On the Mobility Effects of Future Transport Modes

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Summary

This dissertation discusses how mode and route choice behavior might change with the introduction of future transportation modes when potential users are unfamiliar with such systems. It uses discrete choice models and supernetwork models without mode-specific constants and parameters with revealed preference data of current modes to understand how future modes could impact mobility effects such as mode choice, travel times, and resistance.

About the Author

Koen de Clercq conducted his PhD research at Delft University of Technology at the faculty of Civil Engineering and Geosciences at the Transport and Planning department. He holds a Master's Degree in Mechanical Engineering from Delft University of Technology.

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Nothing has such power to broaden the mind as the ability to investigate systematically and truly all that comes under thy observation in life.

Marcus Aurelius

Acknowledgement

Writing a PhD dissertation is the most challenging thing I have ever done (so far) in my life. Completing a PhD degree is something you carry with you for the rest of your life. It requires perseverance, critical thinking, and constructive decision-making. I feel that I further developed my mindset and aim to bring the mentioned skills into my next steps in my professional and private life. This journey contained elements of highs and lows, where during each step along the way I have learned more about myself and the world around me.

Let us start with some of the high points: the first time my supernetwork model showed (plausible) results, presenting part of my work at several conferences and external meetings, and the continuous joy of solving this large, challenging puzzle. Less nice to write about, but some of the lower points I would like to mention: my struggle to find motivation somewhere halfway through this journey, and receiving desk-rejections after sending manuscripts to journals.

All academics know these elements are part of doing research and are definitely part of pursuing a PhD degree. In this section, I would like to give my gratitude to the people around me that have contributed and guided me through this PhD project.

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Bart was always interested in hearing about my new findings and giving good feedback on how to refine my scope and position my work in existing literature, helping me to be more confident and develop my research skills. Maaike understands very well how I think and how I can be motivated. Furthermore, she helped me with improving my modelling, mathematics and coding, increasing the added value of my work. Arjan was really good in finding the exact definitions and phrasing of my work, which brought my writing and the positioning of my work in the literature to a much higher level.

So, thank you all for the help along the way. I hope you can be proud of the good energy you gave me and I wish that all other PhD researchers can experience the same quality of supervision.

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As a last remark, I want to remind everyone (and maybe myself the most) to also have fun during our endeavours. Whether that's pursuing a PhD or something else, it is important to enjoy the process and enjoy the daily things in life.

Gijsbert Koen de Clercq
Delft, February 2024

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Chapter 1

Introduction

The accessibility and livability of urban areas are under pressure (Arbib & Seba, 2017). Therefore governments seek solutions that result in fewer vehicles that can transport more people using less space and producing fewer emissions (Kuss & Nicholas, 2022). At the same time, innovators and companies propose new mobility systems with the aim of providing a better service that improves the travel experience of travellers and increases their market share and profits. In this way, in the last decades, numerous transport modes, such as shared bicycles, shared scooters, automated cars, ride-hailing services, electric bicycles, and other personal light electric vehicles have been developed, proposing to improve accessibility and livability. The use of such future modes could potentially change the way our urban areas function and look substantially in terms of spatial use, sustainability, health, equity, safety and economic opportunities (Fagnant & Kockelman, 2015; Shaheen et al., 2019; Milakis et al., 2017; van Arem et al., 2019).

Introducing future modes might lead to a change in accessibility (e.g., changing travel resistances and congestion), and this, in turn, can lead to a change in land use and activities. A conceptual model is proposed to describe this development (see Figure 1.1). The model structures the dominant relationships found in the literature and is an adaptation of the Land Use and Transport (LUT) feedback cycle from (Wegener, 2004). Future modes are placed in the centre of the conceptual framework to represent the main source of effects on mode choice. When a future mode is deployed, the available transport options change, which can change the mode choice behaviour (e.g., people use a future mode instead of busses, trams, or metros or as part of multimodal trips) and thus change the modal split (first-order effect: blue arrow). A change in mode choice could indicate a change in accessibility (e.g., due to adding a mode, the travel resistance will probably reduce and that is likely to improve accessibility) (second-order effect: red arrow). If accessibility changes, urban areas change (e.g., more people move there) and can be used more intensively in the long term as well (a change in land use), which will again put pressure on the transport systems and might evoke the need for new improvements. Note that introducing future modes affects livability as well, but this conceptual model illustrates specifically the effects of future modes on accessibility,

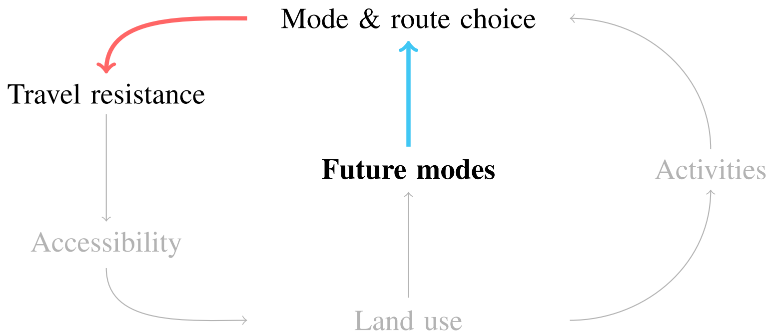

Figure 1.1: Conceptual framework of the dominant relationships of the effects of future modes on mode/route choice and resistance. Adaptation from Wegener (2004). The blue arrow depicts the explained first-order effect of a changing mode and route choice and the red arrow depicts the described second-order effect of a changing travel resistance due to a change in mode and route choice.

land use and activities. This dissertation focuses on the coloured parts (mode & route choice and travel resistance) in the conceptual framework (see Figure 1.1) and aims to develop a mathematical model supporting the design of future mobility systems.

The choices people make regarding future modes are crucial to determining the mobility effects, but we do not understand well how these choices regarding future modes are made and how these choices affect the mobility system. This dissertation looks at how a transport model supporting the design of future modes can be developed such that its effects on mobility systems can be analyzed.

In this chapter, Section 1.1 introduces the problem statement. Section 1.2 gives an overview of the current literature and state-of-the-art models to estimate the effects of future modes. Using the knowledge gaps from the literature, Section 1.3 introduces the main aim of this dissertation and its scientific and societal contributions. Lastly, Section 1.4 describes the outline of this thesis.

Defining a future transport mode

To analyze the effects of future modes on the mobility system, it is important to consider what a transport mode entails and when such a mode can be considered a future transport mode. A mode can be defined as a set of components that provides a means or service of transport for people and/or goods. This dissertation focuses on passenger transport. Transport modes are highly integrated into society and, therefore, challenging to analyze and describe due to their complex, large-scale, interconnected, open, and socio-technical nature (Sussman et al., 2014). Modes can be differentiated and categorized on the basis of a multitude of attributes (e.g., costs, travel speeds, comfort, and active driving task) (Kennisinstituut voor Mobiliteitsbeleid, 2018).
A mode can be considered a *future* mode in a specific area if it substantially differs from already implemented modes. The novelty of a mode is, therefore, relative and depends on the context: a mode can already exist somewhere in the world, but can be considered a future mode for a specific area or when its implementation differs from the implementation in other areas. For example, a metro system can be considered a future mode in one city, changing people to start using the metro instead of cars, whereas increasing the metro frequency of an already existing metro system in another city is not considered a future mode, since the metro in this context is already available. Another example of a future mode is a fully-autonomous car in an area without fully-automated cars. A third example can be the introduction of electric steps in an area where no revealed preference data of the use of electric steps are available or revealed preference data of electric steps in other areas cannot be used in the researched area, since the area's characteristics are substantially different. In this dissertation, we consider a future mode as follows:

> *future modes are substantially different compared to already existing implemented modes in the research area or in similar areas*

1.1 Problem statement

As explained earlier, the choices people make regarding future modes are crucial to determining the mobility effects, but we do not understand well how these choices regarding future modes are made and how these choices affect the mobility system. Specifically, we need to know how we can actually estimate what effects future modes could have on the mobility system before they are available and which future mode could best be introduced to improve the mobility system the most. In this dissertation we define the improvement of the mobility system as the reduction of total travel resistance (i.e., total generalized travel time). Which brings us to the central problem statement of this dissertation:

How can the ultimate future mode of a mobility system be determined before it is available?

Note that in this dissertation the phrasing 'ultimate future mode' is used for the future mode that improves an existing mobility system the most. This ultimate future mode can be seen as the best *additional* mode in a mobility system and *not* as a perfect mode that replaces all other modes (in other words, a mode with zero travel resistance for each traveller). The next section explains the current state-of-the-art and knowledge gaps regarding modelling the effects of future modes on the mobility system.

1.2 Modelling future modes

As mentioned in the previous section, assessing the mobility effects of future modes is needed to understand how future modes can contribute to existing mobility systems. This dissertation uses discrete choice models to assess the mode choice effects and assignment models to assess the impact of future modes on the network performance and combines both into a supernetwork model. The following sections dive into the literature to understand how discrete choice models, traffic assignment models and supernetworks are used to determine the effects of future modes.

1.2.1 Discrete choice models

Discrete choice models can be used to understand how people make decisions (including choosing their transport mode). Discrete choice models have a set of available options which are captured in a formula to calculate the probability that a specific option will be chosen out of a set of available options. The multinomial logit model is a well-known discrete choice model. For instance, a multitude of studies use logit models to model mode choice in the context of unimodal trips for automated driving (Puylaert et al., 2018; Snelder et al., 2019), and shared driving (Zhou et al., 2020; Daisy et al., 2018; Choudhury et al., 2018; Ikezoe et al., 2020; Winter et al., 2020b), and for multimodal trips (Fan et al., 2019; Bovy & Hoogendoorn-Lanser, 2005).

The multinomial logit model assumes that the alternatives are significantly different (Independence from Irrelevant Alternatives (IIA)). If this does not hold, then the so-called 'red/blue bus paradox' occurs when two alternatives are too similar. This could lead to an overestimation of the probability that one is chosen if an unaltered multinominal logit model would be applied. The IIA constraint might be violated for future modes that are or can be seen as further developments of existing modes. To overcome this overestimation, other types of discrete choice models, such as a nested or mixed logit model, can be used (Ortuzar & Willumsen, 2011). Such approaches introduce mode-specific scaling parameters that reflect the similarity of modes, the value whereof has to be estimated and estimated again when adding a future mode.

The attractiveness of an alternative in a discrete choice model is described by a generalized utility function covering mode attributes and personal characteristics (Ortuzar & Willumsen, 2011). These utility functions contain, inter alia, mode attributes and mode and person-specific constants and parameters. The mode attributes describe the characteristics of each mode and the mode and person-specific constant describes the implicit bias of travellers towards a certain mode (e.g., a car has a higher level of status compared to taking the bus). The mode attributes are estimated for personal preferences by parameters. Note that the person-specific indicator can be based on personal characteristics, such as age and income, but can also be based on a certain type of traveller as part of a subgroup (cluster). The mode and person-specific constant contains all other mode attributes that are not made explicit in the mode attribute set (i.e., they are not available in the dataset).

In order to describe these utility functions, it is necessary to know which characteristics to include. Mode choice is determined by numerous characteristics that can roughly be separated into three categories: mode attributes (e.g., costs, travel time), personal characteristics (e.g., age, gender, and income), and trip characteristics (e.g., origin and destination location, trip purpose, and precipitation). Characteristics are sometimes mode-specific, which are called mode-specific parameters, or are called mode-specific constants when bundled together (implicitly). Traditionally, attributes such as transport cost and transport speed, are used to describe mobility systems. Additional mode attributes, such as type of ownership (e.g., buying, leasing), protection against weather, space for luggage, and availability in time, play a role in describing mobility systems in more detail (Bagley & Mokhtarian, 2002). Mode attributes that are suitable for describing existing modes can be seen as 'identified attributes'; the utility of a specific mode is described by a combination of different values for these identified attributes and mode-specific constants and parameters.

Future modes can have other values for already identified attributes, but can also introduce new attributes and can, therefore, be described by appending and/or replacing attributes (e.g., car availability instead of car ownership) (Soteropoulos et al., 2019)). For instance, Mobility-as-a-Service (MaaS) adoption can be estimated by introducing a so-called 'loyalty subscription scheme'-factor for existing modes using different classes of travellers in their choice model for people that demonstrate loyalty to their current mode and people that are more keen on trying out new modes Gu & Chen (2023). Zijlstra et al. (2020) has a similar approach and identifies five factors (innovativeness, being tech-savvy, needing travel information, having a multimodal mindset, wanting freedom of choice) to determine the willingness of travellers to switch modes easily. Mo et al. (2021) defines two main factors determining the adoption of MaaS: the positive evaluations and current use of ride-hailing services. Acheampong et al. (2020) looks at trip characteristics as well by conducting a survey. They concluded that the use of a mode is primarily determined by personal characteristics, perceived benefits, safety risks, and car dependency. Furthermore, it was concluded that when looking at trip characteristics, the use of a mode is influenced by the availability of a mobility-on-demand service, specifically in a suburban context. These types of factors help to estimate mode-specific constants and parameters, and model-specific parameters (for certain types of discrete choice models) and are ideally estimated using stated or revealed preference data.

Empirical research uses stated and revealed preference surveys to estimate the relevant parameters to model mode choice. Revealed preference research helps to understand how people make choices in the real world by measuring people's actual travel behaviour, but can only test how existing mobility systems are used. Stated preference research can be performed to find out how and when people start to use future modes, such that the change in mode choice and travel behaviour can be analyzed. These findings cannot be used to analyze the effects when a certain future mode is completely integrated and adopted in a transport system, since the 'novelty' of a mode is not there anymore and other parameters might be determining mode choice. In other words, it is challenging to perform stated preference research to determine future mode choice when these are completely integrated and adopted (Cherchi & de Dios Ortúzar, 2006).

Since revealed preference data of future modes is by definition not available, these studies need to make assumptions about mode-specific parameters (e.g., time is often valued differently in an automated car than in a conventional car) and mode-specific constants for those future modes. For instance, Snelder et al. (2019) looked at multiple future modes, such as automated vehicles and automated (shared) taxis and vans using assumptions of values of mode-specific parameters for these future modes, but basing the choice behaviour of current modes on a revealed preference dataset.

Aiming to overcome the need for assumptions, studies often try to analyze mode choice using pilots. Although implementations are often limited, since temporary pilots do not change long-term mode choice behaviour, it already gives some insight into how a future mode might be used in the real world (Anagnostopoulou et al., 2020; Mundorf et al., 2018).

Stated preference research (people stating what their travel behaviour will look like, which can be different from their actual travel behaviour) can also play a role in estimating future mode choice. However, it can be challenging to determine how results from stated preferences studies translate into actual behaviour, due to the difficulty for people to estimate how their actual (revealed) choice behaviour differs from their stated choice behaviour. This is because stated preference research is, by definition, based on a representation of reality, where certain (unknown) attributes are not taken into account in the research (Cherchi & de Dios Ortúzar, 2006; Daly & Rohr, 1998).

Stated preference research is used to estimate the choice behaviour and change in mode attribute valuation (e.g., change in value of time) when a new future mode is introduced (Arentze & Molin, 2013; Smit et al., 2019). For example, Correia et al. (2019) specifically researches the impact of automated driving on the value of time while performing other activities in the car using a stated preference survey. Stevens et al. (2022) assessed the financial viability of autonomous mobility-on-demand systems in

Rotterdam, the Netherlands with mode-specific constants based on stated preference data.

The main advantage is that these studies give some insight into how these future modes will probably be used, but one limitation is that travellers will still probably behave differently once these future modes are actually introduced (revealed preference) compared to what they state in a stated preference survey.

Stated and revealed preference research can be combined to analyze how future modes might be used. Extrapolating the values of mobility system-specific constants and parameters of current modes based on revealed preference research to a new set of modes, including a new (future) alternative, and, subsequently, normalizing these results using stated preference research is a way to combine stated and revealed preference research (Daly & Rohr, 1998; Polydoropoulou & Ben-Akiva, 2001). This approach, however, has implicit preferences by including values of mobility system-specific constants and parameters of the analyzed mobility systems to model mode choice, so when extrapolating this to future modes, assumptions about implicit preferences are also carried over and influence the predicted modal split of the newly added mode. This means that the estimated modal split of a future mode is difficult to validate, since it is unknown to what extent the current biases influence the modal split of the future mode choice.

From the literature, it is concluded that it is challenging to know how to analyze how choices could change when future modes would be available. This is challenging because potential users are not familiar with such systems yet, so current models with mode-specific constants and parameters, which are estimated using empirical data, do not suffice for this purpose. This means we need to look at other ways of determining how the mobility effects of future modes can be analysed without including implicit preferences of existing modes.

To avoid including implicit preferences of existing modes when describing existing (and future) modes, mode-specific constants and parameters should not be used (Quandt & Baumal, 1966; Jin et al., 2017). Quandt & Baumal developed the so-called abstract mode model, in which mode choice is assumed to be explained only by attributes such as speed, frequency of service, comfort, and cost (Quandt & Baumal, 1966). Their abstract model does not include mode-specific constants or parameters related to the perceived (partly unexplained) overall utility of a mode. The model describes a mode by merely looking at the type of service that travellers get for an unlabelled mode (e.g., mode A instead of a car). Quandt & Baumal's explorative study considers the choice situations of different unlabelled modes characterized by different combinations of attributes such as speed, frequency of service, comfort, and cost. Their approach aims to expose the 'true' trade-offs by travellers between the attribute's levels by introducing extra mode-attributes that capture the choices and remove the need for mode-specific constants and parameters. These are mode-specific and can therefore not be used to estimate the choice behaviour when future modes are introduced. The unlabelled mode modelling approach has been applied in several papers. DeSalvo & Huq implemented Quandt & Baumal's approach to analyze mode choice of existing modes and urban household behaviour by considering costs, commuting time, speed and distance (DeSalvo & Huq, 2005). Malalgoda & Lim used a similar approach to research the use of existing public transit in the U.S. by considering the variables passenger miles, unlinked passenger trips, vehicle hours, operating employees, fuel, fare, income and population (Malalgoda & Lim, 2019). Malalgoda & Lim used this approach because of its ability to consider continuous modes, and therefore, find mathematical optimums.

Based on the literature review, the unlabelled mode modelling approach can be particularly useful to expose trade-offs based on attributes by travellers, making choices between existing and non-existing modes, such that the future modal split can be estimated. The knowledge gap is that the unlabelled mode modelling approach has not been used yet to estimate the modal share of future modes using revealed preference data of existing modes. An important requirement to leave out a mode-specific constant and parameters is the availability of a complete and coherent set of attributes that can represent both existing and future modes. Another way to look at this is the requirement that the mode-specific constants and parameters can be sufficiently described by a number of *non* mode-specific attributes. Another assumption that needs to be made is that the valuation of the modes attributes by travellers will not change when a future mode is introduced.

1.2.2 Traffic assignment models

In order to determine mobility effects, such as changes in travel times, resistance and network effects, such as rerouting due to congestion, need to be modelled with a given travel demand and (multimodal) transport network. This can be done using traffic assignment models.

A multitude of studies discuss the types of traffic assignment models and distinguish between static, quasi-dynamic, and dynamic modelling approaches. A static model assumes that traffic conditions are in equilibrium and do not depend on time and can use functions to determine the travel time on certain road segments using, for example, a BPR-function (Ortuzar & Willumsen, 2011; Bureau of Public Roads, 1964). A quasi-dynamic model assumes that traffic conditions are in equilibrium, but also model effects of spillback and queueing (Van Eck et al., 2014; Ortuzar & Willumsen, 2011; van Wageningen-Kessels et al., 2015). Finally, dynamic models can capture emergent effects that cannot be captured in the other models. A dynamic model assumes that traffic conditions change over time and also includes spillback and queueing, making it possible that effects such as congestion and rerouting can be modelled using, for instance, the cell or link transmission models to determine changing traffic conditions (Yperman et al., 2005; Daganzo, 1995). (Quasi-)dynamic models, however, are computationally more demanding than static models, so depending on the goal of the model and the level of precision needed from the model, (fully) dynamic models are not always the best choice.

Generally, four levels of detail can be distinguished when discussing traffic assignment models; 1) microscopic models that describe the behaviour of individual agents (travellers or vehicles), 2) macroscopic models that describe the behaviour of agents as a continuous flow, 3) mesoscopic models that describe agents using aggregated terms, e.g., in probabilistic terms and clusters of agents, but behavioural rules are defined on an individual level and agents still make 'their own decisions', (Ortuzar & Willumsen, 2011) and 4) models that combine a network fundamental diagram with a choice model (Snelder et al., 2019). Emergent effects can be theoretically observed in micro- and mesoscopic models. The computational complexity ranges from high to low for micro-, meso-, and macroscopic models respectively (Ortuzar & Willumsen, 2011; van Wageningen-Kessels et al., 2015).

Traffic assignment models have been used to analyze the mobility effects of certain future modes, since these effects can influence mode choice and the performance of the network. For example, Wang et al. (2019) developed a multiclass traffic assignment model to analyze the mobility effects of connected and automated vehicles. Madadi et al. (2019) used a macroscopic dynamic model with a separate infrastructure to simulate the effects of automated driving. Furthermore, Snelder et al. (2019) used a network fundamental diagram to analyse the effects of automated driving and shared mobility on modal split, vehicle kilometres, delays and parking revenue.

1.2.3 Supernetworks

Future modes can be used as the main mode of transportation and as a first- and last-mile mode (e.g., shared bicycles available at train stations are especially valuable as a last-mile mode) (Van Eck et al., 2014). A way to assess the mobility effects of future modes is to include both unimodal and multimodal trips in the analysis by using supernetworks. Supernetworks can be defined as a network with subnetworks/layers each representing a different category (i.e., in the context of this study: transport modes interconnected via transfers) (Nagurney & Dong, 2002; Sheffi, 1984). Supernetworks have a wide array of applications from modelling knowledge-intensive systems (Nagurney & Dong, 2005) and supply chain systems (Nagurney et al., 2002) to transportation networks (Arentze & Timmermans, 2004; Lozano & Storchi, 2002).

These supernetwork models need to define where people are allowed to switch between modes (e.g., where the mobility hubs or transfer links are located) (Arentze & Timmermans, 2004; Nagurney et al., 2003). For instance, such models are applied to model the effects of fleet size, spatial availability of floating shared modes and parking fees on the use of shared cars (Li et al., 2018). Vo et al. (2021) used a supernetwork to explore the effects of the interaction between private cars and transit modes on the activity-travel choices of individuals defining the locations where individuals can switch modes without predefined route sets.

One limitation that the above-mentioned studies have in common is that they all predefined specific future modes to analyse. These studies assume the choice behaviour based on stated preference research and use constants and parameters of these future modes to analyse the mobility effects of a future mode on urban areas.

The multimodal mobility effects of future modes are analyzed in this dissertation by combining discrete choice models with the unlabelled mode modelling approach (Section 1.2.1) and simultaneous mode choice and traffic assignment models (Section 1.2.2) in a supernetwork.

1.3 Main aim and contributions

This dissertation aims to develop a supernetwork model to analyze how the ultimate future mode of a mobility system can be determined before it is available. More specifically, it aims to develop an unlabelled supernetwork, without the use of mode-specific constants and parameters, that can be used to assess the mobility impacts of any future mode and to design future mobility systems, where no revealed preference data of these future modes are available, that minimize the travel resistance of the mobility system. The main and sub-research questions are stated below.

