHG: greenhouse gas

GTFS: general transit feed specification

GVA: gross value added

HRP: household reference person

ICE: internal combustion engine

IPCC: Intergovernmental Panel on Climate Change

IT: information technology

ITSUMO: Intelligent Transportation System for Urban MObility

JADE: Java Agent DEvelopment framework

LTN: low traffic neighbourhood

MaaS: Mobility as a Service

MATSim: Multi-Agent Transport Simulation

MSOA: middle super output area

NAO: National Audit Office

NE: North East

NHS: National Health Service

NTAS: National Travel Attitudes Survey

NTS: National Travel Surveys

OA: output area

OD: origin destination

OECD: Organization for Economic Cooperation and Development

ONS: Office for National Statistics

OS Ordnance Survey

OSM: Open Street Map

PHE: Public Health England

PIP: personal independence payment

QGIS: Quantum GIS

SBB: Swiss federal railway

SIM: Spatial interaction modelling

SUMO: Simulation of Urban MObility

SPENSER: Synthetic Population Estimation and Scenario Projection Model

TADU: Traffic and Accident Data Unit

UK: United Kingdom

UKERC: UK Energy Research Centre

UKRI: UK Research and Innovation

UN: United Nations

XML: Extensible Markup Language

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