Main research question:

How can the ultimate future mode of a mobility system be determined before it is available?

The main research question can be answered by answering the three sub research questions in order of appearance. The main scientific and societal contributions are stated in Sections 1.3.1 and 1.3.2.

Sub research questions:

1. *How can the modal split of unimodal trips with any future mode be determined?*

   This sub research question is answered in Chapter 2, where an unlabelled modelling approach is developed in a discrete choice model to estimate the modal split of unimodal trips of two examples of when future modes (i.e., shared autonomous vehicles and electric steps) are available.

2. *How can the modal split and network effects of multimodal trips with any future mode be determined?*

   This sub research question is answered in Chapter 3, where the unlabelled modelling approach of Chapter 2 is extended with a traffic assignment network using a supernetwork with one layer per mode. A novel shortest path function determining the mode and route choice for each agent combining addable (e.g., cost per km) and non-addable (e.g., weather protection for 70% of route) mode attributes into route resistances is developed. This is done to analyse other mobility effects besides modal split, especially the change in experienced total 'resistance' or disutility for travelers in the network. This enables the inclusion of multimodal trips and rerouting (including changing modes) effects due to the density of traffic on certain routes. A neutral layer is introduced to explicitly model the embarking and disembarking of modes and include all multimodal combinations without predefining mode and route choice sets. This approach is demonstrated using the same two example future modes as in Chapter 2 (shared autonomous vehicles and electric steps).

An application of the supernetwork model is described in Chapter 4, where the approach is applied on one OD-pair between Delft and Rotterdam to analyse the effects of shared electric bicycles. Appendix A explains the usage and computational aspects of this supernetwork model.

3. *How can the ultimate future mode be determined?*

   This sub research question is answered in Chapter 5, where the supernetwork model is extended and applied on the network of Delft (see Figure 1.2) to find the 'ultimate' future mode which contributes the most to an existing mobility system in terms of reducing the network resistance. This is done in a 2-step approach. First, by varying the future mode attributes disregarding cost and travel speed to minimise the generalized travel resistance of the mode. And second, by using the outcome of the first step in simulations where (realistic) cost and travel speed are included. The supernetwork modelling approach from the second sub research question is extended with a transit-layer in which transit lines are explicitly modelled using a sub-neutral layer and sub-layers representing specific transit lines. This chapter analyses the mobility effects for each type of traveller in the network and aims to give guidelines to develop the ultimate future mode in other networks as well.

1.3.1 Scientific contributions

This dissertation makes multiple main scientific contributions, which are listed below. To the authors' knowledge, this is the first time that the modal split and network effects of introducing future modes is calculated using revealed preference data of existing modes and by combining a discrete choice model with a traffic assignment model in a supernetwork approach. This dissertation also identifies knowledge gaps and identifies possible pathways for future research on theories and methods to assess the impact of future modes on mode choice, accessibility and livability.

Summarized, the main scientific contributions of this dissertation are:

- The development of an unlabelled modelling approach using revealed preference data to find the modal split with future modes of unimodal trips (Chapter 2).

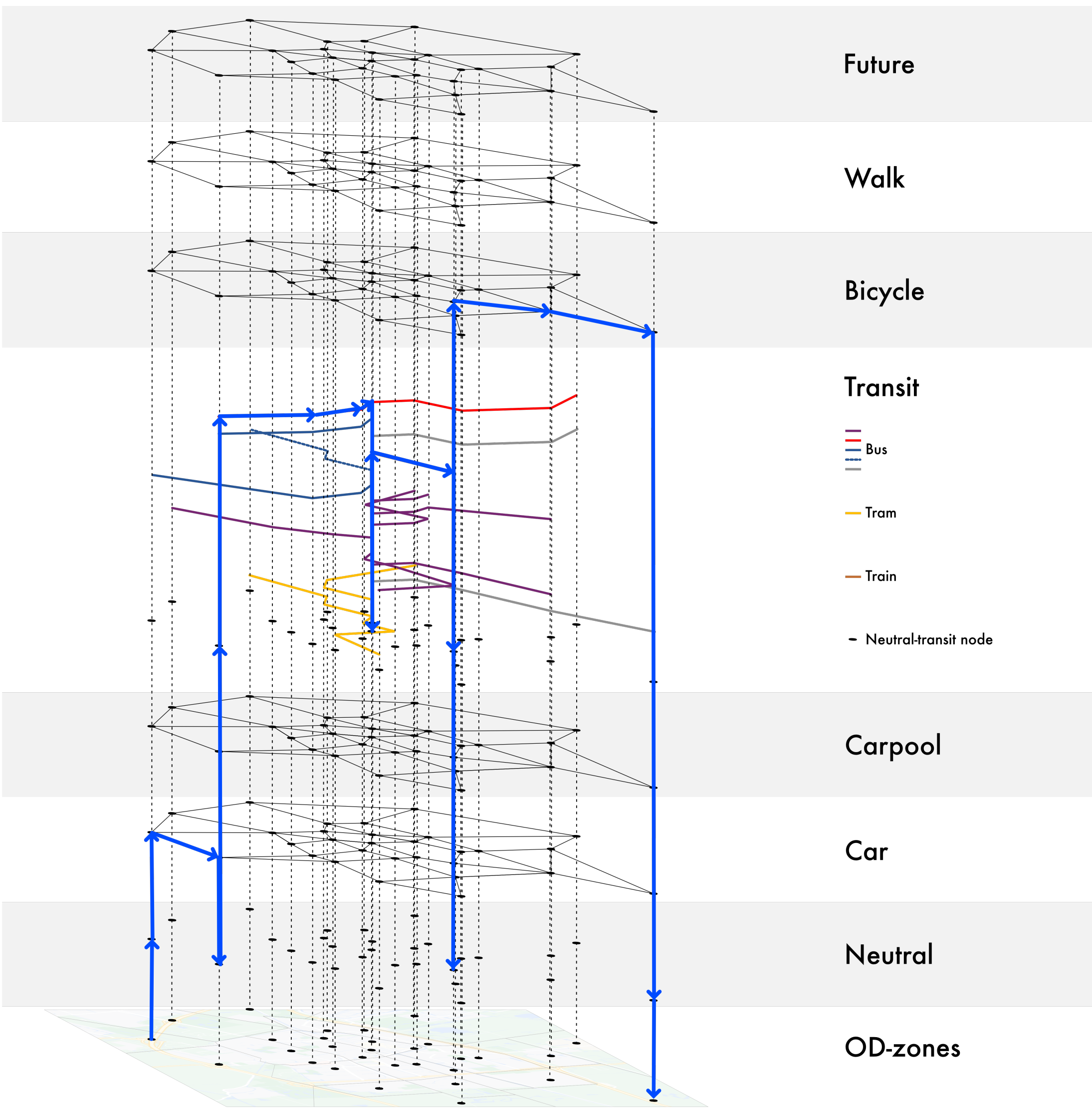

Figure 1.2: Multimodal supernetwork of Delft. Each layer represents one transport mode and the vertical lines represent the changing of one mode to another through a neutral layer and through a neutral sub-layer for transit. An example route from origin (O) to destination (D) is depicted in blue.

- The development and implementation of an unlabelled choice model in a supernetwork model enabling the analysis of network effects and multimodal trips (Chapter 3).

- The implementation of a novel shortest path function determining the mode and route choice for each agent in the simulation combining addable (e.g., cost per km) and non-addable (e.g., weather protection for 70% of route) mode attributes into route resistances (Chapter 3).

- The use of a so-called neutral layer in the supernetwork to automatically capture all mode and route choice combinations for multimodal trips including the effort to embark and disembark transport modes (Chapter 3).

- The application of a supernetwork model to find the 'best' combination of mode attributes that minimizes the travel resistance to define the combination of mode attributes that describes an ultimate future mode. This is done using a computational feasible approach consisting of two main phases: 1) a future mode attribute combination enumeration and 2) a supernetwork application (Chapter 5).

- The implementation of multiple public transit lines in sub-layers in the supernetwork to enable the modelling of explicit transit lines in the supernetwork model (Chapter 5).

- An approach to aggregate a traffic network by estimating the capacities of equivalent (aggregated) edges by varying the amount of traffic in the original network using the BPR-function in simulations (Chapter 5).

These contributions help advance the current body of knowledge by developing the unlabelled mode modelling approach and the supernetwork model, which have not been developed before to estimate the mobility effects of future modes and to find the ultimate future mode.

1.3.2 Societal contributions

This dissertation makes six main societal contributions. Policy-makers, researchers and manufacturers can use the approaches in this dissertation for the approaches listed below in other case-studies as well.

- The application of the unlabelled mode modelling approach using revealed preference data of current modes to estimate mode choice effects of any future mode in the Netherlands, such that researchers and policy-makers can analyse to what extent future modes will influence mode choice (Chapter 2).

- The demonstration of how mode choice and other mobility effects, such as changes in travel times and travel resistance, of any future mode can be analysed for the Sioux Falls network (Chapter 3) and two example case-studies in the Netherlands using a supernetwork model, such that policy-makers and researchers understand how introducing any future mode can influence the travel times and travel resistance of an urban area (Chapter 4 and 5).
- The description of the implementation and computational aspects of a supernetwork model to make it easier for other researchers, policy-makers and consultants to further use, research and develop the supernetwork modelling approach (Appendix A).
- Making the supernetwork model completely available and open-source (Appendix A).
- An application of the supernetwork approach to analyse the effects of shared e-bicycles on the modal split between Delft and Rotterdam, such that policy-makers and consultants understand how to use the supernetwork model for their case-studies (Chapter 4).
- The demonstration of how a supernetwork model can be used to analyse the effects of adding an ultimate future mode to the existing infrastructure in Delft, such that policy-makers and researchers understand how the supernetwork approach can be used for a specific case-study with public transport lines (Chapter 5).

1.4 Thesis outline

An overview of the thesis is shown in Figure 1.3. Note that the colours of the components match with the coloured arrows in the conceptual framework in Figure 1.1 to illustrate how the different parts of the thesis connect to each other and where the main and sub-research questions are answered. Chapter 1, this introduction, describes the background, aim and main methods.

First, the effects of future modes on mode choice are analysed in Chapter 2 (blue part in Figure 1.3). Chapter 2 answers RQ1 and uses the findings of Chapter 2 to propose an unlabelled multinomial and nested logit model to analyze the potential modal share of future modes. The parameters are estimated for a case study in the Netherlands to determine the modal split in case future modes, such as shared autonomous cars and electric steps are introduced.

Subsequently, the effects of future modes on travel time and travel resistance are analysed in Chapters 3 to 5 (red part in Figure 1.3). Chapter 3 answers RQ2 and describes how a multimodal supernetwork can be used to simulate the mobility effects of shared autonomous vehicles and electric steps for the case-study of Sioux Falls. The utility function and parameters that have been derived in Chapter 2 are used to describe the resistance of the edges in this supernetwork. Appendix A goes into the software architecture, implementation and computational aspects of the supernetwork model. Chapter 4 analyzes the effects of shared electric bicycles between Delft and Rotterdam. This is done using the supernetwork model from Chapter 3.

An approach to finding the ultimate future mode in Delft is developed to answer RQ3 in Chapter 5 using and extending the supernetwork model of Chapter 3. Generally, the edge resistances of the future mode are minimized to offer the lowest resistance in the network. The mobility effects for different types of travellers are analysed and observations for optimizing a transport network from the perspective of reducing the travel resistance (i.e., mode (dis)utility) are given.

Finally, Chapter 6 combines and discusses the conclusions from previous chapters about the estimating parameters of a discrete choice model and setting up a supernetwork model and describes possible directions for future research.

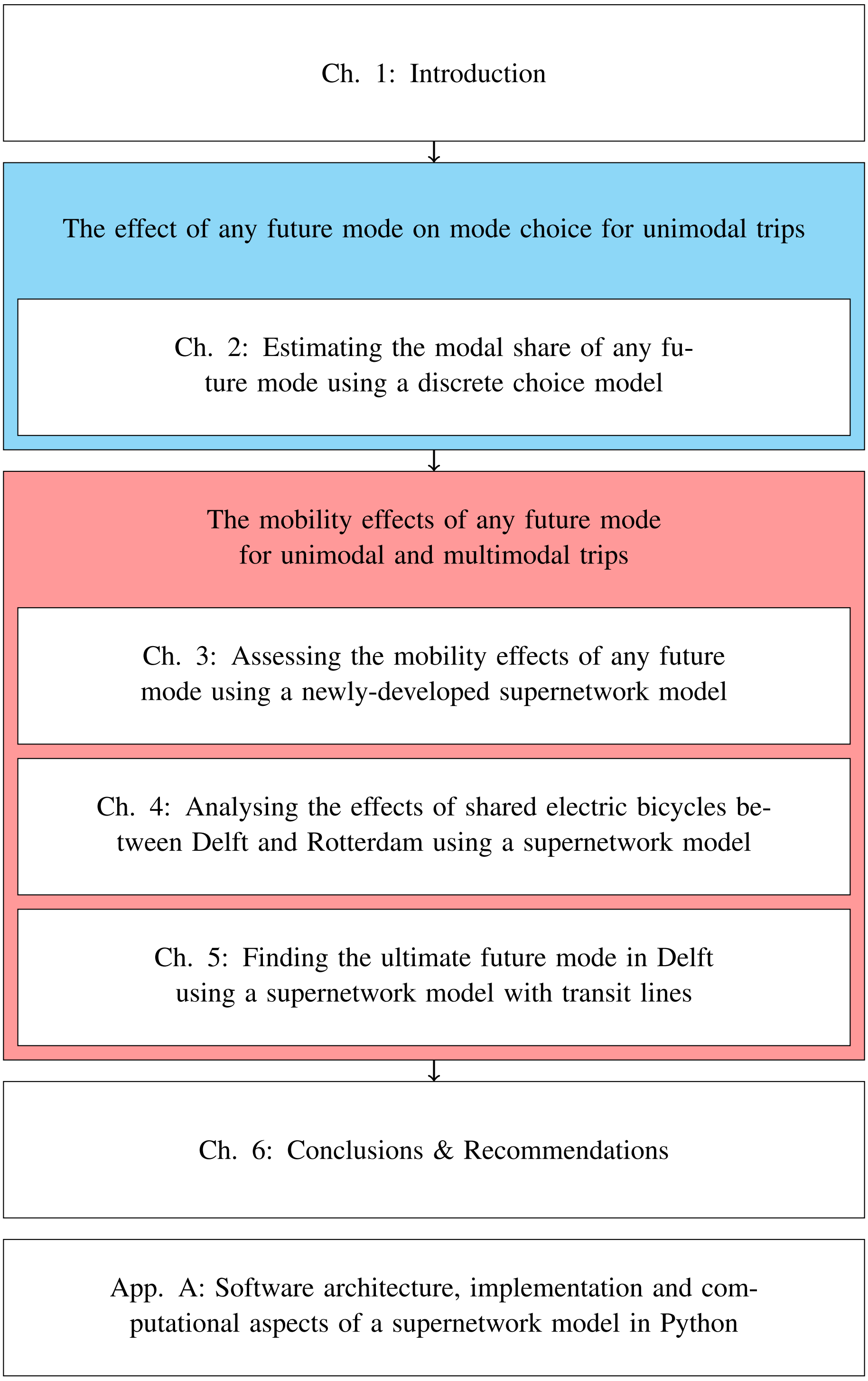

Figure 1.3: Thesis outline

Chapter 2

Estimating the modal share of any future mode using a discrete choice model

Chapter 1 identified knowledge gaps and possible pathways for assessing the impact of future mobility systems on mode choice using an unlabelled mode modelling approach without the need for mode-specific constants and parameters. Chapter 2 develops and implements this approach by estimating the parameters for a discrete choice model without mode-specific constants and parameters to analyze the potential modal split of two future modes: shared autonomous cars and electric steps using OViN-data from 2017 for the Netherlands (Centraal Bureau voor de Statistiek, 2017). Chapter 2 demonstrates how revealed preference data can be used to estimate a discrete mode choice model without using mode-specific constants and mode-specific parameters for unimodal trips, linear attribute combinations of utility and multinomial and nested logit models. The next chapter adds onto the discrete modelling approach of Chapter 2 by introducing a supernetwork model that can analyse mobility effects, such as changes in travel time and resistance, for both uni- and multimodal trips.

Section 2.1 contains the abstract. Section 2.2 introduces the problem and main aim. In Section 2.3 related works are discussed. Section 2.4 explains the methodology of how the valuation of mode attributes has been determined and how the modal split of future modes can be calculated. Section 2.5 describes the found modal splits and this chapter finishes with a discussion and conclusions in Sections 2.6 and 2.7.

This chapter is a version of the following publication: de Clercq, G. K., A. van Binsbergen, B. van Arem, M. Snelder (2022) Estimating the Potential Modal Split of Any Future Mode Using Revealed Preference Data, *Journal of Advanced Transportation*, 2022.

2.1 Abstract

Mode choice behaviour is often modelled by discrete choice models in which the utility of each mode is characterized by mode-specific parameters reflecting how strong the utility of that mode depends on attributes such as travel speed and cost and a mode-specific constant value. For future modes, the mode-specific parameters and the constant in the utility function of discrete choice models are not known and are difficult to estimate on the basis of stated preference data/choice experiments and cannot be estimated on basis of revealed preference data. This chapter demonstrates how revealed preference data can be used to estimate a discrete mode choice model without using mode-specific constants and mode-specific parameters. This establishes a method that can be used to analyse any future mode using revealed preference data and discrete choice models and is demonstrated using the OViN 2017 dataset with trips throughout the Netherlands using a multinomial and nested logit model. This results in a utility function without any alternative specific constants or parameters with a rho-squared of 0.828 and an accuracy of 0.758. The parameters from this model are used to calculate the future modal split of shared autonomous vehicles and electric steps, leading to a potential modal split range of 24–30% and 37–44% when using a multinomial logit model and 15–20% and 33–40% when using a nested logit model. An overestimation of the future modal split occurs due to the partial similarities between different transport modes when using a multinomial logit model. It can therefore be concluded that a nested logit model is better suited for estimating the potential modal split of a future mode than a multinomial logit model. To the authors' knowledge, this is the first time that the future modal split of shared autonomous vehicles and electric steps is calculated using revealed preference data of existing modes using an unlabelled mode modelling approach.

Keywords: Mode choice; modal split; future modes; revealed preference data; discrete choice modelling; shared autonomous vehicles; electric steps.

2.2 Introduction

In the last decades, numerous mobility systems, such as shared bicycles, shared scooters, automated cars, ride-hailing services, electric bicycles, and other personal light electric vehicles have been developed. Such future modes could potentially change the way our urban areas look substantially in terms of spatial use, sustainability, health, equity, safety, and economic opportunities (Fagnant & Kockelman, 2015; Shaheen et al., 2019; Milakis et al., 2017; van Arem et al., 2019). For instance, it is estimated that the yearly impact of automated vehicles (AV) alone could approach 4,000 generalized US dollars per person per year, including economic benefits, crash cost savings, travel time reductions (due to reduction in congestion) and lower parking costs (Fagnant & Kockelman, 2015).

A commonly accepted definition of future modes does not exist in literature. To define future modes, it is important to consider what a mobility system entails and when such a system can be considered new. In our research, we define a mobility system as a set of components that as such and as a whole provides a means of transport for people and/or goods. Mobility systems are highly integrated into society and, therefore, challenging to analyze and describe due to their complex, large-scale, interconnected, open, and sociotechnical nature (Sussman et al., 2014). Systems can be differentiated and categorized on the basis of a multitude of attributes (Kennisinstituut voor Mobiliteitsbeleid, 2018). A mobility system can be considered a future mode in a specific area, if it substantially differs from already implemented mobility systems, such that mode choice changes can be expected when introduced. The novelty of a system is, therefore, relative and depends on the context: a system can already exist somewhere in the world, but can be new for a specific area or its implementation differs from the implementation in other areas. For example, a metro system can be considered a future mode in one city, changing people to start using the metro instead of cars, whereas increasing the metro frequency of an already existing metro system in another city, leads to strengthening the competitive position of and a (further) modal shift to the metro system in that city, and is not considered a future mode. Another example: introducing shared bikes in an area without local public transport, facilitates specifically last-mile trips, enabling new public transport trips and tours. In this chapter, a future mode is defined as follows: *future modes are substantially different compared to already existing implemented modes in the research area or in similar areas.*

Introducing future modes might lead to a change in accessibility (e.g., changing travel times and congestion) and this, in turn, can lead to a change in land use and activities. A conceptual model to describe this development has been proposed (see Figure 2.1. The model structures the dominant relationships found in the literature and is an adaptation of the LUT feedback cycle from Wegener (Wegener, 2004). future modes are placed in the centre of the conceptual framework to represent the main source of effects on mode choice. When a future mode is deployed, the available transport options change, which can change the mode choice behaviour (e.g., people use shared AVs instead of busses, trams, and metros) and thus modal split. A change

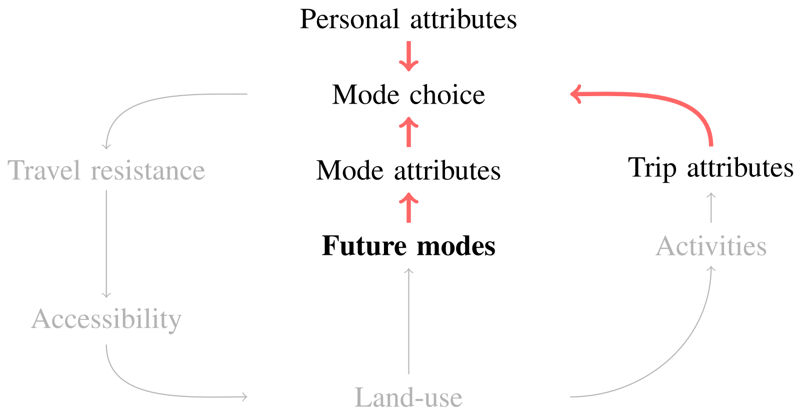

Figure 2.1: Dominant relationships of the effects of future modes on mode choice. Adaptation from Wegener (Wegener, 2004).

in mode choice indicates improved accessibility (e.g., due to the high use of shared AVs, the average travel time decreases). If accessibility improves, urban areas might become more attractive (e.g., more people move there) and be used more intensively in the long term as well, which will again put pressure on the transport systems and might evoke the need for new improvements. Note that this study focuses on the red part in the conceptual framework and that the grey part is outside of the scope.

Analyzing how mode choice behaviour could change when future modes are available is challenging, since potential users are not familiar with such systems yet. Mode choice is determined by numerous attributes that can roughly be separated into three categories: mobility system (e.g., costs), personal (e.g., age, gender, and income), and trip (e.g., origin and destination location, trip purpose, and precipitation) attributes. Traditionally, attributes, such as transport cost and transport speed, are used to describe mobility systems. Additional attributes, such as type of ownership (e.g., buying, leasing), protection against weather, space for luggage, and availability in time, play a role in describing mobility systems as well (Bagley & Mokhtarian, 2002). future modes can change the values of already identified attributes, but can also introduce new attributes and can, therefore, be described by appending and/or replacing attributes (e.g., car availability instead of car ownership) (Soteropoulos et al., 2019).

A way to avoid introducing implicit preferences towards existing modes when describing existing (and future) modes is to not use any mode-specific constants and parameters (Quandt & Baumal, 1966; Jin et al., 2017). Quandt & Baumal developed the so-called unlabelled mode modelling approach, in which mode choice is assumed to be explained only by attributes such as speed, frequency of service, comfort, and cost (Quandt & Baumal, 1966). Their model does not include a mode-specific constant related to the perceived (partly unexplained) overall utility of a mode. The model describes a mode by merely looking at the type of service that travellers get for an unlabelled mode (e.g., 'mode A' instead of labelling the mode as 'a car', thereby avoiding the implicit inclusion of unidentified 'car' attributes). Quandt & Baumal's explorative study considers the choice situations of different modes characterized by different combinations of attributes such as speed, frequency of service, comfort, and cost. Their approach aims to expose the 'true' trade-offs by travellers between the attribute's levels. The unlabelled mode modelling approach has been applied in several papers. DeSalvo & Hug implemented Quandt & Baumal's approach to analyze mode choice of existing modes and urban household behaviour by considering costs, commuting time, speed and distance (DeSalvo & Huq, 2005). Malalgoda & Lim used a similar approach to research the use of existing public transit in the U.S. by considering the variables passenger miles, unlinked passenger trips, vehicle hours, operating employees, fuel, fare, income and population (Malalgoda & Lim, 2019). Malalgoda & Lim used this approach because of its ability to consider continuous modes, and therefore, find mathematical optimums.

Based on the literature review, we expect that the unlabelled mode modelling can be particularly useful to expose tradeoffs based on objectifiable attributes by travellers, making choices between existing and non-existing modes, of which the mode-specific constant cannot be known, such that the future modal split can be estimated. An important requirement to leave out a mode-specific constant and parameters is the availability of a complete and coherent set of attributes that can represent both existing and new mobility modes and the assumption that the valuation of the modes attributes by travellers will not change when a future mode is introduced.

This chapter demonstrates how revealed preference data and discrete choice models without mode-specific constants and parameters can be used to give insight into how future modes could change mode choice. This method is demonstrated by calculating the future modal split of shared autonomous vehicles and electric steps. To the authors' knowledge, this is the first time that the future modal split of shared autonomous vehicles and electric steps using revealed preference data of existing modes is calculated. It also identifies knowledge gaps and possible pathways for future research on theories and methods to assess the impact of future modes on mode choice.

2.3 Literature on discrete choice modelling

A common practice to model the way people choose their transport mode is to use discrete choice models using a generalized utility function (see Eq. 2.1 covering mobility system attributes and personal attributes (Ortuzar & Willumsen, 2011).

$$U_{ij} = \alpha_{ij} + \Sigma_{k=1}^{nk} \beta_{ijk} \chi_{jk} + \varepsilon_{ij} \tag{2.1}$$

where;

U = utility of mode for person (i) of mode (j);

α = mode and person-specific constant for personal preference (i) of a mode (j) (excluded in unlabelled mode choice modelling);

β = estimated parameter for personal preference (i) of mode attribute (k) of a mode (j);

χ = mode attribute value of mode attribute (k) of a mode (j);
i = persons (or clusters);
j = mobility system;
k = mobility system attributes;
nk = number of mobility system attributes; and
ε = error-term (excluding the mobility system constant α).

Understanding the generalized utility of future modes is of vital importance to understanding how future modes affect mode choice. For instance, a multitude of studies use (nested) logit models to model mode choice in the context of automated driving (Snelder et al., 2019; Puylaert et al., 2018), shared driving (Daisy et al., 2018; Zhou et al., 2020; Choudhury et al., 2018; Ikezoe et al., 2020; Winter et al., 2020a), and multimodal trips (Fan et al., 2019; Bovy & Hoogendoorn-Lanser, 2005). These studies all make assumptions about mobility system-specific parameters (e.g., time is often valued differently in an automated car than in a conventional car) and mobility system-specific constants which are used to capture effects that cannot be explained by the used mobility system attributes (e.g., a car has a higher level of status compared to taking the bus). These mode-specific constants can only be calibrated when using data of modes of which choice data is available, so these cannot be used when aiming to predict the modal share of future modes. The multinomial logit model assumes that the attributes of all alternatives are orthogonal (no correlation between attributes). If this does not hold, then the so-called 'red/blue box paradox' occurs when two alternatives are too similar, which leads to an overestimation of those alternatives. To overcome this overestimation, other types of discrete choice models, such as a nested logit model, can be used (Train, 2003). This introduces other model-specific scaling parameters that need to be estimated and (manually) estimated when adding a future mode. For a nested logit model, one scaling parameter to define to what extent the alternatives within a nest have Independence from Irrelevant Alternatives (IIA) outside of the said nest needs to be defined (Train, 2003). This parameter is based on the similarity between the attributes of two alternatives and defines to what extent the nest behaves as a nest or as two alternatives (as in a multinomial logit model). The similarity between all attributes of two alternatives can be defined by taking the normalized multidimensional distance between two alternatives (Baikousi et al., 2011), see Formula 2.2. The similarity is defined as 1 minus the multidimensional distance. Subsequently, the mode with the highest similarity to the future mode and the future mode are put in one nest in a nested logit model.

$$Dist = \frac{(\Sigma_{k=1}^{nk} |\chi_{norm,1} - \chi_{norm,2}|}{nk} \tag{2.2}$$

where;
$Dist$ = normalized multidimensional distance;
k = mobility system attributes;
nk = number of mobility system attributes; and

$\chi_{norm,i}$ = normalized mobility system attribute.

To create overlapping nests when alternatives do not fit in one nest in the nested logit model, a cross-nested model or a paired-combinatorial logit model can be used. For a cross-nested logit, between two and the number of alternatives scaling parameters need to be estimated (Train, 2003; Bierlaire, 2006; Prato, 2009), which becomes complex quickly. When using a paired combinatorial logit model, 1+2*number of alternatives (including future alternatives) scaling parameters need to be estimated, which comes down to 13 scaling parameters in the case of five existing alternatives and is computationally extremely difficult without preference data about the future mobility system (Prato, 2009). The mobility system-specific parameters and constants and model-specific scaling parameters are ideally estimated using stated or revealed preference data. This is, however, challenging for future modes as explained in the next section.

Empirical research uses large-scale stated and revealed preference surveys to estimate the relevant parameters to model mode choice. Stated preference research can help to understand mode choice, but it can be challenging to determine how results from stated preference studies translate to the real world. This is because stated preference research is, by definition, based on a representation of reality, where certain (unknown) attributes are not taken into account in the research (Cherchi & de Dios Ortúzar, 2006; Daly & Rohr, 1998). Instead, revealed preference research helps to understand how people make choices in the real world, but can only test how existing mobility systems are used. Revealed preference research to find out how and when people start to use future modes, such that the change in mode choice and travel behaviour can be analyzed, is limited (Cherchi & de Dios Ortúzar, 2006). Although studies often try to analyze mode choice using pilots with sometimes limited implementations, it already gives insight into how a future mode might be used in the real world (Anagnostopoulou et al., 2020; Mundorf et al., 2018).

Stated and revealed preference research can be combined to analyze how future modes might be used. Extrapolating revealed preferences (read: values of mobility system-specific constants and parameters) to a new set of mobility systems with a new (unused) alternative and, subsequently, normalizing these results using stated preference research is a way to combine stated and revealed preference research (Daly & Rohr, 1998; Polydoropoulou & Ben-Akiva, 2001). This approach, however, has implicit preferences by including values of mobility system-specific constants and parameters of the analyzed mobility systems to model mode choice, so when extrapolating this to future modes, assumptions about implicit preferences are also carried over and influence the predicted modal split of the newly added mobility system.

2.4 Methodology to estimate modal split of any future mode

This chapter first describes the way a utility function of a discrete choice model without mode-specific constants and parameters can be estimated on basis of revealed preference data from OViN 2017 (Centraal Bureau voor de Statistiek, 2017). This chapter then demonstrates that the modal split of a subset of current systems can be estimated on the basis of that function. This chapter subsequently demonstrates how this approach can be used to estimate the modal share of additional (also new) modes, insofar as the main choice-determining characteristics of such a mode can already be experienced in current transport systems.

For the revealed preference dataset, it is assumed that all attributes are orthogonal (no correlation between attributes). Furthermore, since generalized utility functions, without mobility system-specific parameters or constants, are used, it must be assumed that people are familiar with all mobility systems and the initial familiarization and adoption have occurred. Therefore, we assume that, if a future new transport system can be described as a combination of already known transport system characteristics, we can calculate its mode choice and modal share.

Two studies demonstrating the method are performed to estimate the potential modal split of future modes with (1) synthetic data and (2) revealed preference data. The algorithm below describes all the steps involved in using revealed preference data. The algorithm is the same for synthetic data, except for the first step of importing the dataset, which has been generated (Algorithm 2.1).

Algorithm 2.1: Estimate future modal split using revealed preference data

Initialize

1. Import full OViN dataset
2. Perform latent class analysis to define a 'minimum performance benchmark'
3. Define clusters based on personal and trip attributes using k-means and elbow function in the full dataset
4. Retrieve train (80%) and test (20%) dataset
5. Define general utility function

Estimate current modal split (with and without mode-specific constant)

6. Estimate parameters of the utility function of a discrete choice model with 5 modes per cluster using the train dataset
7. Calculate the modal split of 5 modes per cluster in the test dataset
8. Compare calculated modal split with recorded modal split in the full test dataset

Estimate future modal split

9. Define attributes of future mode, incl. variations of $\pm 20\%$ for sensitivity analysis (SA)
10. Calculate similarity of all modes and future mode to estimate scaling parameter in a nest (only for nested logit), see Eq. 2.2
11. Calculate modal split ranges (SA) of 6 modes per cluster in the test dataset using results of the modal split of step 6 (without mode-specific constant)
12. Create a Sankey diagram (excl. variations of $\pm 20\%$)

Table 2.1: Synthetic dataset person and trip attributes

Attribute	Range
Age (year)	18 – 90, steps of 1
Income (€/year)	10.000 - 200.000, steps of 10.000
Distance (km)	0.5 - 100.5, steps of 1

Table 2.2: Synthetic dataset mobility system attributes

Attribute	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Future*
Average speed (km/hour)	60	50	40	30	20	25
Cost (€)	Distance / 2	Distance / 4	Distance / 8	Distance / 16	0	Distance / 32
Time (hour)	Distance / average speed					

2.4.1 Synthetic data

To demonstrate the method synthetic data with a utility function with two main attributes is created. First, a utility function (see Equation 2.3) is defined to create a training (80%) and test (20%) dataset with 5 modes. All permutations of age, income and distance are used to create the datasets, where distance defines the cost and time of each mode (see Table 2.1 & Table 2.2 with 147,460 entries). After the training dataset is inserted into Biogeme (Bierlaire, 2023), Biogeme estimates the two parameters ($\beta_{time}, \beta_{cost}$) using a logit model where the probability of a certain mode choice is calculated (see Equation 2.4, (Bierlaire, 2023)).

Subsequently, the parameters can be filled in the utility function to calculate the modal split using the test dataset. This calculated modal split with 5 modes can be compared to the training dataset. This comparison can be done by looking at how well the mode choices of the original synthetic dataset match the mode choices in the test set using rho-squared (see Equation 2.5, (Bierlaire, 2023)) and modal split, where it is expected that the performance of both indicators is (almost) perfect due to the synthetic nature of the data. Now, the attributes of a future mode can be added when calculating the modal split using the test dataset because the utility function is the same for each mode and the parameters are estimated already. When filling in the utility function for a future mode, the modal split including this future mode can be calculated. To verify this method and check if the code is behaving as expected, the calculated modal split based on the test dataset with 6 modes can be compared with the modal split of the synthetically generated test dataset with 6 modes.

$$U_{ij} = \beta_{time} * age_i * time_j + \beta_{cost} * \frac{200.000}{income_i} * cost_j \tag{2.3}$$

where;

β = parameters;

age = age of person i;

$time$ = travel time of mode j depending on distance of trip;

$cost$ = cost of mode j depending on distance of trip;

i = persons; and

Table 2.3: Mode attributes based on OViN (Centraal Bureau voor de Statistiek, 2017) and assumptions

Mode attribute	Source and determination
Cost (€)	Car, transit, cycle and walk from data; carpool = costs of car / 2
Time (min)	Car, carpool, transit, cycle and walk from data
Driving task (-)	Car, cycle = 1; carpool, transit, walk = 0
Skills (-) (i.e., drivers license)	Car = 1; carpool, transit, cycle, walk = 0
Weather protection (-)	Car, carpool, transit = 1; cycle, walk = 0
Luggage (-)	Car, carpool = 1; transit = 0.5; cycle, walk = 0
Shared (-)	Car, carpool, transit, cycle and walk from data
Availability (-)	Car = 1; carpool = 0.1; transit = urban density origin (from 1 to 5) * urban density destination (from 1 to 5) / 25; cycle = 1, walk = 1
Reservation (-)	Car, carpool, cycle, walk = 1; transit = 0
Active (-)	Car, carpool, transit = 0; cycle, walk = 1
Accessible (-)	Carpool, transit = 1; Car, cycle, walk = 0

j = mobility system.

2.4.2 Revealed data

A study demonstrating the method is performed to estimate the potential modal split of future modes with revealed preference data, enriched with precipitation by TNO, from OViN (Centraal Bureau voor de Statistiek, 2017). This labelled dataset was restructured to add 9 more mode attributes (see Table 2.3). The labelled dataset contains 75,043 entries, with 11 personal attributes, 9 trip attributes, and 11 mode attributes, 5 modes (car, carpool, transit (BTM), bicycle, and walk) and the mode choice for each entry. This dataset is shuffled and separated into a training (80% of entries) and a test (20% of entries) dataset. It was decided that a minimum acceptable performance (e.g., minimum rho-squared or accuracy) for the discrete choice model was to be defined by inserting the dataset into a latent class analysis (so without alternative specific constants or parameters). This was done to benchmark the minimum (and added) accuracy of a discrete choice model compared to a latent class analysis. Any performance lower than a latent class analysis was assumed to indicate that more 'information was still embedded in the dataset that could predict mode choice'. A latent class analysis was assumed to be a benchmark since this method requires no special analytical preparation or definition of parameters. A latent class analysis does not require clustering of similar travellers beforehand. This allows for understanding how much the data 'itself' can explain mode choice behaviour. Then, a discrete choice model should be an improvement by adding utility functions, parameters and other additional constants to extract more information on mode choice behaviour. Comparing the improvement over the performance of a latent class analysis will give insight in the added value of using a discrete choice model.

Next, a k-means cluster analysis is performed to take into account personal and trip attributes by grouping similar entries in one cluster (Shoabjareh et al., 2021). This is done using a k-means clustering algorithm and the elbow method to determine the

Table 2.4: Ranges of mode attributes of future modes

Mode attribute	Range
Cost (€)	[0, 4, 8, 12, 16, 20] & [0.05, 0.15, 0.25] * distance (km)
Time (min)	distance (km) / [10, 20, 40, 60, 80, 100] / 60
Driving task (-)	[0, 1]
Skills (-) (i.e., drivers license)	[0, 1]
Weather protection (-)	[0, 1]
Luggage (-)	[0, 1]
Shared (-)	[0, 1]
Availability (-)	[0, 0.5, 1]
Reservation (-)	[0, 1]
Active (-)	[0, 1]
Accessible (-)	[0, 1]

optimal number of clusters (Syakur et al., 2018). The elbow method determines the optimate number of clusters in a dataset by calculating the variance explained for each number of clusters and then taking the number of clusters when a higher number of clusters does not explain the data better any longer. This dataset is fed to a multinomial logit model where the probability of a certain mode choice is calculated (see Eq. 2.4) in Biogeme (Bierlaire, 2023) using a predefined utility function with mode attributes from the dataset (see Eq. 2.1), where the mobility and person-specific constant is equal to 0) with randomized initial values of the parameters between -0.5 and 0.5. Note that this is done for each cluster. In this way, personal and trip attributes (read: dummy variables) do not need to be included in the generalized utility function, since similar attributes are already clustered (Ding & Zhang, 2016).

Subsequently, the modal split of the 5 modes can be calculated by filling in the parameters of the utility function to calculate the modal split of the test dataset. Rho-squared (see Eq. 2.5), precision (see Eq. 2.6), recall (see Eq. 2.7), f1-score (see Eq. 2.8) and accuracy (see Eq. 2.9) were used to analyze the performance of the estimation.

$$P_{ij} = \frac{e^{U_{ij}}}{\Sigma_{k=1}^{nk} e^{U_{ik}}} \tag{2.4}$$

where;
U = generalized utility;
i = persons; and
j = mobility system;
nk = number of mobility system;
k = mobility system.

$$\rho^2 = 1 - \frac{L^*}{L^i} \tag{2.5}$$

where;
L^* = final log-likelihood of correct mode choice; and
L^i = initial log-likelihood of correct mode choice.

$$Precision = \frac{TP}{TP + FP} \tag{2.6}$$

where;
TP = True positive; and
FP = False positive.

$$Recall = \frac{TP}{TP + FN} \tag{2.7}$$

where;
TP = True positive; and
FN = False negative.

$$f1_{score} = 2 * \frac{precision * recall}{precision + recall} \tag{2.8}$$

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{2.9}$$

where;
TP = True positive;
TN = True negative;
FP = False positive; and
FN = False negative.

The modal split of the 5 modes is also calculated with a mode-specific constant to see whether the performance changes and whether the approach without a mode-specific constant is appropriate. Note that the rho-squared and the calculated modal split are based on the log-likelihood of a certain choice (the outcome of Equation 2.3, whereas precision, recall, f1-score and accuracy do not consider the probability of a choice, merely the choice with the highest 'generalized random utility'. This calls for a thorough analysis and interpretation of each metric, since the comparison of metrics is not trivial (e.g., accuracy cannot be compared with rho-squared).

When using a nested logit, the similarity between each mode and the future mode is calculated by normalizing the values of all attributes and calculating the so-called multidimensional distance between each mode (see Eq. 2.2 (Baikousi et al., 2011)). The distance between two modes for cost and time is calculated by taking the normalized squared difference and for all other attributes, the absolute normalized difference is taken. Then, this value is divided by the number of attributes to determine the multidimensional distance. The similarity is defined as 1 minus the multidimensional distance. Subsequently, the mode with the highest similarity to the future mode and the future mode are put in one nest in a nested logit model.

Subsequently, a future mode is added and the modal split of this mobility system is calculated using the same utility function and parameters of the estimated discrete choice model without the future mode. The values of the attributes of the future mode are varied within reasonable ranges (see Table 2.4) to find the ranges of the modal split when a future mode is introduced. This is to account for uncertainties and to see which attributes of future modes will affect the modal split.

2.5 Results

The latent class analysis used the full dataset to estimate mode choice. The accuracy was 0.41 and the Brier score was 0.53. This will serve as a baseline to compare the accuracy of the discrete choice model. Note that the accuracy is based on the final mode choice, without taking into account probabilities (i.e., variations of individual choice behaviour).

In mode choice research, a wide range (0.20 – 1.00) of rho-squared (see Equation 2.5) seems to be acceptable as a result (Haque et al., 2019; Ashkrof et al., 2019; Ton et al., 2019). Using the standard in the field and taking the findings of the latent class analyses, it was decided that in this research a rho-squared of 0.60 or higher and an accuracy of at least 0.45 will serve as the minimum performance requirements. The results of the synthetic data are shown in Table 2.5. The estimation of the parameters in Biogeme resulted in a rho-squared of 0.998. As can be observed, the calculated modal split (columns 3 and 4) is the same as the modal split in the dataset (columns 1 and 2). The accuracy of the calculated modal split with 6 modes is 1.000. Therefore, it can be concluded that estimating future modal split can work with a synthetic dataset.

The estimation of the parameters with a utility function without alternative specific constants and two parameters scaling the utility of cost and time resulted in a rho-squared of 0.265. Since this rho-squared is considered too low, all mode attributes and the personal information of having a driving license in the dataset have been added as input as well, increasing the total number of parameters to 12. This resulted in a rho-squared of 0.540 and an accuracy of 0.663. To account for socio-economic and trip-specific attributes, without complicating the utility function by adding dummy variables and enhancing accuracy (Ding & Zhang, 2016), 6 clusters were identified based on personal and trip attributes. Two out of 6 clusters were based on trip purpose (business and work (cluster 2), home (cluster 3)). Three other clusters had a trip purpose of ‘other’, where one cluster only contained trips with people who do not own a car (cluster 1) and the other two clusters contained trips with people that own a car. These two clusters were differentiated by the information that people are (cluster 6) or are not the main car user (cluster 5). The last cluster (cluster 4) was differentiated by both high precipitation and car ownership. An overview of the mode attributes valuations per cluster can be found in Table 3.2.

Estimating the parameters of the utility function for each cluster resulted in a rho-squared of 0.828 and an overall accuracy of 0.758 (see Table 2.6). It can be observed that the performance metrics in Table 2.6 for modes with a larger modal split (i.e., car, cycle, and walk) are higher compared to modes with a smaller modal split (i.e., carpool and transit). Moreover, it can be observed that the total macro average f1-score is lower than the total weighted average f1-score, indicating the discrete choice model is optimized more for modes that have a larger modal split in the dataset. Note that the modal split in Table 2.5 is based on probabilities that a mode was chosen and that the metrics in Table 2.6 are based on the final mode choice with the highest utility.

This study also demonstrates that the exclusion of an alternative specific-constant in the utility function leads to a comparable result using the current 5 modes. Using a utility function with 12 parameters and 1 alternative specific constant (with the alternative specific constant of the car set to 0) leads to a rho-squared of 0.823 and an overall accuracy of 0.740, this is similar to the performance without an alternative specific constant. It should be noted that the values of the alternative specific constants vary between -1.57 and 1.27. Because of the similar performance between the discrete choice models with and without alternative specific constants, it was concluded that the effect of an alternative specific constant, in this case, even including the mentioned outliers, is negligible and therefore we can use the results without the alternative specific constant to calculate the future modal split.

Before estimating the future modal split with a multinomial logit model, the so-called 'red/blue bus paradox' is tested by adding each mode as a future mode and subsequently calculating the total modal split for each mode (see Table 2.7). The largest difference is observed for the mode 'cycling' (7.5 percentage point difference). A nested logit model is also estimated to overcome the 'red/blue bus paradox'. The modal shares of each model can be compared with each other to see whether (attributes of) the modes are orthogonal and a nested logit is needed to calculate the future modal split.

The estimation of these parameters is used to calculate the future modal split by calculating the modal split of each permutation of a future mode according to Table 2.4. The modal split of future modes ranges between 4.7% and 88% with an average modal split of 45%. This means that by varying all attributes a wide range of modal splits is found, which is to be expected, since all possible combinations are included. From these results, one can find the modal split for any future mode by defining the attributes of this mode.

In this chapter, two example future modes were defined to demonstrate the consequences of using a multinomial logit and a nested logit model. The first one is a shared autonomous car and the second one is a rented electric step; their properties are defined in Table 2.9. Estimating the mode choices and modal split in the setting with the additional modes results in modal shares of 24% for the shared autonomous car and 37% for the electric step when using the multinomial logit model. When applying a nested logit model, first the nests are determined by taking the highest similarity index of an existing mode compared to both of the future modes (see Table 2.8). This resulted in putting the future mode shared autonomous car into one nest with the carpool, and the electric step in the nest with the cycle. Application of the thus defined nested logit

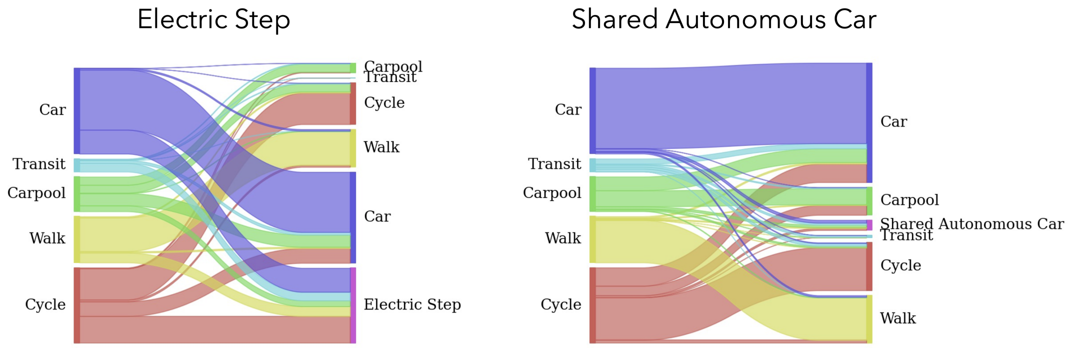

Figure 2.2: Sankey diagram of current mode choice (left on each diagram) and future mode choice (right on each diagram) for the nested logit model

Table 2.5: Results synthetic data

Mode	Modal split synthetic dataset		Calculated modal split	
	5 modes	6 modes	5 modes	6 modes
Mode 1	3.6 %	3.6 %	5.6 %	5.6 %
Mode 2	46 %	46 %	43 %	43 %
Mode 3	37 %	37 %	36 %	36 %
Mode 4	8.3 %	5.6 %	9.4 %	9.0 %
Mode 5	5.2 %	3.8 %	5.7 %	3.2 %
Future	-	4.1 %	-	3.2 %

model resulted in an estimated modal share of 15% for the shared autonomous car and 33% for the electric step. Sensitivity analyses are performed to get a better understanding of how robust the calculated modal splits are. The sensitivity analysis is performed by varying all mode attributes that can be varied with $\pm 20\%$. The results can be found in Table 2.10 and Table 2.11. Sankey diagrams (see Figure 2.2) visualize how people's mode choice changes from the currently available modes and the future available modes using the standard values (i.e., not the varied mode attributes of the sensitivity analysis) for the nested logit model.

Table 2.6: Results modal split estimation OViN data for 6 clusters

Mode	Precision	Recall	f1-score
Car	0.670	0.971	0.792
Carpool	0.492	0.321	0.369
Transit	0.934	0.232	0.358
Cycle	0.857	0.691	0.728
Walk	0.898	0.944	0.917
Total macro average	0.708	0.514	0.533
Total weighted average	0.756	0.758	0.716
Overall accuracy	0.758		

Table 2.7: Results modal split double mode ('red/blue bus paradox')

	Original	Car 2x	Carpool 2x	Transit 2x	Cycle 2x	Walk 2x
Car	33 %	40 %	30 %	32 %	30 %	33 %
Carpool	14 %	11 %	20 %	13 %	12 %	13 %
Transit	4.9 %	4.0 %	4.4 %	7.8 %	3.9 %	4.8 %
Cycle	30 %	27 %	28 %	29 %	37 %	29 %
Walk	18 %	18 %	18 %	18 %	18 %	19 %
Max. difference between original and 2x		6.7 %	6.4 %	2.8 %	7.5 %	1.3 %

Table 2.8: Similarity index for each mode compared to the future mode

Future	Car	Carpool	Transit	Cycle	Walk
Shared autonomous car	0.62	0.82	0.66	0.48	0.52
Electric step	0.49	0.22	0.35	0.88	0.75

Table 2.9: Attributes shared autonomous car and electric steps with sensitivity analysis values between square brackets based on a 20% variation of all mode attributes

Mode attribute	Shared autonomous car	Electric step
Cost (€)	0.05 [0.04 0.045 0.05 0.055 0.06] per km	4 [3.20 3.60 4.00 4.40 4.80]
Time (min)	distance (km) / 60 [48 54 60 66 72] (km/h) / 60	distance (km) / 10 [8 9 10 11 12] (km/h) / 60
Driving task (-)	0	1
Skills (-) (i.e., drivers license)	0	0
Weather protection (-)	1	0
Luggage (-)	1	0
Shared (-)	0	0
Availability (-)	0.5 [0.4 0.45 0.5 0.55 0.6]	1 [0.8 0.9 1]
Reservation (-)	1	0
Active (-)	0	1
Accessible (-)	1	0

Table 2.10: Calculated modal split electric step with sensitivity analysis ranges between brackets based on a 20% variation of all mode attributes

Mode	Current modal split	Future modal split	
		MNL	NL (in nest with bicycle)
Car	33 %	20 [17 – 20] %	24 [20 – 24] %
Carpool	14 %	9.5 [8.8 – 9.5] %	9.7 [8.9 – 9.7] %
Transit	4.9 %	2.1 [1.8 – 2.1] %	2.4 [2.0 – 2.4] %
Cycle	30 %	19 [17 – 19] %	18 [16 – 18] %
Walk	18 %	13 [12 – 13] %	14 [13 – 14] %
Shared electric step	-	37 [37 – 44] %	33 [33 – 40] %

Table 2.11: Calculated modal split shared autonomous car with sensitivity analysis ranges between brackets based on a 20% variation of all mode attributes

Mode	Current modal split	Future modal split	
		MNL	NL (in nest with bicycle)
Car	33 %	25 [22 – 25] %	31 [29 – 31] %
Carpool	14 %	10 [9.5 – 10] %	9.0 [8.8 – 9.0] %
Transit	4.9 %	3.6 [3.3 – 3.6] %	4.1 [3.9 – 4.1] %
Cycle	30 %	23 [21 – 23] %	25 [23 – 25] %
Walk	18 %	15 [14 – 15] %	16 [15 – 16] %
Shared autonomous car	-	24 [24 – 30] %	15 [15 – 20] %

2.6 Discussion

This study presents an approach for calculating the mode choice and modal split of new transport modes in a future situation in which such modes are well established using a discrete choice model without alternative specific constants, of which the parameters are estimated based on revealed preference data. This study uses the examples of an electric step and a shared autonomous car to explore this method. First, the accuracy of this method is discussed. Then, is it discussed if a multinomial logit or nested logit model can calculate the modal share of a future mode better by taking into account the so-called 'red/blue bus paradox'. Finally, some assumptions and computational challenges are scrutinized.

As expected, the accuracy is higher (0.76) for the final estimation with 12 parameters and 6 user clusters than when performing the latent class analysis (0.41). For currently known modes, it is demonstrated that using an alternative specific constant in the utility function does not give significantly different results than our approach. Therefore, it can be concluded that the unlabelled mode choice modelling approach is valid for this dataset.

When applying the estimated utility logit function to predict future mode choice, it can be observed that the future modal shares of the future modes seem to be relatively high when using a multinomial logit model. This could be an overestimation caused by a violation of the IIA assumption, i.e., some modes are in the model regarded as being completely different while in fact there are partially overlapping characteristics. Due to its formulation, the model tends to overestimate the mode choice of such overlapping modes. The overestimation when using 'double modes' is quite substantial, up to 7.5 percentage points in the multinomial logit model with this dataset.

To overcome the similarity issue, a nested logit was implemented as well; using that approach, the future modal shares seem to be more modest with up to 9 and 4 percentage points lower modal split for shared autonomous cars and electric steps respectively. The nest in this nested logit model consists of the future mode and the most similar existing mode, which is determined by calculating the multidimensional distance of each pair of modes (Baikousi et al., 2011). Knowing from the 'red/blue bus paradox' that an overestimation of the future modal split occurs when using a multinomial logit model, it can be concluded that the nested logit is the preferred discrete choice model in this case.

What should be noted as well is that the attributes (values) that can be derived from empirical data from the current mobility systems do not necessarily properly represent the attributes for future systems (e.g., what is shared exactly?) and new attributes might become significant which are not measured currently (e.g., fear of autonomous driving). Moreover, preferences are changing over time, one example would be the changing trend that people prefer to lease rather than own a car. Further note that the mode attributes in the utility function are considered linear additive, this might not always be the case for some attributes. For example, if a mode is active, the valuation is dependent on the distance in a non-linear (longer distances tire people substantially, whereas shorter distances might not tire people at all). This should be taken into account when interpreting these results and extrapolating these results to other modes or changing traveller preferences.

Calculating the future modal splits using all presented combinations (41,472) requires a lot of calculations and can take a lot of computation time (up to 7 days) on a Macbook Pro with a 2,4 GHz Quad-Core Intel Core i5 and 8GB of RAM. For the presented future modes, fewer combinations (up to 125) are tested and the computation times remain relatively limited (up to 30 minutes). To use this approach in workshops with policy-makers or stakeholders, it is recommended to implement a Monte Carlo estimation instead of a test set to reduce the computation time even more. To achieve this, the distribution of variables (i.e., personal, trip and future mode attributes) of the training set needs to be determined to create the input for the Monte Carlo simulation.

2.7 Conclusions and future research

This study successfully explores an approach for calculating the mode choice and modal split of new transport modes in a future situation when such modes are well established. This is achieved by calculating the modal split of two future modes (shared autonomous car and electric step). This is done by estimating a multinomial logit model and a nested logit model without alternative specific constants and parameters such that this utility function can be used to calculate the modal split of a future mode. Note that the main choice determining characteristics of the future transport modes are already experienced in current transport systems. This study demonstrates that using a utility function without any alternative specific constants or parameters resulted in a rho-squared of 0.828 and an overall accuracy of 0.758 when using clusters grouping similar people and similar trips. The approach is applied to a dataset based on empirical data (OViN (Centraal Bureau voor de Statistiek, 2017)) with 5 existing modes and 2 future modes, where each future mode is analysed separately.

When predicting the modal split of a future mode using a multinomial logit model, it might be concluded that an overestimation of the future modal split occurs due to the partial similarities between different transport modes. For this reason, this study also implemented a nested logit model, which can solve this challenge and can be generalized by automatically nesting the future mode in a nest with the ‘most similar’ existing mode. It can be concluded that a nested logit model is better suited for estimating the potential modal split of a future mode than a multinomial logit model.

Mixed logit models can overcome the methodological shortcomings (assumption of IIA, unobserved preferences, and individual preferences over time) of both MNL and NL. The main aim of this study is to demonstrate that revealed data preference can be used to calculate the potential modal share of a future mode using a discrete choice model without mode-specific constant. The distributions for each mode attribute coefficient would need to be assumed in order to cope with the open-form expression of a mixed logit. Future studies can extend this approach by comparing a mixed logit model with the multinomial and nested logit models.

Further exploration can be done with other types of discrete choice models (e.g., cross-nested logit, paired combinatorial logit) to get a better grasp on the calculation of the modal split of future modes. The main challenge with modelling these more detailed discrete choice models is that multiple scaling parameters need to be simultaneously estimated for the future mode for which there is no revealed preference data available.

As demonstrated in this study, different future modes can be analyzed based on merely their attributes. This also means this approach has a practical application in policy-making. Specifically, subsidies and tax reductions can be analyzed for existing and future modes by reducing, e.g., the value of the cost attribute for future autonomous cars, increasing the cost for conventional cars or calculating the needed capacities for (new) modes and their infrastructure. Several combinations of policies and available modes can be analyzed and combined into multiple scenarios to help policy-makers make effective policies.

Lastly, it is recommended to connect this modal split model to a traffic assignment model to see how the second and third-order aspects change (e.g., activities, accessibility, and land use).

Chapter 3

Assessing the mobility effects of any future mode using a newly-developed supernetwork model

Chapter 2 demonstrates how the modal split of a future mode can be determined by using a discrete choice model without mode-specific constants for unimodal trips. This discrete choice model cannot determine how travel times and travel resistance change when future modes are introduced. As explained in Chapter 1, analysing other mobility effects and the effect of future modes on first- and last-mile mode choice in multimodal trips is also important for policy-making. Therefore, Chapter 3 develops a supernetwork model with the discrete modelling approach with linear attribute combinations of utility by calculating how mode and route choice changes when future modes are introduced with the aim of analysing the mobility effects for both uni- and multimodal trips. This is done for three simple, but exemplary networks and the Sioux Falls network using the Dutch OViN dataset (Centraal Bureau voor de Statistiek, 2017). Although the Sioux Falls network is U.S. American and the OViN dataset is Dutch, these case-studies do illustrate how the mobility effects of any future mode can be assessed using the supernetwork model. Chapter 4 further develops this proof-of-concept by applying the supernetwork model on an OD-pair between Delft and Rotterdam. Chapter 5 further extends the supernetwork model with explicit transit lines in Delft and introduces an approach to identify characteristics for an ‘optimal future mode’.

Section 3.1 contains the abstract. Section 3.2 introduces the problem and main aim. Section 3.3 contains the methodology and the results. And Sections 3.4 and 3.5 contain the discussion and conclusions.

This chapter is currently under review at a journal.

3.1 Abstract

Future modes are believed to have the potential to change the way in which we travel thereby having an impact on accessibility and livability. To understand their impact and design our future mobility systems ex-ante impact assessment is needed. The growing body of research on impact assessment of future modes either uses costly stated preference data (with assumptions about how a future mode will function) to estimate the parameters of utility functions for future modes or makes expert-based assumptions about these parameters. These assumptions about future modes reduce the reliability of these studies. To overcome this challenge, unlabelled mode choice models that do not have mode-specific constants and parameters and can be estimated using revealed preference data have been introduced to assess the mode choice effects of future modes for unimodal trips. In this chapter, we extend this approach by introducing unlabelled utility functions in supernetworks, where each mode is represented by a layer/subnetwork in the main network. This approach enables multimodal (i.e., intermodal trips including access and egress modes) impact assessment in terms of mode and route choice including transfer possibilities between modes at nodes and network performance. The main scientific contributions are 1) the inclusion of unlabelled utility functions in agent-based supernetworks in combination with a novel shortest path approach to deal with fixed and variable components of the utility function, 2) the introduction of a 'neutral' layer to capture all modal combinations in multimodal trips. We demonstrate this approach by introducing two future modes (electric steps and shared autonomous vehicles), which are characterized by unlabelled utility functions clearly differentiating them from existing modes. The resulting mobility effects are analysed in three small yet exemplary networks and the well-known Sioux Falls test network. Results show that introducing electric steps or shared autonomous vehicles in the Sioux Falls network reduces the average travel time from 53.6 minutes to 48.8 or 46.6 minutes respectively and the travel resistance by 14% and by 8% respectively.

Keywords: agent-based modelling; future modes; multimodal; unlabelled mode choice; supernetwork

3.2 Introduction

Several future modes with different characteristics, ranging from shared electric steps to autonomous vehicles, have been developed and some of these have been introduced in varying degrees – from test implementation to local initiatives – in urban areas. These future modes will, for instance, affect the level of sustainability and accessibility of urban areas (Fagnant & Kockelman, 2015; Shaheen et al., 2019; Milakis et al., 2017; van Arem et al., 2019). It can be challenging to define what a future mode is exactly, since it is not intuitive to define when a mode is a future mode compared to existing modes. In this chapter we characterize a future mode as *being substantially different compared to already existing implemented modes in the research area or in similar areas.*

The goal of this chapter is to understand how the introduction of future modes affects the modal split, travel times and travel resistance (i.e., 'generalized' travel time) and the effect on first- and last-mile mode choice. Unlabelled discrete choice models can be used to estimate modal split of future modes for unimodal trips (Quandt & Baumal, 1966; de Clercq et al., 2022). Traffic assignment models can be used to simulate travel times and travel resistance for unimodal trips. This chapter combines an unlabelled discrete choice model and simultaneous mode and route choice assignment models using a supernetwork to assess the mobility effects of *any* future mode enabling the analysis of both uni- and multimodal trips, as is necessary as explained in Chapter 1.

Discrete choice models are often used to assess mode choice effects. The parameters and constants of these models are usually estimated using revealed preference or stated preference data. Revealed preference research is based on data collected in the real world, but can only test how existing mobility systems are used. Since revealed preference data of future modes is by definition not available, revealed preference data can typically not be used to estimate the mode-specific parameters and constants of future modes (Cherchi & de Dios Ortúzar, 2006). To overcome this challenge, generally, three different approaches have been used in literature.

Firstly, data from pilots is used which already gives some insight into how a future mode might be used in the real world (Anagnostopoulou et al., 2020; Mundorf et al., 2018). However, this data is limited and may not be fully representative because there may be a difference between the travel behaviour of the early adopters and the eventual users.

Secondly, stated preference research is used to estimate the parameters and constants of future modes based on data from surveys about hypothetical choice situations which include the future mode (Arentze & Molin, 2013; Smit et al., 2019). Correia et al. (2019) specifically researches the impact of automated driving on the value of time while performing other activities in the car using a stated preference survey. Stevens et al. (2022) assessed the financial viability of autonomous mobility-on-demand systems in Rotterdam, the Netherlands with alternative specific constants based on stated preference data. However, it can be challenging to determine how results from stated preferences studies translate in practice, due to the difficulty for people to estimate how their actual choice behaviour differs from their stated choice behaviour. This is because stated preference research is, by definition, based on a hypothetical representation of reality, where certain (unknown) attributes are not taken into account in the research (Cherchi & de Dios Ortúzar, 2006; Daly & Rohr, 1998). The main advantage is that these studies give some insight into how these future modes will probably be used, but one limitation is that travellers will still probably behave differently once these future modes are actually introduced (revealed preference) compared to what they state in a stated preference survey.

Thirdly, expert-based assumptions about mode-specific parameters (e.g., time is often valued differently in an automated car than in a conventional car) and mode-specific constants for those future modes are made. For example, Snelder et al. (2019) looked at multiple future modes, such as automated vehicles and automated (shared) taxis and vans using assumptions of mode-specific parameters for these future modes, but basing the choice behaviour of current modes on a revealed preference dataset. The downside of this is that these assumptions of mode-specific parameters can be different in reality if future mode attributes are slightly different or the perception of these future mode attributes are different.

Stated and revealed preference research can also be combined to analyze how future modes might be used. Extrapolating the values of mobility system-specific constants and parameters of current modes based on revealed preference research to a new set of modes, including a new (future) alternative, and, subsequently, normalizing these results using stated preference research is a way to combine stated and revealed preference research (Daly & Rohr, 1998; Polydoropoulou & Ben-Akiva, 2001). This approach, however, has implicit preferences by including values of mobility system-specific constants and parameters of the analyzed mobility systems to model mode choice, so when extrapolating this to future modes, assumptions about implicit preferences are also carried over and influence the predicted modal split of the newly added mode. This means that the estimated modal share of a future mode is difficult to validate, since it is unknown to what extent the current biases influence the modal share of the future mode choice.

To overcome the disadvantages of revealed and stated preference data, we developed an abstract, or unlabeled, mode modelling approach using a discrete choice model (see Chapter 2) of which the parameters and constants can be estimated using revealed preference data. Quandt & Baumal (1966) first introduced the unlabelled mode modelling approach and formulated a discrete choice model by describing the utility (i.e., resistance) of each mode as a specific composite of attributes (with mode characteristics related values). In the unlabelled mode choice modelling approach, the same attributes are used for describing all modes, but the parameters are not mode-specific and the mode-specific constants are omitted. In Chapter 2, the unlabelled mode modelling approach was used to show that any future mode can be modelled as long as the future mode can be described as a (new) combination of existing attributes of which the relative importance can be assessed based on revealed preference data. If this is the case, the generalized utility (i.e., resistance) function of the future mode can be reliably defined and thus the future mode can be added as an option in the choice set of a discrete choice model. Previous work on unlabelled mode choice focused on unimodal mode choice of the main mode of a trip. However, already in the current situation, a considerate portion of trips are part of multimodal travel, and it is expected that future modes can play an important role in, e.g., access and egress transport for transit and in shared and hub-based transport. Therefore, to assess the modal share of future modes it is necessary to include multimodal trips which can capture first and last-mile modes (e.g., shared bicycles available at train stations are especially valuable as a last-mile mode) (Van Eck et al., 2014).

Different types of models exist to model multimodal mode and route choice. Generally, two approaches can be distinguished. The first uses multimodal mode choice models in combination with traffic assignment models, where mode choice and route choice take place sequentially (Zhou et al., 2023). The second approach combines mode and route choice in a supernetwork model where mode and route choice takes place simultaneously (Li et al., 2018; Liao et al., 2014). The main advantage of the second approach is that it is not needed to define all multimodal mode and route combinations upfront, because in a supernetwork these combinations are captured automatically (Liao, 2016; Van Eck et al., 2014; Liao et al., 2010). Supernetworks can be defined as a network with subnetworks/layers each representing a different transport mode (Sheffi, 1984; Nagurney & Dong, 2002, 2005; Lozano & Storchi, 2002). Supernetworks are different from 'conventional' networks because supernetworks are multilayered, with each layer containing a different mode, described by multiple attributes and where communication between different modes/layers takes place to describe the network and the interaction between modes, allowing for simultaneous mode and route choice for uni- and multimodal trips. 'Conventional' traffic assignment networks, on the other hand, integrate all transport modes in 'one' layer, not allowing for simultaneous mode and route choice of uni- and multimodal trips (Nagurney & Dong, 2005).

These supernetwork models only specify where travellers can make mode/route choice decisions (e.g., where travellers can switch modes and reconsider their routes) (Nagurney et al., 2003; Arentze & Timmermans, 2004). For instance, such models are applied to model the effects of fleet size, spatial distribution (read: availability) of floating shared modes and parking fees on the use of shared cars (Li et al., 2018). In Vo et al. (2021), a multimodal supernetwork is used to explore the effects of the interaction between private cars and transit modes on the activity-travel choices of individuals defining the locations where individuals can switch modes without predefined route sets.

The literature shows that multistate supernetworks can be developed to analyse how travel patterns can be simulated without predefining mode and route choice sets. Liao et al. (2014) explored how full daily multi-activity travel patterns can be modelled using a so-called multistate supernetwork with space-time prisms to simulate the opening and closing times of certain travel options to explore how full daily multi-activity travel patterns can be simulated. Although multimodal supernetworks are an attractive option to analyse how travel patterns change in different scenarios, a downside is that simulations are computationally expensive, which can lead to long simulation times and/or the use of high-performance computers (Van Eck et al., 2014). These models are developed only with modes with available choice data, including mode-specific parameters and constants, and carry over biases of current modes to future modes whilst keeping the attributes that form that bias implicit (e.g., cars have a 'higher status', the bias of a car might be used in a future mode, but it is not known if this future mode will have the same 'higher status'.) as long as mode-specific biases are used.

This chapter introduces an unlabelled supernetwork-based simultaneous mode and route choice traffic assignment model. One of the reasons to use a traffic assignment model in combination with a discrete choice model is that a change in the traffic volume changes the travel times and thus the mode and route choice. This change in traffic volume cannot be derived from a discrete choice model. Following a similar logic as with the previously mentioned discrete choice model in Chapter 2, one can add the future mode, including new travel options, by describing each mode with the same mode attributes as the attributes of the current modes and without any mode-specific parameters and constants to assess the effect of this future mode on the modal split and travel times of an urban area. Our approach introduces a neutral layer to capture all multimodal trips without predefining any mode and route choice sets. We assume that so-called agents, that represent travellers, can travel from each modal layer through this neutral layer to another modal layer over transit edges for embarking and disembarking each mode. Furthermore, a novel implementation of a shortest path function is developed to capture different types of mode attributes and consider multiple (multimodal) mode and route options and changes in density on the infrastructure.

This chapter contributes to the scientific literature by developing a supernetwork model that can simulate the mode and route choice of multimodal trips including different future modes using a neutral layer and using a novel implementation of a shortest route function where different types of mode attributes are considered to automatically consider all (multimodal) mode and route choice options.

The multimodal supernetwork with unlabelled modes is applied to assess the impact of two different future modes, namely electric steps and shared autonomous vehicles on the modal split and the travel times for an imaginary case study area. The next section describes the methodology of the supernetwork approach. The two sections thereafter describe two applications of the supernetwork approach using three test networks and the Sioux Falls network. Subsequently, the interpretation of the findings is given in a discussion. Finally, conclusions and future research recommendations are given.

3.3 Methodology to assess the mobility network effects of any future mode using a supernetwork model

This section explains the supernetwork approach that is developed for this chapter to model the impact of future modes on mode and route choice and travel times. Trip generation and distribution (including departure times) are considered exogenous. The model calculates mode and route choice simultaneously based on the resistance per edge and then assigns agents (traveller, not a vehicle) to the supernetwork. A mesoscopic dynamic assignment is used that models individual agents with aggregated link travel time computations. The dynamic approach is chosen to be able to assess the change in the quality of modes/routes under the influence of their use for modes operating without a schedule (e.g., cars) and to model the consequential effects in mode/route choice. The agent-based approach makes it possible to trace all individuals over time and therewith deal with the availability of shared modes at different locations in a later stage.

Figure 3.1 describes the structure of the model. First, the model is initialized, which is partly based on the discrete choice model from Chapter 2. Note that all elements with a grey background are defined in Chapter 2 and not altered. In this phase, all inputs, parameters, clusters (type of travellers), and network definition ((a) in Figure 3.1) are initialised for the simulation. Second, the simulation takes place. In this phase, all inputs are used to set up a simulation where the combined mode and route choice model is used ((b) in Figure 3.1), the edge and route resistances are calculated ((c) in Figure 3.1) and the network loading model ((d) in Figure 3.1) is used. After simulating all timesteps, the third and last phase starts, which is the analysing phase. In this phase, all positions from agents for each timestep are used to calculate the travel times, change in travel resistance and modal split. The sections below successively describe the network definition (see 3.3.1), the combined mode and route choice model (see 3.3.2), the edge and route resistance definition (see 3.3.3) and the network loading model (see 3.3.4). Different network configurations have been implemented and the properties of the model are analysed to verify the modelling approach and implementation in this study.

3.3.1 Network Definition

The supernetwork consists of one layer for each mode (see the 2 example modes in Figure 3.2). Edges represent aggregated road segments, transit segments (representing aggregated/abstract transit lines) and dummy transition edges from and to a neutral layer. The transport mode edges have a number of attributes (representing the mode and edge attributes), whereas for some modes the ‘travel time’ attribute can change with the use of the edge (i.e., the intensity). The dummy transition edges have a length of 0, but with a resistance equal to the effort it requires to get on or off the mode (including parking, waiting for public transport, etc.). This supernetwork introduces

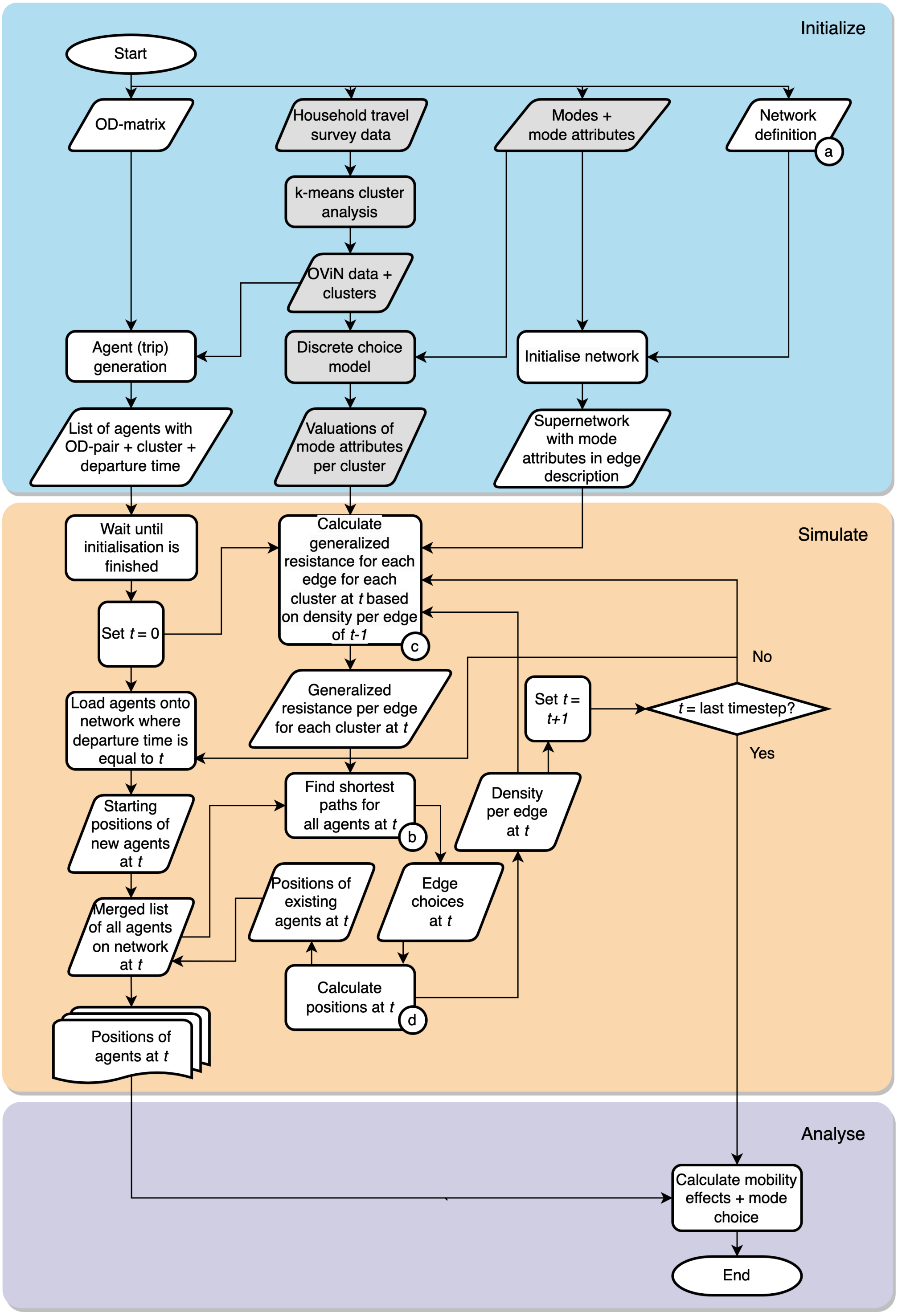

Figure 3.1: Model structure of multimodal supernetwork. The grey background indicates the components originating from Chapter 2. (a) refers to the network definition (see 3.3.1), (b) to the combined mode and route choice model (see 3.3.2), (c) to the edge and route resistances (see 3.3.3), and (d) to the network loading model (see 3.3.4).

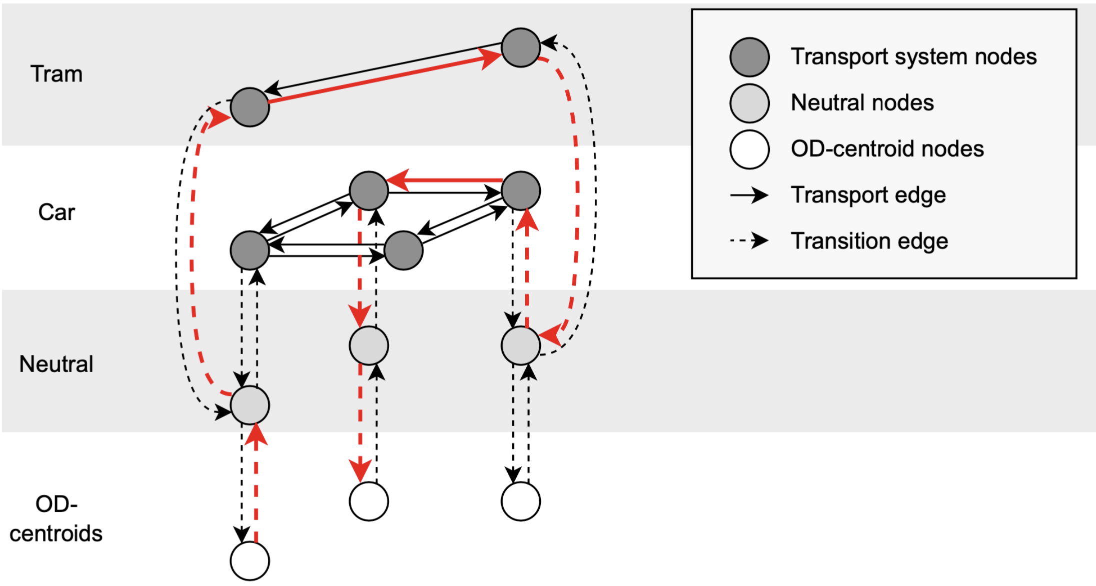

Figure 3.2: Supernetwork example with 2 modes (upper two layers) with transition edges between modes through a neutral layer. One possible multimodal route is visualized in red.

the use of a neutral layer. This neutral layer serves as a hub for agents to switch modes. Often, multimodal supernetworks use one main mode as the base layer to have agents switching towards and from the main mode to another mode (Liao, 2016; Arentze & Timmermans, 2004; Liao et al., 2010; Fiorenzo-Catalano et al., 2004). This approach does not allow the model to turn multimodal trips on and off explicitly, since the main mode will always be available as an option. By using a neutral layer, one can restrict access to walking and/or switching to other modes explicitly in an unimodal scenario, because all multimodal behaviour occurs when moving between layers of the defined modes via the neutral layer. This approach allows for explicit comparison of travel times and mode choice between unimodal and multimodal scenarios. Nodes only have a function in defining the network topology, but have no further attributes: all attributes and thus resistance factors are defined in edges. Spillback and queueing are not modelled in this study.

3.3.2 Mode and Route Choice

Agents start and end their trip in Origin(D)/Destination(D) centroid nodes. Agents move from one (transition) node to another via edges, thereby creating the route that results from the combined mode and route choice model. A 'route' in the model is defined as a specific sequence of edges (could represent one or more transport mode edges) and one or more transition edges (if the route includes one or more switches between modes). Routes are determined en-route. When an agent reaches a node, the

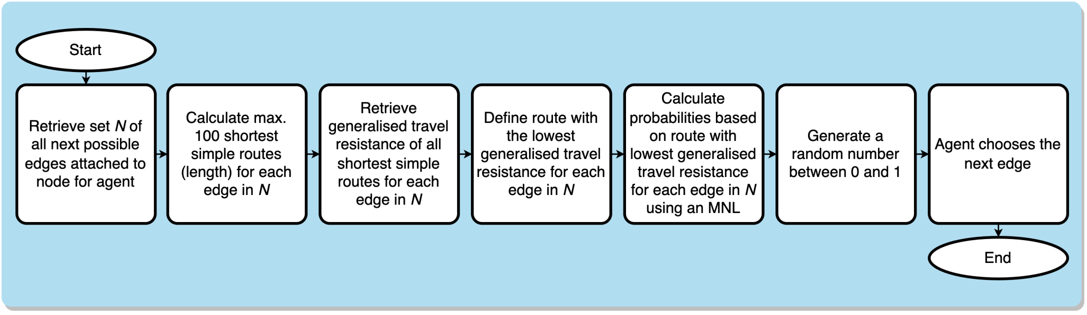

Figure 3.3: Algorithm to determine the next node within edge set N for each agent

next node for this agent is determined by calculating the total resistance of all possible next edges.

A multinomial logit model (MNL) (see Eq. 3.1) (Smits et al., 2018) is used to determine the mode/route choice based on the route resistance. In this multinomial logit model, overlap between routes (and thus modes) is considered by using an en-route route choice model that continuously looks for distinctive routes by using each (first) next node only one time in the option set. The result of the MNL is an overview of the probabilities of each of the routes (for each edge connected to the current mode). The shortest path Bellman-Ford algorithm (Bellman & Kalaba, 1960) is used to handle both positive and negative edge resistances setting up the model to establish a more future-proof approach, instead of the computationally less heavy Dijkstra which can only handle positive edge resistances. The next edge for one agent is chosen in three main steps. First, the route resistances of a maximum of R_{max} routes in set N per next possible edge are calculated. These shortest routes are based on the length of the route and are assumed to cover the reasonable routes that should be considered by the agent when determining the next edge. Second, the lowest total resistance of these routes in set N is taken as the resistance of the considered edge. Third, after the lowest possible total resistance of all possible next edges is determined, the MNL is used to calculate the chances that each of the possible edges is chosen. Then, from a uniform distribution, a pseudo-random value between 0 and 1 is extracted (to account for the heterogeneity in agents) and used to determine which next edge each agent chooses. Note that this algorithm is repeated for each agent in each cluster at a certain timestep when the agent needs to consider their next edge and all agents in a certain timestep use the same density information from the previous timestep. No iterations are used to recalculate the travel times. The result of each agent is combined into a list of edge choices, which is the output of (b) in Figure 3.1. These steps are visualized in the flowchart in Figure 3.3.

When an agent reaches the next node, this process is started again. If congestion is becoming too high on one route, it is theoretically possible that an agent goes 'back' to a previous node to find another route. To prevent endless theoretical back-and-forths from happening, the edge that an agent has travelled on previously is removed from the options for this agent when considering the next edge to travel on. Furthermore, the maximum of routes per edge in set N is set to 100 to cover all reasonable possible routes of a maximum of 6 modes and at least 15 routes per mode to be considered. According to a study looking at shortest route algorithms (Taale & Pel, 2019), 6 routes are sufficient to accurately determine the set of routes travellers realistically consider when trying to optimize their route choice. So, the assumption of the maximum of routes per edge in set N of 100 is assumed to be more than sufficient in most networks and especially the exemplary networks and the Sioux Falls network.

$$P_{r,t,c} = \frac{e^{U_{r,t.c}}}{\sum_{p \in R} e^{U_{p,r,t,c}}}, \forall r \in R, \forall t \in T, \forall c \in C \tag{3.1}$$

where;

U_r = resistance of route r [-];
U_p = resistance of route p [-];
R = subset of shortest 6 routes [-];
T = set of timesteps [-];
C = set of clusters [-];
r = selected route [-];
t = timestep [-];
c = cluster index [-];
p = route index of subset R for denominator; and
$P_{r,t,c}$ = probability that route r is chosen at timestep t, for cluster c.

3.3.3 Edge and Route Resistance

A route is composed of an acyclic succession of edges. The total resistance per route is defined as the sum of the edge resistances in that route. Edge resistances are the sum of a series of products of mode attributes and the valuations of these attributes by users. For the modelling approach, homogeneous groups of users are combined in clusters. This means that the resistance of each edge is different for each cluster. A certain mode/route could be attractive for agents in one cluster, whereas, for an agent with the same OD-pair from another cluster, the same mode/route could be much less attractive.

There are two categories of mode attributes; one category which is addable over the route regardless of the length of each edge and the length of the route (e.g., travel time, costs) (see Eq. 3.2) and one category which is not addable over the route (e.g., weather protection). The attributes within this last category need to be weighted with the length of each edge within the route to come to a weighted average value for those attributes (e.g., weather protection on 70% of the total length of the route (Eq. 3.4)) (see Eq. 3.3). These two edge resistance calculations are combined in Eq. 3.5, where the resistances of all edges in one route are summed and divided by the length of that route to get the ratio of the mode attributes of each edge respective to their share in the total route.

$$E_{i,t,a}^{addable} = \sum_{c \in C} \sum_{k \in K} \beta_{c,k} \gamma_{a,c} \chi_{k,i,t}, \forall i \in I_r, \forall t \in T, \forall a \in A \tag{3.2}$$

$$E_{i,t,a}^{non-addable} = len_i * \sum_{c \in C} \sum_{m \in M} \beta_{c,k} \gamma_{a,c} \chi_{m,i,t}, \forall i \in I_r, \forall t \in T, \forall a \in A \tag{3.3}$$

$$L = \sum_{i=1}^{I_r} len_i \tag{3.4}$$

$$U_{r,t,a} = \sum_{i \in I} \left(E_{i,t,a}^{addable} + \frac{E_{i,t,a}^{non-addable}}{L}\right), \forall r \in R, \forall t \in T, \forall a \in A \tag{3.5}$$

where;

$E_{i,t,a}^{addable}$ = edge resistance addable component [-];
$E_{i,t,a}^{non-addable}$ = edge resistance non-addable component [-];
$U_{r,t,a}$ = route resistance for agent a travelling on route r at time t [-];
β = cluster valuation of mode attribute [-];
$\gamma_{a,c}$ = dummy variable indicating if agent a belongs to cluster c [-];
χ = value of mode attribute [-];
len = length of edge [km];
L = length of route [km];
i = edge index of edges within route [-];
k = addable mode attribute index [-];
m = non-addable mode attribute index [-];
t = timestep [-];
a = agent index [-];
c = cluster index [-];
r = route [-];
I_r = set of edges in route r;
K = set of addable mode attributes (e.g., travel time);
M = set of non-addable mode attributes (e.g., weather protection);
T = set of timesteps;
A = set of agents;
C = set of clusters; and
R = set of routes.

The resistances for the edges as described from Eq. 3.2 till 3.5 are determined based on Chapter 2, in which it was shown that any future mode can be modelled using the unlabeled mode modelling approach as long as the future mode can be described as a (new) combination of existing attributes of which the relative importance can be assessed based on revealed preference data describing trips including personal, trip,

Table 3.1: Mode attribute assumptions

Mode attribute	Addable	Source and determination
Initial cost (€)	Yes	Car, carpool, cycle, walk = 0; transit = 1 (assumed)
Cost/km (€)	Yes	Car = 0.19; transit = 0.20; walk = 0; carpool = 0.19 / 2 (assuming 2 people in one car); bicycle = 100 purchase costs, with 4 trips per day for 5 years equal to 0.014 per trip
Time (min)	Yes	Average velocity per mode from OViN (CBS 2017), refactored as travel time for all modes
Driving task (-)	No	Car, bicycle = 1; carpool, transit, walk = 0
Skills (-) (i.e., driver's license)	No	Car = 1; carpool, transit, bicycle, walk = 0
Weather protection (-)	No	Car, carpool, transit = 1; bicycle, walk = 0
Luggage (-)	No	Car, carpool = 1; transit = 0.5; bicycle, walk = 0
Shared (-)	No	Car, bicycle, walk = 0; carpool, transit = 1
Availability (-)	No	Car = 1; carpool = 0.1; transit = 0.5; bicycle = 1, walk = 1
Reservation (-)	No	Car, carpool, bicycle, walk = 1; transit = 0
Active (-)	No	Car, carpool, transit = 0; bicycle, walk = 1
Accessible (-)	No	Carpool, transit = 1; Car, bicycle, walk = 0

*Addable and non-addable attributes are implemented differently in the edge/route resistance calculations (see Eq. 3.2 and Eq. 3.3).

and mode information (Centraal Bureau voor de Statistiek, 2017). A requirement for this approach is that the revealed preference data contains a complete and coherent set of mode attributes that can describe current and future modes adequately. Furthermore, it must be assumed that the travellers' valuation of the mode attributes does not change with the introduction of a future mode.

In total 12 attributes are included in the resistance function that describe existing and future modes: Initial cost (€); Cost/km (€); Travel time (min); Driving task (-); Skills (-) (i.e., driver's license); Weather protection (i.e., roof) (-); Luggage (-); Shared (ownership or space) (-); Availability (-); Reservation (-); Active (-); Accessible (-). The mode attribute assumptions per mode are shown in Table 3.1.

Building on Chapter 2, we omit the mode-specific constants, assuming the attributes sufficiently capture the relevant aspects. The parameters of the attributes (i.e., betas) are also no longer mode-specific and therewith transferable to future modes.

In total 6 clusters of travelers have been distinguished using a k-means cluster analysis. Two out of 6 clusters were based on trip purpose (business and work (cluster 2), home (cluster 3)). Three other clusters had a trip purpose of 'other', where one cluster only contained trips with people who do not own a car (cluster 1) and the other two clusters contained trips with people that own a car. These two clusters were differentiated by the information that people are (cluster 6) or are not the main car user (cluster 5). The last cluster (cluster 4) was differentiated by both high precipitation and car ownership. The attribute valuations per cluster are shown in Table 3.2. A negative value means that the edge resistance goes up and a positive value means that the edge resistance goes down.

The route resistance also depends on the effort it takes to transfer from one layer to another through a 'neutral' layer which an agent needs to go through to go from their origin to a mode layer, to switch to other mode layers, and to go to their destination.

Table 3.2: Mode attributes valuations per cluster

Cluster	1	2	3	4	5	6
(Initial) Cost	-1.53	-0.0846	-0.12	-0.0932	-0.196	-0.15
Time	-0.156	-0.4608	-0.04566	-0.0441	-0.03036	-0.03768
Driving task	-0.25	2.11	0.63	-0.0327	0.694	-0.136
Skills	-0.0606	2.36	0.928	0.924	-2.69	1.29
Weather protection	0.107	-0.471	0.0254	0.486	-0.959	-0.125
Luggage	0.193	-0.755	-0.143	-1.11	-0.384	0.458
Shared	-0.137	-1.21	-0.833	-1.07	1.75	-1.16
Availability	0.205	-4.22	-1.76	0.395	-1.65	-2.61
Reservation	0.186	-1.34	0.0491	-1.9	1.91	0.314
Active	0.293	0.131	-0.195	-0.666	1.39	0.455
Accessible	0.213	-1.07	-0.753	-0.248	0.848	-1.24

Table 3.3: Assumed time to switch modes

Mode	Neutral to mode [min]	Mode to neutral [min]
Car	2 (get in car)	2 (parking)
Carpool	10 (wait for driver)	2 (get out of car)
Transit	7.5 (average waiting time)	5
Bicycle	1 (get on bicycle)	1 (parking)
Walk	0	0

This effort is reflected in the resistance of the transition dummy edge from one layer to another; the resistance is based on an assumed time that it takes to switch (see Table 3.3) and the ‘initial cost’ of a mode (see Table 3.1), the other attributes are assumed equal to 0. This is a slight simplification where changing modes can, for instance, be more difficult when carrying luggage and where different locations might have different switching times (e.g., one station is larger than another station). These assumed times are weighted with a factor of 3 to represent the extra mental effort it takes for users to switch modes and wait for the next mode according to (Wardman, 2004).

3.3.4 Network Loading

In this study, it is assumed that all transit is using a separate infrastructure, so transit is not taken into account in the congestion calculation. Transit is modelled with a (fixed) frequency-based schedule, where waiting time and transfer time are added to the assumed time as in Table 3.3 in the transfer edges from the neutral layer to the respective transit layer. This model assumes sufficient availability of shared modes (e.g., shared bicycles) at hubs in which such a mode is an option. This means that it is assumed that a shared mobility provider can always plan and allocate sufficient vehicles to the hubs.

It is assumed that the car, carpool and bicycles use the same infrastructure for all road types. This is implemented by using PCU values to determine the density on an edge. The PCU value of the mode chosen by the agent determins how much the density on an edge increases. So, if agents choose a car, carpool or bicycle, the density for these three modes is adjusted, assuming a PCU value of 1.0 for the car and carpool, and a

PCU value of 0.2 for bicycles. Note that carpool is assumed to consist of a car with a passenger, where the driver is not a traveller in the network. This is different from a car where the driver is also the traveller in the network. This carpool can take the shape of a taxi or personal carpool (friend or family-member drives the car to transport the passenger). If a future mode is added, it can be implemented with or without the use of the current infrastructure and, if using the current infrastructure, by adding a PCU factor influencing the congestion of other modes and the future mode.

Note that the supernetwork approach offers the flexibility to adjust above mentioned assumptions. The model could, for instance, easily be adjusted such that transit (e.g., buses) use the same infrastructure as cars and/or bikes use separate infrastructure on parts of the network or the whole network.

A mesoscopic dynamic model is used for network loading with a strict weak order of agents (people) per edge, where agents entering on the same timestep are loaded on the edge at the same time, as commonly used in mesoscopic models (van der Gun et al., 2016). A strict weak order means that multiple agents can leave and enter the edge per timestep and agents have an order (read: ranking/position) on the edge, but can overtake each other. The number of agents already present on an edge at a certain timestep determines the travel times, which partly describes the edge resistance; therefore, this might affect route choice for agents considering entering the edge at a later time. A timestep of 0.01 hours is used to update the positions of all agents. This timestep is chosen such that an agent will spend at least two timesteps on the edge with the shortest free-flow time (0.02 hours) considering the highest free-flow speed in this model (64 km/h or 40 mph (Bar-Gera et al., 2013)). No iterations are carried out, which means it is assumed that agents will not readjust their routes en-route in response to travel times on each edge of the previous timestep.

This supernetwork needs to account for the change in travel resistance when future modes are introduced and when the density on an edge changes. Daganzo's (Daganzo & Geroliminis, 2008) triangular fundamental diagram (see Eq. 3.6 till 3.8) for car, carpool and bicycle is used to compute the speed of the agents on an edge based on the current density. Other interactions between agents on an edge (lane-switching, headway, etc.), spillback and queueing are not modelled. Travel times for cars, carpoolers and cyclists are based on the free-flow velocity, critical density, jam density, number of lanes, PCU values of each agent, and the number of agents present on that edge.

The implementation of the fundamental diagram is simplified, since it is assumed that different modes can overtake each other. Wierbos et al. (2021) proposes a new way to include multi-user classes in the fundamental diagram calculations (specifically combining cars and bicycles) and looks into assuming different critical headways to calculate the velocity of cars and bicycles. Since the multimodal supernetwork approach needs to be able to capture multiple modes, it is assumed that different modes can overtake each other, where the overall velocity is calculated based on the sum of all pcu values of each agent present on the edge for each mode. This can be interpreted as follows; modes can overtake each other, albeit at a lower velocity if the overall density in that edge is higher. In this study, the critical density (k_{crit}) and the jam density (k_{jam})

are assumed to be 125 pcu/h and 25 pcu/h respectively. Density is calculated as the sum of all pcu values of all agents present on that edge, normalized for the length of that edge (see Eq. 3.10). The capacity is calculated as shown in Eq. 3.9.

$$k < k_{crit} \Rightarrow v = v_{ff} \tag{3.6}$$

$$k_{jam} \geq k \geq k_{crit} \Rightarrow v = \frac{k_{jam} - k}{k} \frac{q_{crit}}{k_{jam} - k_{crit}} \tag{3.7}$$

$$k > k_{jam} \Rightarrow v = 0 \tag{3.8}$$

$$q_{crit} = u_{ff} * k_{crit} \tag{3.9}$$

$$k = \frac{\sum_{a \in A} pcu_a}{len} \tag{3.10}$$

where;
v = current velocity [km/hour];
v_{ff} = free flow velocity [km/hour];
k = current density [pcu/km];
k_{crit} = critical density [pcu/km];
k_{jam} = jam density [pcu/km];
q_{crit} = capacity (i.e., critical intensity) [pcu/h];
pcu_a = pcu-factor for agent a [pcu]; and
len = length of edge [km].

In order to assess the validity of the results of the approach, the elasticity of the model can be compared with elasticity from the literature. The elasticity of the model is determined by increasing and decreasing the travel costs and travel times for cars and transit. Table 3.4 shows the elasticity of this study and two reference studies. It can be observed that this study's elasticity falls within the guidelines of the Dutch Regional model (which is based on a multitude of other studies) except for the transit cost, which shows a slightly lower elasticity than the guidelines. TNO (Snelder et al., 2021) also shows a slightly lower cost than the guidelines and argues that the lower elasticity might come from the free and unlimited transit subscriptions that students have in the Netherlands and that they are therefore less price sensitive. Since all other elasticities fall within the boundaries of the guidelines and our value for transit cost is only slightly lower than the TNO study and falls just outside the guidelines of the Dutch Regional model, it is concluded that the elasticity with this study is sufficient.

It is possible to set up large realistic networks with this multimodal supernetwork approach. The computational complexity is high, like other supernetwork models, and equal to $O(KN^3)$, where K is the number of shortest paths and N is the number of

Table 3.4: Elasticity of vehicle kilometres for car and transit (BTM) by varying travel times and costs with +-10%

Mode	Attribute	Elasticity		
		This study	Guidelines GM 2.4.0 of the Dutch Regional model (Snelder et al., 2021)	TNO study (Snelder et al., 2021)
Car	Cost	-0.24	-0.2 to -0.5	-0.40
	Time	-0.49	-0.3 to -0.7	-0.51
Transit (BTM)	Cost	-0.55	-0.6 to -1.2	-0.59
	Time	-1.30	-0.6 to -1.3	-0.75

nodes, from the so-called k-shortest path approach (Yen, 1971). Note that the total number of paths is dependent on the number of nodes, edges, and layers (i.e., modes).

The supernetwork assignment model is set up using Python 3.10.2 and the NetworkX package (Hagberg et al., 2008). Reducing the computational complexity and implementation of multicore processing was necessary due to the extremely long computation time (>8 hours for Sioux Falls network per timestep). This was done by considering only the minimum number (6) of shortest paths to achieve high accuracy. According to a study looking at shortest route algorithms (Taale & Pel, 2019), 6 routes are sufficient to accurately determine the set of routes travellers realistically consider when trying to optimize their route choice. Therefore, the maximum number of next edges (set N in Figure 3.3) considered is also set to 6. Furthermore, implementing parallel programming where possible made the total script approximately 20 times faster when using 32 cores (4 CPUs with 8 cores with 32GB RAM in total) on a high-performance computer and 7 times faster on a personal computer with 8 cores (4 CPUs with 2 cores with 8GB RAM in total).

3.3.5 Test networks to verify the modelling approach

The multimodal supernetwork modelling approach is first applied to three small yet exemplary networks that are shown in Figure 3.4 to verify the method and the plausibility of the effect that occurs when multimodal trips are considered.

For every test network, a scenario is run with the possibility to opt for multimodal trips enabled and disabled respectively. The run with multimodal trips disabled is compared with the modal split that results from directly applying the MNL model that was assessed in Chapter 2 based on the OVIN data set (Centraal Bureau voor de Statistiek, 2017) without using the supernetwork approach. Thereafter, the model is run including multimodal trips with transfer edges between modes and the neutral layer and the modal split and travel times are extracted. The edge lengths are varied between 1 and 2 km, to test if the modal split shifts to faster modes for longer edges. All three configurations are run with current modes, and two future modes, see the attributes in Table 3.5. It is assumed that the shared autonomous car is using the current infrastructure with a PCU factor of 1.0 and that the electric step is also using the current infrastructure with a PCU factor of 0.2 (same as the bicycle). 166 Trips are simulated

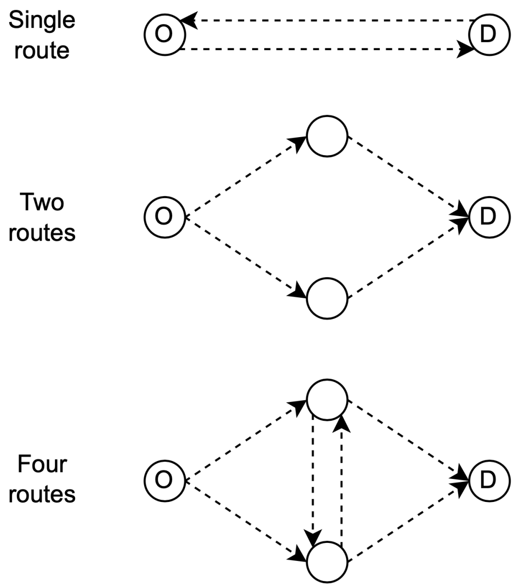

Figure 3.4: Small networks to validate model set-up

Table 3.5: Attributes shared autonomous car and electric steps [with sensitivity analysis values for the Sioux Falls network between square brackets based on a 20% variation of all mode attributes]

Mode attribute	Shared autonomous car	Electric step
Initial cost [€]	0	4 [3.20 4.00 4.80]
Cost [€]	0.05 [0.04 0.05 0.06] per km	0
Time [min]	distance [km] / 60 [48 60 72] [km/h] / 60	distance [km] / 10 [8 10 12] [km/h] / 60
Driving task [-]	0	1
Skills [-] (i.e., driver's license)	0	0
Weather protection [-]	1	0
Luggage [-]	1	0
Shared [-]	0	0
Availability [-]	0.5 [0.4 0.5 0.6]	1 [0.8 1]
Reservation [-]	1	0
Active [-]	0	1
Accessible [-]	1	0
PCU factor [-]	1.0, uses all road-type infrastructure	0.2, uses all road-type infrastructure
Neutral to mode effort [min]	5 [4 5 6]	3 [2.4 3 3.6]
Mode to neutral effort [min]	2 [1.6 2 2.4]	2 [1.6 2 2.4]

for each cluster (996 trips in total) travelling from node O to D, with a simulation period of 2 hours and a timestep of 0.01 hours with all trips leaving during the first hour (timestep 1-100) with a uniform distribution.

The test network simulations were run on a MacBook Pro with a 2,4 GHz Quad-Core Intel Core i5 and 8GB of RAM and it took approximately an hour to finish all 36 configurations (3 networks, unimodal & multimodal trips, 1 and 2 km edges, and current modes + 2 future modes).

The results are shown in Table 3.6 to Table 3.10. In all networks with a future mode, we see that future modes are actually used, and where multimodal trips are available, we can observe that multimodal trips occur. The results in Table 3.6 show that electric steps mainly attract trips from carpool, walking and cycling (e.g., Scenario 9) and that shared autonomous vehicles attract trips from all modes (e.g., Scenario 11). Furthermore, it can be seen that the modal shares between networks with edge lengths of 1 and 2 km differ (e.g., Scenarios 14 and 32), with a modal shift from walking and cycling towards faster modes, like cars and shared AV, when the edge length increases. For instance, the modal share of walking in the configurations with edges of 1 km is 8.0% on average and 4.4% on average in the configurations with edges of 2 km (see Table 3.6). The maximum share of multimodal trips is observed in the configuration with two routes with edges of 1 km long with current modes (Scenario 10) and is 18.5% of the total trips (see Table 3.7). Similar trends are observed when looking at the modal split in terms of travelled distance (see Table 3.8 and Table 3.9). The average speed, distances and trip durations are given as well in Table 3.10. In the configuration with four routes, a longer average trip distance can be observed, which means that agents do choose to 'cross over' on the vertical links between the upper and lower routes. This behaviour is to be expected when agents are presented with the option to change routes, for instance, when congestion on the upper-right or lower-right edges becomes higher and the other route becomes more attractive.

Furthermore, when multimodal trips are enabled, travellers choose these multimodal options, even though the average trip duration is longer for multimodal configurations compared to unimodal configurations. This can be explained by the other attributes that are captured in the calculation of the route resistance and the density changes on edges for certain modes. When shared AVs are introduced, the modal share for walking goes up in this test network. This can be explained by the change in velocity for all modes using a PCU factor and using the same infrastructure. Walking is not using the same infrastructure, so then becomes more attractive (in this test network), since it cannot be congested and some clusters value an active mode higher than a motorized mode.

Table 3.6: Modal split (% of trips) of all test networks

Scenario	Network	Edge lengths [km]	Multimodal trips enabled?	Future mode	Modal split [%] Car	Carpool	Transit	Bicycle	Walk	Future	Mixed
1	Single route	1	-	-	25.4	39.9	1.4	20.5	12.9	-	-
2			Yes		24.6	39.8	1.7	21.7	12.2	-	-
3			-	Electric Step	19.5	26.6	0.8	12.9	11.2	29.0	-
4			Yes		17.9	26.6	1.0	15.5	9.8	29.2	-
5			-	Shared Auto-	23.4	39.1	1.8	17.0	11.3	7.4	-
6			Yes	nomous Car	24.4	37.2	1.1	18.7	11.0	7.5	-
7	Two routes		-	-	28.4	43.1	1.9	19.1	7.5	-	-
8			Yes		26.1	37.0	1.1	14.7	6.6	-	14.5
9			-	Electric Step	19.9	27.3	0.8	15.1	7.3	29.6	-
10			Yes		18.0	22.1	0.9	11.7	5.1	23.7	18.5
11			-	Shared Auto-	24.9	42.0	1.7	16.6	7.0	7.8	-
12			Yes	nomous Car	22.9	32.6	0.9	14.2	4.7	7.6	17.1
13	Four routes		-	-	28.2	43.9	2.2	18.2	7.5	-	-
14			Yes		26.7	36.3	1.2	16.4	5.9	-	13.5
15			-	Electric Step	20.2	28.9	0.3	15.2	5.6	29.8	-
16			Yes		17.7	25.1	0.6	11.5	4.8	26.3	14.0
17			-	Shared Auto-	26.2	40.1	1.2	17.4	7.9	7.2	-
18			Yes	nomous Car	23.9	32.9	1.1	14.7	5.5	5.8	16.1
19	Single route	2	-	-	28.3	43.6	1.6	18.2	8.3	-	-
20			Yes		28.8	41.6	2.4	19.3	7.9	-	-
21			-	Electric Step	18.7	29.9	1.4	15.3	6.4	28.3	-
22			Yes		21.3	28.8	0.5	13.6	7.3	28.5	-
23			-	Shared Auto-	26.9	37.7	1.3	16.7	7.6	9.8	-
24			Yes	nomous Car	24.1	39.9	1.9	17.6	6.9	9.6	-
25	Two routes		-	-	31.5	44.2	2.2	17.7	4.4	-	-
26			Yes		28.2	38.6	1.1	15.1	2.8	-	14.3
27			-	Electric Step	24.5	31.6	0.9	14.9	2.4	25.7	-
28			Yes		19.3	28.3	0.2	11.8	1.3	25.2	13.9
29			-	Shared Auto-	29.2	41.8	2.3	14.3	3.2	9.2	-
30			Yes	nomous Car	24.7	34.0	0.9	14.0	3.6	8.4	14.4
31	Four routes		-	-	30.6	44.3	2.3	19.1	3.7	-	-
32			Yes		29.7	37.1	2.0	13.6	3.1	-	14.5
33			-	Electric Step	22.6	33.3	1.1	13.7	2.5	26.8	-
34			Yes		20.9	28.0	0.7	11.5	2.1	22.2	14.6
35			-	Shared Auto-	26.5	42.8	1.3	14.7	3.4	11.3	-
36			Yes	nomous Car	24.8	35.6	1.6	11.6	2.3	8.7	15.3

Table 3.7: Modal split (% of trips) of all multimodal trips within multimodal test networks

Scenario	Network	Edge lengths [km]	Future mode	Modal split of mixed trips [%]* Car	Carpool	Transit	Bicycle	Walk	Future
8	Two routes	1	-	56.3	56.9	7.6	39.6	39.6	-
10			Electric Steps	46.7	53.3	7.1	28.8	23.9	40.2
12			Shared Autonomous Vehicles	51.2	52.9	5.3	31.8	31.8	27.1
14	Four routes		-	52.2	58.2	10.4	49.3	38.8	-
16			Electric Steps	50.4	51.8	1.4	32.4	31.7	39.6
18			Shared Autonomous Vehicles	53.1	53.8	7.5	35.6	35.0	25.0
26	Two routes	2	-	65.5	69.0	7.7	39.4	18.3	-
28			Electric Steps	55.8	52.9	2.9	35.5	16.7	36.2
30			Shared Autonomous Vehicles	52.4	51.0	4.9	49.7	12.6	29.4
32	Four routes		-	61.1	67.4	9.7	43.8	25.0	-
34			Electric Steps	53.8	59.3	3.4	29.7	17.2	40.7
36			Shared Autonomous Vehicles	54.6	57.2	7.9	29.6	22.4	33.6

*The modal split of mixed trips amounts to more than 100%, since multiple modes can occur in one single trip. This number can be interpreted as a certain percentage of the mixed trip contains a certain mode.

3.3.6 Case-study: Sioux Falls network

The method is applied to the well-known Sioux Falls network to demonstrate that the supernetwork approach can also be used in more extensive networks to calculate modal split and travel times.

All flows, OD-data, and network information from the Sioux Falls network (Bar-Gera et al., 2013) are available and used to run the model (see Figure 3.5). Only OD-

Table 3.8: Modal split (% of distance) of all test networks

Scenario	Network	Edge lengths [km]	Multimodal trips enabled?	Future mode	Modal split [% of distance] Car	Carpool	Transit	Bicycle	Walk	Future	Mixed
1	Single route	1	-	-	25.4	39.9	1.4	20.5	12.9	-	-
2			Yes		24.5	39.7	1.7	21.6	12.2	-	-
3			-	Electric Step	19.5	26.6	0.8	12.9	11.2	29.0	-
4			Yes		17.8	26.6	1.0	15.4	9.8	29.2	-
5			-	Shared Autonomous Car	23.4	39.1	1.8	17.0	11.3	7.4	-
6			Yes		24.3	37.2	1.1	18.6	11.0	7.5	-
7	Two routes		-	-	28.4	43.1	1.9	19.1	7.5	-	-
8			Yes		26.1	37.0	1.1	14.7	6.6	-	14.5
9			-	Electric Step	19.9	27.3	0.8	15.1	7.3	29.6	-
10			Yes		18.0	22.1	0.9	11.7	5.1	23.7	18.5
11			-	Shared Autonomous Car	24.9	42.0	1.7	16.6	7.0	7.8	-
12			Yes		22.9	32.6	0.9	14.1	4.7	7.6	17.1
13	Four routes		-	-	28.5	43.6	2.3	18.4	7.2	-	-
14			Yes		27.0	35.2	1.2	15.8	5.6	-	15.1
15			-	Electric Step	21.0	29.4	0.3	15.7	5.4	28.2	-
16			Yes		17.7	24.7	0.6	11.7	4.4	24.9	16.0
17			-	Shared Autonomous Car	26.2	38.9	1.4	18.1	7.8	7.5	-
18			Yes		24.3	31.6	1.0	14.5	5.2	5.7	17.7
19	Single route	2	-	-	28.3	43.6	1.6	18.2	8.3	-	-
20			Yes		28.8	41.6	2.4	19.3	7.9	-	-
21			-	Electric Step	18.7	29.9	1.4	15.3	6.4	28.3	-
22			Yes		21.3	28.8	0.5	13.6	7.3	28.5	-
23			-	Shared Autonomous Car	26.9	37.7	1.3	16.7	7.6	9.8	-
24			Yes		24.1	39.9	1.9	17.6	6.9	9.6	-
25	Two routes		-	-	31.5	44.2	2.2	17.7	4.4	-	-
26			Yes		28.2	38.5	1.1	15.1	2.8	-	14.3
27			-	Electric Step	24.5	31.6	0.9	14.9	2.4	25.7	-
28			Yes		19.3	28.3	0.2	11.8	1.3	25.2	13.9
29			-	Shared Autonomous Car	29.2	41.8	2.3	14.3	3.2	9.2	-
30			Yes		24.7	34.0	0.9	13.9	3.6	8.4	14.4
31	Four routes		-	-	31.6	43.4	2.2	19.4	3.3	-	-
32			Yes		30.0	35.3	1.9	13.6	3.2	-	15.9
33			-	Electric Step	23.4	33.2	1.1	13.9	2.7	25.7	-
34			Yes		21.2	27.2	0.7	11.5	2.0	20.5	16.8
35			-	Shared Autonomous Car	27.8	40.7	1.3	14.8	3.3	12.0	-
36			Yes		25.0	33.8	1.7	11.0	2.2	9.0	17.3

Table 3.9: Modal split (% of distance) of all multimodal trips in multimodal test networks

Scenario	Network	Edge lengths [km]	Future mode	Modal split of mixed trips [% od distance] Car	Carpool	Transit	Bicycle	Walk	Future
8	Two routes	1	-	4.1	4.1	0.6	2.9	2.9	-
10			Electric Steps	4.3	4.9	0.7	2.7	2.2	3.7
12			Shared Autonomous Vehicles	4.4	4.5	0.5	2.7	2.7	2.3
14	Four routes		-	4.1	4.1	0.7	3.5	2.7	-
16			Electric Steps	4.1	3.7	0.2	2.4	2.2	3.3
18			Shared Autonomous Vehicles	4.6	4.5	0.6	3.2	2.7	2.1
26	Two routes	2	-	4.7	4.9	0.6	2.8	1.3	-
28			Electric Steps	3.9	3.7	0.2	2.5	1.2	2.5
30			Shared Autonomous Vehicles	3.8	3.7	0.4	3.6	0.9	2.1
32	Four routes		-	4.9	4.9	0.8	3.3	1.9	-
34			Electric Steps	4.7	4.6	0.3	2.4	1.3	3.6
36			Shared Autonomous Vehicles	5.1	4.5	0.8	2.3	1.7	3.0

data for car trips are available, and for this case study, these are used as a proxi for all demand (which is therefore an underrepresentation of real total demand). Further note that trips within zones might be underrepresented due to the use of only OD-data for car trips. The Sioux Falls network is represented with an centroid-layer, a neutral layer and one layer per mode (assuming the same physical road network as the car network for each mode). Five modes (car, carpool, transit (BTM, as one mode), bicycle, and walk) are initially included in the network and their parameter values are based on the results of Chapter 2 using Dutch revealed preference data. This dataset is further enriched with the mode attributes for all current modes (see Table 3.1).

The simulated period in the model is 4 hours representing a morning peak hour from 6 AM to 10 AM. All trips are leaving with a uniform distribution during the 4

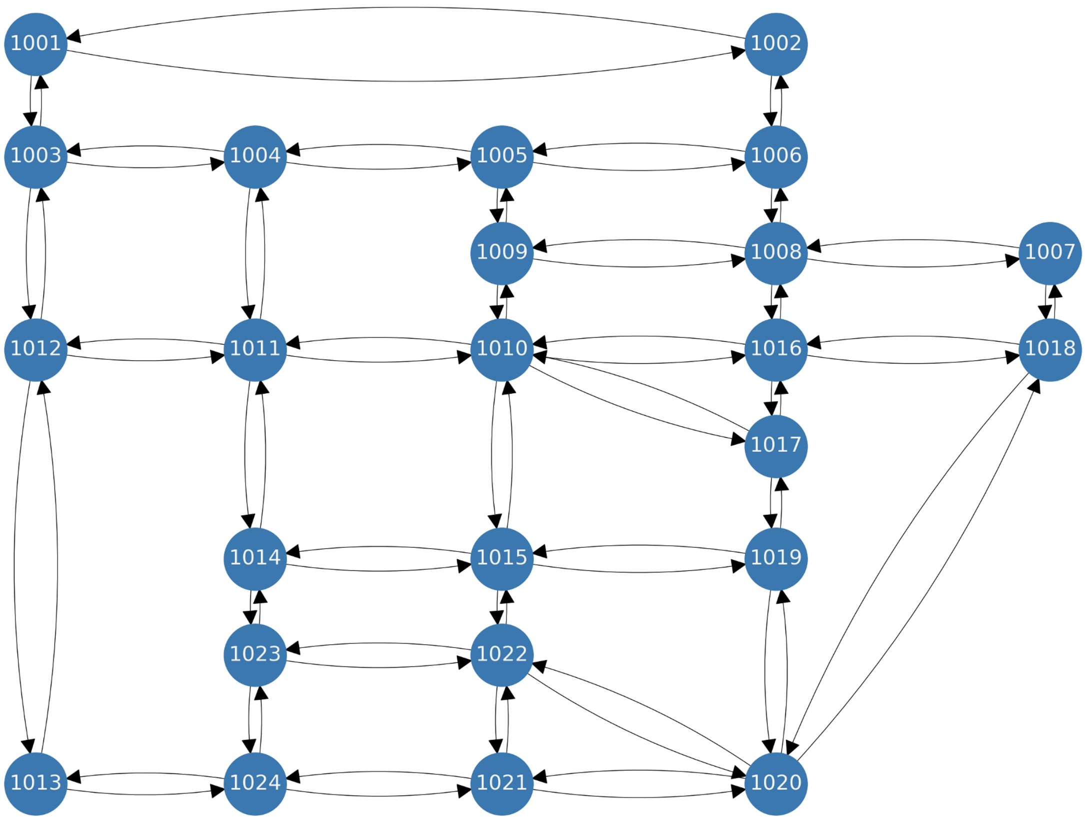

Figure 3.5: Sioux Falls test network (Zhou et al., 2012)

Table 3.10: Average speed, distance and trip duration in all test networks

Scenario	Network	Edge lengths [km]	Multimodal trips enabled?	Future mode	Average speed [km/h]	Average distance [km]	Average duration [min]
1			-	-	12.57	1.00	6.01
2			Yes		8.97	1.00	6.61
3	Single route		-	Electric Step	12.87	1.00	5.66
4			Yes		9.73	1.00	6.19
5			-	Shared Auto	12.42	1.00	6.04
6			Yes	-nomous Car	8.92	1.00	6.61
7			-	-	17.14	2.00	8.61
8			Yes		13.41	2.00	9.85
9	Two routes		-	Electric Step	16.36	2.00	8.80
10		1	Yes		13.17	2.00	9.80
11			-	Shared Auto	17.08	2.00	8.50
12			Yes	-nomous Car	13.26	2.00	9.75
13			-	-	17.88	2.42	9.73
14			Yes		14.75	2.46	11.25
15	Four routes		-	Electric Step	17.23	2.38	9.48
16			Yes		14.50	2.40	10.68
17			-	Shared Auto	17.60	2.41	9.87
18			Yes	-nomous Car	14.55	2.45	11.32
19			-	-	17.16	2.00	8.67
20			Yes		14.06	2.00	9.40
21	Single route		-	Electric Step	16.58	2.00	8.64
22			Yes		14.09	2.00	9.28
23			-	Shared Auto	16.70	2.00	8.71
24			Yes	-nomous Car	14.04	2.00	9.22
25			-	-	20.87	4.00	13.55
26			Yes		18.90	4.00	14.33
27	Two routes	2	-	Electric Step	19.87	4.00	13.50
28			Yes		18.13	4.00	14.30
29			-	Shared Auto	21.24	4.00	12.86
30			Yes	-nomous Car	18.93	4.00	14.56
31			-	-	21.69	4.74	15.12
32			Yes		19.31	4.74	16.92
33	Four routes		-	Electric Step	20.62	4.71	15.42
34			Yes		18.63	4.71	16.53
35			-	Shared Auto	22.55	4.78	14.57
36			Yes	-nomous Car	19.94	4.71	15.84

hours as defined by the hourly flows of the Sioux Falls network. Calculation times are reduced by aggregating agents in groups of agents (i.e., these agents behave the same) of 66 on the network, 66 is chosen to have at least 10 agents for all OD pairs.

The same seed number is used to reduce the variance between different scenarios (unimodal versus multimodal and including versus excluding future modes). The number of transfers between modes in the multimodal networks is limited to 2 to manage the computational complexity, which is assumed to be realistic (first-mile, main transport mode, and last-mile). It is assumed that the shared autonomous car is using the current infrastructure with a PCU factor of 1.0 and that the electric step is also using the current infrastructure with a PCU factor of 0.2 (same as the bicycle). Two super-networks with one future mode each (see attributes in Table 3.5) are created, including 20% variations for all mode attributes that can be varied to perform a sensitivity analysis. The models are run with and without multimodal trips and the model split and travel times are extracted and compared with the model with the current modes.

The Sioux Falls network was simulated on the Delft Blue supercomputer (a high-performance computer with up to 218 2x Intel XEON E5-6248R 24C 3.0GHz with 48 cores and 192GB of RAM) (Delft High Performance Computing Centre, 2022). Due to setting up simulations in a parallel manner, one run simulating 4 hours takes up to 3 hours with the Delft Blue supercomputer using 4 CPUs with 32GB per CPU reserved. More than 80% of the computation time was spent on the shortest route function.

For the Sioux Falls network, the results of the simulations, including sensitivity analysis, are shown in Table 3.11 to Table 3.16. It can be observed that the modal share (% of distance) of shared AV ranges between 18.7 and 44.5% and the modal share (% of distance) of electric steps ranges between 14.7 and 39.7% (see Table 3.13). When looking at the total distance travelled per mode, it is interesting to point out that walking becomes less dominant for all scenarios, compared to the modal share for walking when looking at the number of trips (33.6% of the number of trips and 27.0% of the distance travelled). This indicates that walking occurs on average for shorter trips and that faster modes are used for longer trips.

Furthermore, the average travel times (Table 3.15) reduce when a future mode is introduced. The average travel time for all modes when the electric step was introduced went down from 51.4 minutes to 47.2 minutes in the unimodal scenario and from 53.6 to 48.8 minutes in the multimodal scenario. The average travel time for all modes when the shared AV was introduced went down from 51.4 minutes to 44.3 minutes in the unimodal scenario and from 53.6 minutes to 46.6 minutes in the multimodal scenario. Multimodal trips have a shorter trip distance compared to unimodal trips and the average speed also went down in the multimodal scenarios compared to the unimodal scenarios (see Table 3.15). It can be observed that when the average speed and the average distance both went down in Scenario 4 compared to Scenario 2, the average travel time still reduced, indicating that the average distance reduction is more dominant compared to the reduction in average speed.

For Scenario 6, the distribution of trips per mode over the trip distance is visualized in Figure 3.6. Notice that walking mostly occurs for trips shorter than 5 km. Moreover, when the trip distance increases to more than 10 km, multimodal trips become the most dominant type of trip and both the car and shared AV are taken for short and long trips. The carpool remains dominant in shorter trips up to approximately 20 km and then the car and mixed trips are dominant for trips longer than 20 km. It can be hypothesized that multimodal trips are dominant for larger distances because of the flexibility of multimodal trips. Since all combinations of first, main, and last-mile options are possible these are more likely to occur when the origin is further away from the destination. In these cases, switching modes become more attractive to avoid congestion and optimize waiting time, even though switching mode costs time it can still have a lower observed route resistance for the agent. Note that mixed trips consist of multiple trips and cannot be visualized as such in Figure 3.6. For reference to the modal share of modes in multimodal trips, it is best to read Table 3.12 and Table 3.14.

Finally, it can be observed that the modal share of electric steps is higher compared to the modal share of shared AV and that the average speed for the whole network is lower for the scenario with electric steps compared to the scenario with shared AV (see Table 3.11). This means that, although the average speed is lower for electric steps, other attributes of the electric steps are more attractive than the other attributes of the shared AV, compensating for the downside of having a longer travel time. This can be explained by the other attributes that are captured in the travel resistance. The travel resistance is calculated by taking the sum of the experienced route resistance of each

Table 3.11: Modal split (% of trips) of the Sioux Falls network

Scenario	Multimodal trips enabled?	Future mode	Modal split [%] Car	Carpool	Transit	Bicycle	Walk	Future	Mixed
1	-	-	17.5	16.6	10.8	14.1	40.9	-	-
2	Yes		13.3	11.5	5.6	10.0	33.6	-	25.8
3	-	Electric Step	11.1 [10.3 - 12]	13.5 [13.1 - 13.8]	5.0 [4.6 - 5.6]	10.8 [9.4 - 10.9]	31.4 [29.9 - 32.7]	28.2 [25 - 32.6]	- -
4	Yes		8.9 [8.1 - 8.9]	10.1 [10.1 - 10.3]	2.2 [2.2 - 2.6]	8.3 [8 - 8.5]	27.0 [25.9 - 27.8]	18.7 [16.6 - 21.2]	24.7 [24 - 25]
5	-	Shared Autonomous Car	13.1 [12.8 - 13.1]	13.7 [13.2 - 13.7]	8.0 [7.9 - 8.2]	11.3 [11.3 - 11.4]	28.3 [27.3 - 29.4]	25.6 [24.7 - 27.4]	- -
6	Yes		9.8 [9.8 - 10.4]	9.8 [9.6 - 9.8]	4.0 [3.8 - 4.1]	8.2 [8.2 - 8.3]	22.5 [22.1 - 23.2]	18.9 [17.6 - 19.4]	26.5 [26.2 - 26.5]

Table 3.12: Modal split (% of trips) of multimodal trips in the Sioux Falls network

Scenario	Future mode	Modal split of mixed trips [%]* Car	Carpool	Transit	Bicycle	Walk	Future
2	-	54.4	44.1	37.5	43.5	62.7	-
4	Electric Step	44.4 [43.9 - 44.4]	36.4 [35.5 - 38]	29.1 [27.6 - 29.8]	35.1 [34.9 - 35.5]	48.9 [48.9 - 49.2]	51.8 [49.7 - 53.9]
6	Shared Autonomous Car	47.0 [45.4 - 47]	36.9 [36 - 37.8]	31.5 [31.5 - 32.2]	35.7 [35.7 - 37]	50.8 [50.8 - 52.8]	52.7 [50.9 - 52.7]

*The modal split of mixed trips amounts to more than 100%, since multiple modes can occur in one single trip. This number can be interpreted as a certain percentage of the mixed trip contains a certain mode.

Table 3.13: Modal split (% of distance) of the Sioux Falls network

Scenario	Multimodal trips enabled?	Future mode	Modal split [%] Car	Carpool	Transit	Bicycle	Walk	Future	Mixed
1	-	-	12.7	13.5	25.4	10.8	37.6	-	-
2	Yes		8.2	7.3	6.7	6.4	27.0	-	44.4
3	-	Electric Step	8.3 [7.2 - 9.2]	10.4 [9.7 - 11]	12.0 [10.4 - 13.7]	8.4 [7.1 - 9]	28.4 [25.8 - 30.3]	32.5 [26.8 - 39.7]	- -
4	Yes		5.4 [4.8 - 5.7]	6.2 [6.2 - 6.4]	2.4 [2.2 - 3]	5.4 [5 - 5.4]	20.2 [18.9 - 21.3]	17.6 [14.7 - 21]	42.7 [41.7 - 43.5]
5	-	Shared Autonomous Car	7.4 [6.9 - 7.8]	8.7 [7.8 - 8.7]	15.3 [14.7 - 16.2]	6.9 [6.7 - 7.2]	21.1 [19.5 - 22.3]	40.5 [38.3 - 44.5]	- -
6	Yes		5.3 [5.3 - 5.6]	5.3 [5.2 - 5.6]	4.1 [3.7 - 4.2]	4.6 [4.4 - 4.7]	14.8 [14.4 - 15.5]	20.1 [18.7 - 21.1]	45.9 [45.7 - 45.9]

Table 3.14: Modal split (% of distance) of multimodal trips in the Sioux Falls network

Scenario	Future mode	Modal split of mixed trips [% of distance] Car	Carpool	Transit	Bicycle	Walk	Future
2	-	8.7	6.4	9.7	6.8	12.8	-
4	Electric Step	6.4 [6.3 - 6.5]	5.0 [4.6 - 5.4]	6.6 [6.1 - 7.2]	5.1 [4.8 - 5.2]	8.6 [8.6 - 9.3]	11.1 [9.9 - 11.4]
6	Shared Autonomous Car	6.6 [6.1 - 6.6]	4.9 [4.8 - 5]	7.4 [7.3 - 7.7]	5.0 [5 - 5.2]	9.0 [9 - 9.3]	13.0 [12.4 - 13]

Table 3.15: Average speed, distance, trip duration and travel resistance in the Sioux Falls network

Scenario	Multimodal trips enabled?	Future mode	Average speed [km/h]	Average distance [km]	Average duration [min]	Average normalised resistance [-]*
1	-	-	9.8	7.41	51.4	100
2	Yes		7.9	6.81	53.6	100
3	-	Electric Step	10.5 [9.7 - 11.6]	7.37 [7.2 - 7.6]	47.2 [45.2 - 48.8]	86 [82 - 90]
4	Yes		9.0 [8.4 - 9.8]	6.97 [6.9 - 7.1]	48.8 [46.9 - 50.8]	97 [97 - 97]
5	-	Shared Autonomous Car	16.1 [14.6 - 18.2]	8.96 [8.7 - 9.4]	44.3 [43.4 - 45.1]	92 [89 - 92]
6	Yes		12.2 [11.2 - 12.9]	7.66 [7.5 - 7.7]	46.6 [46.2 - 47.5]	98 [97 - 98]

*Resistance is set to 100 for base scenario's without multimodal trips (Scenario 1) and with multimodal trips (Scenario 2)

Table 3.16: Average trip duration for each cluster in the Sioux Falls network

Scenario	Multimodal trips enabled?	Future mode	Average duration [min] Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
1	-	-	30.8	75.1	48.5	43.6	58.0	52.48
2	Yes		29.7	96.3	52.7	39.9	49.9	53.37
3	-	Electric Step	30.8 [29.9 - 30.8]	55.5 [50 - 63.6]	46.1 [44.7 - 46.5]	42.1 [40 - 42.7]	56.8 [56.8 - 58]	51.9 [50.1 - 51.9]
4	Yes		29.7 [28.7 - 30.4]	85.6 [83.2 - 90.1]	45.4 [42.3 - 46.8]	34.1 [31.2 - 38.4]	48.6 [48 - 48.8]	49.7 [48.1 - 50.1]
5	-	Shared Autonomous Car	21.0 [19.9 - 22]	65.8 [64 - 65.8]	41.6 [39.5 - 43]	39.7 [39.7 - 40.6]	54.3 [54.2 - 55]	43.6 [43.3 - 45.4]
6	Yes		19.1 [18.7 - 20.4]	95.9 [94 - 95.9]	41.5 [41.5 - 42.8]	35.6 [35.1 - 35.7]	45.3 [45.3 - 46.1]	42.5 [41.9 - 44.7]

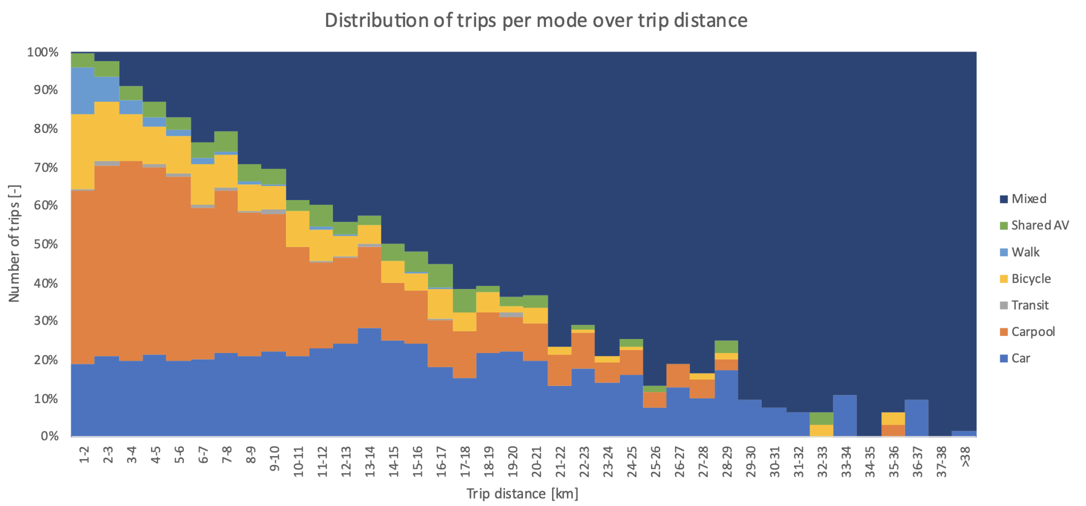

Figure 3.6: Distribution of trips per mode over trip distance for the scenario with multimodal trips for the future scenario with shared AV (Scenario 6 in Table 3.11)

agent in the network. Table 3.15 indeed shows that the travel resistance for networks with both future modes for both unimodal and multimodal configurations goes down compared to the base scenario without any future mode. Also note that the average trip duration for all clusters in all configurations remains similar or goes down when a future mode is added, indicating that all clusters of travellers benefit (in terms of trip duration) from adding a future mode.

3.4 Discussion

This study presents an approach for calculating the modal split and travel times of new transport modes in a future situation in which such modes are well established. This is done by developing a supernetwork where each layer represents a mode and multimodal trips can be simulated by transferring from one layer to another. Nodes and edges are used to describe the network. The resistances of the edges (as a function of a set of attributes without an alternative specific constant) are based on Chapter 2 where a discrete choice model is assessed using revealed preference data and on the network topology. This study uses the examples of an electric step and a shared autonomous car to explore an unlabelled choice model in a supernetwork approach. In this section, first, the accuracy of this method is discussed. Then, a possible overrepresentation of the future mode share is discussed. Finally, some assumptions and computational challenges are scrutinized.

The results of the simple yet exemplary networks (both uni- and multimodal) show results that seem logical: longer edge lengths show a shift towards faster modes and multiple routes/modes are chosen and show logical results when looking at average travel times, average distance and average speed. To demonstrate the application of the supernetwork approach in more complicated situations where multiple routes and OD-pairs are analysed, verification took place based on analysing the logic of results for multiple scenarios for the Sioux Falls network using the OD-matrix of car trips of Sioux Falls and the parameter estimation from Chapter 2 based on the Dutch OViN dataset (Centraal Bureau voor de Statistiek, 2017). Multimodal trips do occur and first- and last-mile mode choices are present for 15.8-17.4% of the trips. The distance in multimodal trips varies between 49.0 and 53.4% of the total distance travelled, indicating that multimodal trips are more likely to occur when the trip distance is longer. These aspects indicate that the model is simulating agents logically. Further observe that the ranges of modal shares of the future mode can vary substantially (between 14.7 and 44.5% for the two example future modes) with different mode attribute values. This demonstrates that the future mode attribute values do play a large role in the modal split and in the network effects, which is to be expected.

In Chapter 2 where a discrete choice model (DCM) was calibrated using a similar method, a nested logit (NL) model was preferred over an MNL to reduce overestimation of the future mode with partially similar characteristics (attributes, routes) as already existing modes. This effect has been partly taken into account in this current study by using each next possible edge only one time in the MNL to find the shortest route options, even though overlap of edges between options might still occur. This approach partially solves possible overrepresentation of future modes in the modal split. To further improve this approach can be done by accounting for the overlap in route (and similar modes). A path size correction logit model (PSCL) in combination with a multiplicative MNL (Smits et al., 2018) can be applied, since it is expected to work well on real networks (Smits et al., 2018; Bovy et al., 2008). PSCL models exist, for transit only, based on the shared number of transfer nodes, edges and travel times, which have a higher accuracy for transit, but these models cannot be applied to car transport (Dixit et al., 2023). Since both transit and car modes are used, this method is not trivial to implement on a multimodal supernetwork.

Further note that no iterations for mode/route choice are performed for agents, since all agents use the edge density data of the previous timestep. Future studies could implement extra iterations to account for rerouting due to choices other agents make at the same current timestep and study the difference between a single iteration and iterating until some type of equilibrium has been reached.

One limitation in the presented approach is that all modes are modelled in the same manner, whereas in reality, transit, for instance, behaves differently compared to cars or bicycles, since transit contains several service lines and operates according to a schedule. Transit has fixed routes and stops different from other modes, where agents do not have to leave the mode to change the route. Transit in the presented approach is not included in the congestion calculation to avoid rerouting during a trip in a fixed-route option. However, at every node, the agent might reconsider switching to another mode. In reality, transit schedules take into account congestion during peak hours and specific routes, which have not been explicitly modelled in this study. In the presented network, each edge represents a transit line between 2 stops, and passengers may choose to change transit line at each node. This approach can be improved by modelling one fixed transit route per layer (as separate modes), where each transit option is also modelled separately (e.g., buses, trams, metros, and trains have different average speeds) (as done in Chapter 5). In this way, availability, congestion (e.g., buses using the car infrastructure), and rerouting, can be taken into account in a more explicit and detailed manner, where switching transit lines means waiting for another specific option, opening up possibilities to analyse changing specific bus stops or changing the schedules of specific lines.

As indicated, the simulations for the example networks were run on a personal computer and the simulations for the Sioux Falls network were run on a high-performance computer using parallel CPU computing. Due to the nature of the shortest route function, the computational complexity increases with the power of 3 when the number of nodes, edges, modes, or agents increases. This means that for complex/real-life networks, a powerful computer needs to be used and the parallel computing implementation needs to be adjusted. For simple smaller networks, a less powerful personal computer can be used. For larger networks, parallel GPU computing should be applied to keep total simulation time manageable. Furthermore, optimisation of the shortest-path function and smart storage and lookup of results of each timestep (including shortest-path results for Origin/node-Destination pairs) could help reduce simulation time further.

3.5 Conclusions and Future Research

This study successfully demonstrated how the effects of any future mode on the modal split and on the travel times of an urban area can be assessed using a mesoscopic multimodal supernetwork. This is done by describing each available mode as a specific layer within a supernetwork with nodes and edges, where the edges' resistances are described by a set of attributes without mode-specific parameters and without a mode-specific constant. The mode-specific layers are interconnected to a neutral layer with edges (optionally) representing transfer resistances, also described with a set of attributes. This approach is verified in 3 small yet exemplary network configurations while varying the network configuration, available modes, and multimodal trips enabled and disabled. It is observed that adding modes changes the outcome of the models, these results are going in the expected direction, and the elasticity of the model is comparable to other studies. From this, it is concluded that the simulated agents' travel behaviour is logical. Furthermore, this approach is implemented on a Sioux Falls network and the travel behaviour simulation on this network configuration also seems logical in the sense that adding modes changes the outcome of the models and that these results are changing in the expected direction (adding modes reduces the travel resistance). Although the Sioux Falls network is U.S. American and the OViN dataset is Dutch, these case-studies do successfully illustrate how the mobility effects of any future mode can be assessed using the supernetwork model. Chapter 4 improves on this illustration by applying the supernetwork model on an OD-pair between Delft and Rotterdam to generate more practical results.

This supernetwork approach is combined with an agent-based approach. This agent-based approach allows for further exploration of different scenarios and policy interventions, such as adding limited capacities for transit or shared future modes (parking capacities at mobility hubs). Other options that are recommended to explore further are to subsidize certain modes (e.g., free transit or free shared AV), implement a time-based transit schedule (instead of a frequency-based schedule), and add extra mobility hubs (extra nodes).

The multimodal supernetwork approach is computationally expensive for larger networks. It is recommended to research how the computational load can be reduced and how parallel GPU computing can be implemented, whilst still maintaining the agent-based approach and output consisting of modal split and travel times. Special attention to the shortest route-seeking function should be given, as more than 80% of the time the computer was using this specific function.

Furthermore, no disruption scenarios are analysed in this study. In theory, random disruptions could be modelled by increasing the edge resistance in some places. This could be an approach to analyse how a future mode changes the resilience of a system.

Data Availability Statement

The code is openly available on https://github.com/KoendeClercq/Supernetwork. The dataset is not publicly available, but access can be requested for academic purposes for free at the Dutch Central Bureau of Statistics (CBS, 2017). The Github repository includes a simple case-study that can be run without needing the OViN dataset or permissions. The supporting files (for which access can be requested) are available here: https://data.4tu.nl/datasets/e281d623-9d5b-4eda-ad85-7eebb9a9eee4.

Chapter 4

Analysing the effects of shared electric bicycles between Delft and Rotterdam using a supernetwork model

Chapter 2 demonstrates how an unlabelled mode choice model can be used to calculate future modal split. Chapter 3 implements the unlabelled mode choice model of Chapter 2 in a supernetwork model and demonstrates how this supernetwork model can be used to calculate future modal split and the changes in other mobility effects when future modes are introduced. Chapter 4 adds onto the proof-of-concept of Chapter 3 by applying the supernetwork model on an OD-pair between Delft and Rotterdam to assess the mobility effects of shared electric bicycles using the Dutch OViN dataset (Centraal Bureau voor de Statistiek, 2017) resulting in an demonstration with realistic results. Chapter 5 extends the supernetwork model even further by explicitly implementing transit lines in Delft and introduces an approach to identify attributes for an 'optimal future mode'.

Section 4.1 contains the abstract. Section 4.2 introduces the problem and main aim of this chapter. Section 4.3 briefly goes into the set-up of the model and the methodology of setting up the network between Delft and Rotterdam. Section 4.4 shows and discusses the results. Finally, Section 4.5 presents the conclusions.

The contents of this chapter have been presented at hEART 2023 at the ETH in Zürich, Switzerland: de Clercq, G. K., M. Snelder, A. van Binsbergen, B. van Arem (2023) Analysing the Effects of Adding Shared Electric Bicycles as a New Mode on the Modal Split of Multimodal Trips between Delft and Rotterdam Using an Unlabelled Multimodal Supernetwork, in: *Proceedings of 11th symposium of the European Association for Research in Transportation*, Zürich. Retrieved from https://transp-or.epfl.ch/heart/2023/abstracts/hEART_2023_paper_9370.pdf

4.1 Abstract

Assessing to what extent future modes will change modal split is difficult, since empirical data is not available yet to estimate models with mode-specific constants and parameters. To address this, an unlabelled multimodal supernetwork is developed in which mode and route choice are simultaneously modelled. The model has been estimated based on empirical data of existing modes and can be used to assess the impact of any future mode. We applied the model to analyse the effects of several configurations (cost, speed, access/egress) of shared e-bicycles on one Origin-Destination pair between Delft and Rotterdam. The main scientific contribution of this chapter is that it demonstrates how an unlabelled multimodal supernetwork can be used to analyse the effects of shared e-bicycles on the modal split between Delft and Rotterdam. The results show that the modal share of shared e-bicycles is 35.3-40.5% for unimodal trips, which is in line with another study by Sun et al. (2020), and occurs in 36.2-46.3% of multimodal trips, indicating that shared e-bicycles can significantly change the modal split, reducing the modal share of car trips from 45.4% to 25.5-30.4% and the modal share of bike trips from 45.8% to 23.4-25.9%.

Keywords: agent-based modelling; multimodal; shared e-bicycles; supernetwork; unlabelled mode choice

4.2 Introduction

Several mobility systems, ranging from shared electric bicycles to autonomous vehicles, have been developed. These future modes could change the way our societies function in terms of sustainability, equity, accessibility, and safety (Fagnant & Kockelman, 2015; Milakis et al., 2017; Shaheen et al., 2019).

Researching how future modes affect mode choice is difficult, since revealed data of the potential users using these future modes are not available yet, so mode-specific parameters cannot be estimated. In Chapter 2, this challenge has been addressed by developing an abstract, or unlabelled, mode modelling approach to assess the modal share of any future mode and unimodal trips. The unlabelled mode modelling approach was first introduced by Quandt & Baumal and describes a method to formulate a discrete choice model by describing the utility of each mode with the same mode attributes for each mode and by leaving out mode-specific constants and parameters (Quandt & Baumal, 1966). In Chapter 2, it was shown that any future mode can be modelled using the unlabelled mode modelling approach as long as the future mode can be described as a (new) combination of existing attributes of which the relative importance can be estimated based on revealed preference data. In those cases, the utility function of the future mode can be defined and thus the future mode can be added as an option in the choice set of a discrete choice model. However, a shortfall of this approach is that it does not yet cover multimodal trips.

Future modes, such in our case shared electric bicycles, will be often used for the the first- and/or last-mile parts of a trip and will only be available at certain locations (e.g., mobility hubs) (Van Eck et al., 2014). Therefore, to analyse new transport modes, it will be often necessary to analyse their use in a multimodal setting. This can be done by developing a multimodal supernetwork which can model multimodal trips without the need to predefine the combinations of mobility systems and where mode and route choice happen simultaneously (Liao, 2016; Van Eck et al., 2014; Vo et al., 2021). These models only need to know where people are allowed to switch modes (e.g., where the mobility hubs are located).

In our study (Chapter 3), we developed such a supernetwork approach to assess the impact of future modes. Following the same logic as with the previously mentioned unlabelled discrete choice model (Chapter 2), in our supernetwork, one can define the future mode by describing it in terms of a broad set of mode attributes, but without any mode-specific constants, and adding that mode as a new ‘layer’ in the supernetwork. So far, the model has only been applied to theoretical simple networks and a fictive multimodal version of the Sioux Falls network to demonstrate and verify the method. In this chapter, we applied the model in a more realistic case situation. We focus on the introduction of shared electric bicycles on one example Origin-Destination (OD)-pair between Delft and Rotterdam because cycling is a dominant mode of transport in the Netherlands and electric bicycles are becoming increasingly popular (Sun et al., 2020).

This chapter contributes to the existing literature by demonstrating how an agent-based multimodal supernetwork-based traffic assignment model with unlabelled modes that takes into account mode and route choice simultaneously can be applied in a real use-case to gain insight into the influence of shared electric bicycles on a specific OD-pair between Delft and Rotterdam, including the use in the first and last-mile parts of a trip. Knowledge gaps and possible future research directions to research the effects of future modes on the modal split of urban areas are identified and discussed as well.

4.3 Methodology to analyse the effects of shared electric bicycles by applying a supernetwork model

Figure 4.1 summarizes the supernetwork approach that has been applied in this chapter. Trip generation and distribution are considered exogenous. Mode and route choice are calculated simultaneously based on the resistance per edge. Subsequently, per timestep, trips are assigned to the supernetwork using a mesoscopic dynamic traffic assignment approach. The assignment model with the supernetwork is set up using Python 3.10.2 and the NetworkX package (Hagberg et al., 2008). Below, the main elements of the assignment model are described. For an extensive description of the network definition, the combined mode and route choice model and the network loading model, refer to Chapter 3.

The supernetwork consists of one layer for each mode. Within each layer, edges represent aggregated road segments with generalized resistance (i.e., disutility), transit segments (representing aggregated transit lines) and dummy transition edges from and to a neutral layer (representing transfer resistance). The transport mode edges have a length and a number of attributes (representing the mode and link attributes), whereas for modes using the road network the ‘time’ attribute can change with the use of the edge (i.e., the flow).

Twelve mode attribute assumptions (times mode attribute parameters, see Table 4.3) have been used to define the resistance in the edges for all modes: Initial cost (€); Cost/trip (€); Time (min); Driving task (-); Skills (-) (i.e., driver’s license); Weather protection (-); Luggage (-); Shared (-); Availability (-); Reservation (-); Active (-); Accessible (-). The mode attribute assumptions per mode are shown in Table 4.1.

When agents want to switch modes, the resistance in the considered route also contains the time it takes to disembark from the mode, and embark to the mode (see Table 4.2 and the ‘initial cost’ of a mode (see Table 4.1). The times in these edges are multiplied by 3 to represent the extra mental effort it takes for users to switch modes and wait for the next mode (Wardman, 2004).

The total resistance per route is defined as the sum of the edge resistances. Edge resistances are the sum of a series of products of mode attributes and the valuations of these attributes by users. For the modelling approach, homogenous groups of users are combined in clusters. There are two categories of mode attributes; one category which is addable over the route regardless of the length of each edge and the length of the route (e.g., travel time, costs) (see Eq. 4.1) and one category which is not addable over the route. The attributes within this last category need to be weighted with the length

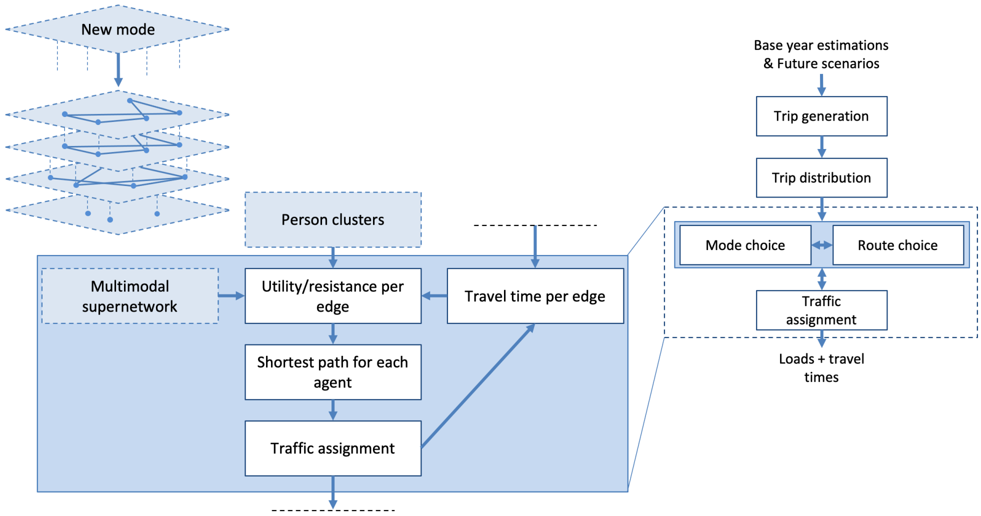

Figure 4.1: General layout of multimodal supernetwork

Table 4.1: Mode attribute assumptions

Mode attribute	Addable*	Source and determination
Initial cost (€)	Yes	Car, transit, cycle, walk = 0
Cost/trip (€)	Yes	Car = 0.19 per km; transit = 0.20 per km; walk = 0; bicycle = 100 purchase costs, with 4 trips per day for 5 years
Time (min)	Yes	Car, transit, bicycle and walk from Google Maps (Travel times Google Maps, n.d.)
Driving task (-)	No	Car, bicycle = 1; transit, walk = 0
Skills (-) (i.e., driver's license)	No	Car = 1; transit, bicycle, walk = 0
Weather protection (-)	No	Car, transit = 1; bicycle, walk = 0
Luggage (-)	No	Car = 1; transit = 0.5; bicycle, walk = 0
Shared (-)	No	Car, bicycle, walk = 0; transit = 1
Availability (-)	No	Car = 1; transit = 0.5; bicycle = 1, walk = 1
Reservation (-)	No	Car, bicycle, walk = 1; transit = 0
Active (-)	No	Car, transit = 0; bicycle, walk = 1
Accessible (-)	No	Transit = 1; Car, bicycle, walk = 0

*Addable and non-addable attributes are implemented differently in the edge/route resistance calculations (see Eq. 4.1 and Eq. 4.2).

Table 4.2: Assumed time to switch modes

Mode	Neutral to mode	Mode to neutral
Car	5 min (get in car)	2 min (parking)
Transit (BTM)	7.5 min (average waiting time, assumed freq.: 4 times/hour)	5 min
Bicycle	1 min (get on bike)	1 min (parking)
Walk	0 min	0 min

of each edge within the route to come to a weighted average value for those attributes (e.g., weather protection on 70% of the total length of the route) (see Eq. 4.2). These two edge resistance calculations are combined in Eq. 4.4, where the resistances of all edges in one route are summed up and divided by the length of that route to get the ratio of the mode attributes of each edge respective to their share in the total route. A multinomial logit model (MNL) (Ortuzar & Willumsen, 2011) with en-route route choice is used to determine the mode/route choice based on the route resistance. IIA (Independence of Irrelevant Alternatives) is assumed for all modes in this study.

$$E_{i,t,a}^{addable} = \sum_{c \in C} \sum_{k \in K} \beta_{c,k} \gamma_{a,c} \chi_{k,i,t}, \forall i \in I_r, \forall t \in T, \forall a \in A \tag{4.1}$$

$$E_{i,t,a}^{non-addable} = len_i * \sum_{c \in C} \sum_{m \in M} \beta_{c,k} \gamma_{a,c} \chi_{m,i,t}, \forall i \in I_r, \forall t \in T, \forall a \in A \tag{4.2}$$

$$L = \sum_{i=1}^{I_r} len_i \tag{4.3}$$

$$U_{r,t,a} = \sum_{i \in I} (E_{i,t,a}^{addable} + \frac{E_{i,t,a}^{non-addable}}{L}), \forall r \in R, \forall t \in T, \forall a \in A \tag{4.4}$$

where;

$E_{i,t,a}^{addable}$ = edge resistance addable component [-];
$E_{i,t,a}^{non-addable}$ = edge resistance non-addable component [-];
$U_{r,t,a}$ = route resistance for agent a travelling on route r at time t [-];
β = cluster valuation of mode attribute [-];
$\gamma_{a,c}$ = dummy variable indicating if agent a belongs to cluster c [-];
χ = value of mode attribute [-];
len = length of edge [km];
L = length of route [km];
i = edge index of edges within route [-];
k = addable mode attribute index [-];
m = non-addable mode attribute index [-];
t = timestep [-];
a = agent index [-];
c = cluster index [-];
r = route [-];
I_r = set of edges in route r;
K = set of addable mode attributes (e.g., travel time);
M = set of non-addable mode attributes (e.g., weather protection);
T = set of timesteps;
A = set of agents;
C = set of clusters; and
R = set of routes.

Table 4.3: Mode attribute valuations per cluster (Chapter 2)

Cluster	1	2	3	4	5	6
(Initial) Cost	0.0193	-0.0267	-0.0343	0.0229	-0.0123	-0.0806
Time	-0.0208	-0.0439	-0.0207	-0.0243	-0.036	-0.0218
Driving task	-0.571	-0.0884	-0.855	-1.21	-0.129	-1.2
Skills	-0.16	2.17	1.44	2.22	-2.81	1.52
Weather protection	-1.07	-0.402	-0.284	-0.781	-1.22	-0.0638
Luggage	-1.08	-1.39	-0.0653	-0.719	-0.952	-0.248
Shared	-0.611	-2.01	-1.25	-3.8	1.3	-1.43
Availability	-1.87	-3.96	-1.44	-8.28	-0.24	-2.46
Reservation	-0.733	-1.74	-0.292	0.313	1.79	0.672
Active	0.74	-0.00596	0.314	0.58	1.22	0.314
Accessible	-0.671	-2.58	-1.25	-3.49	1.41	-1.94

The valuation (i.e., observed preferences for travellers for attributes) of the attributes have been estimated using a large-scale trip survey in the Netherlands (Centraal Bureau voor de Statistiek, 2017) for the year 2017. The dataset contains personal, trip, and mode information. It contains five main transport modes: car, carpool, transit (BTM), bicycle, and walk. This dataset is further enriched with the mode attributes (see Table 4.1). Furthermore, clusters of travellers with similar characteristics have been identified, using k-means clustering and the elbow method to define the optimal number of clusters for the trips. The estimated valuations for the six clusters are shown in Table 4.3. Note that some parameters have different signs per cluster. This can be explained by considering that some clusters value certain traits positively (e.g., higher costs are a status symbol) and other clusters value certain traits negatively (e.g., higher costs make a mode less affordable). Because these attributes capture almost all aspects that determine mode and route choice, mode-specific constants are no longer needed. The valuations of the attributes (i.e., betas) are also no longer mode-specific and therewith transferable to future modes.

Case-study: Delft to Rotterdam

Figure 4.2 visualizes the network with first-mile, main, and last-mile edges for an example OD-relation between Delft and Rotterdam. Nodes depict centroids and mobility hubs (the network definition does not contain centroid feeders). First- and last-mile edges have multiple modes. The origin and the destinations are indicated using O and D respectively. Figure 4.3 gives a supernetwork representation of this network with five modes for which the model has been estimated (the reference case) and an added sixth mode shared e-bicycles (for the 'future mode' alternative). The network contains transition links between modes through a neutral layer. Note that when switching mode, an agent always needs to leave the mode, enter the neutral layer, and enter the future mode. The possible transfers on certain locations (circles) between modes are depicted with the vertical dashed lines. One example multimodal route is visualized in yellow, where the bicycle is used to cycle from the centroid (O, Delft) to the station, transit is used as the main mode and walking is used for the last-mile to the destination (D, Rotterdam).

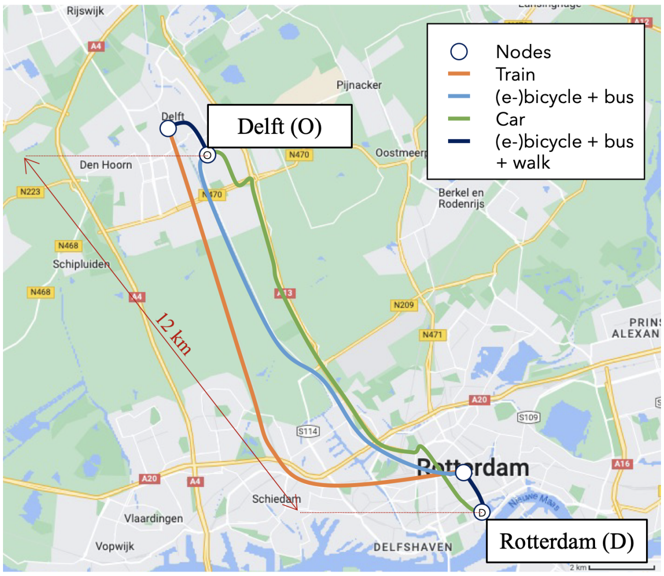

Figure 4.2: OD relation between Delft and Rotterdam

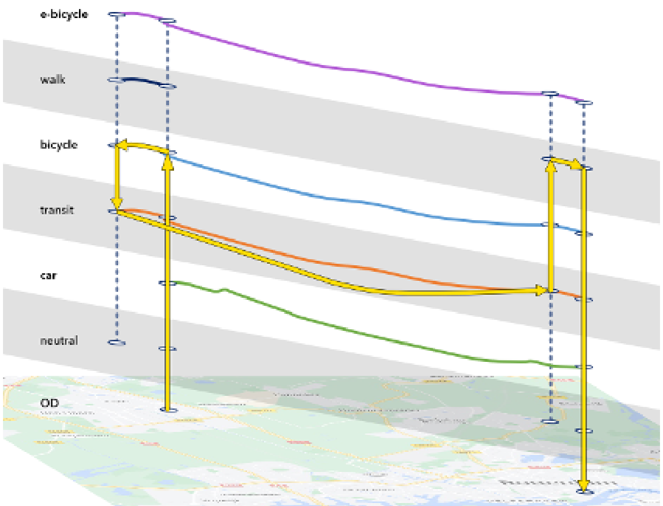

Figure 4.3: Supernetwork of the route between Delft and Rotterdam

Table 4.4: Attribute values

Nr.	Attribute	Pricing policy
1	Initial cost shared electric step [€]	3.2 – 4.0 – 4.8
2	Speed [km/h]	20 – 25 - 30
3	Neutral to e-bike [min]	2.4 – 3.0 – 3.6
4	E-bike to neutral [min]	1.6 – 2.0 – 2.4
5	Network [-]	With/without e-bicycles

The future mode alternative, shared electric bicycles, comes with its own characteristics, including initial costs, speed, the generalized transit times from the neutral layer to shared electric bicycles and vice versa. We also analyse the effects of taking different assumptions for these characteristics to account for different possible configurations of shared electric bicycles. These variants are described in Table 4.4. The possible combinations (81) of these attribute values form scenarios. These scenarios are simulated to analyse the effects of a different level of service of shared electric bikes on the modal split and travel times.

Simulation set-up

For the simulation, the earlier identified six clusters of travellers are used; 166 trips for each cluster are simulated, all traveling between one particular OD-pair. A timestep of 1/100 hours (=36 sec) is used. This time step is chosen such that an agent will spend at least two timesteps on the shortest link (1.8 km) considering the highest free flow speed in this model (90 km/h). The simulated time period in the model is 4 hours representing a morning peak hour from 6 AM to 10 AM. The same seed number is used in all simulations to be able to compare different scenarios. The number of transfers between modes in the multimodal networks is limited to 2 (first-mile $\rightarrow$ main $\rightarrow$ and last-mile). Since transit is modelled in one layer and contains all bus, tram, and metro (BTM) transit, this is assumed to be realistic.

4.4 Results and discussion

The results of the simulations, including sensitivity analysis results between brackets, are shown in Table 4.5 till 4.7. It can be observed that the modal share of shared e-bicycles ranges between 35.3 and 40.5% in unimodal trips and occurs in 36.2-46.3% of the multimodal trips, indicating that shared e-bicycles can significantly change the modal split between Delft and Rotterdam, reducing mainly the modal share of cars, cycling, and, to a lesser extent, transit and walking. When looking at the total distance travelled per mode for all scenarios, it is interesting to point out that walking is used at least in 41.7% of the multimodal trips, but amounts to only a maximum of 0.6% of all distance travelled. This indicates that walking occurs for first- and last-mile as would be expected. The average travel time changes depending on the configuration of shared e-bicycles, indicating that travel time can be improved by introducing shared

Table 4.5: Modal split (trips) with and without shared e-bicycle, including sensitivity analysis results between brackets

	Modal split [%]					
	Car	Transit	Bicycle	Walk	E-bicycle	Multimodal
No e-bicycles	45.4	0.8	45.8	0.0	-	8.0
E-bicycles	28.2	0.5	25.3	0.0	40.5	5.5
	[25.5 - 30.4]	[0.2 - 0.5]	[23.4 - 25.9]	[0.0 - 0.0]	[35.3 - 40.5]	[5.1 - 5.8]
	Modal split of multimodal trips [%]*					
	Car	Transit	Bicycle	Walk	E-bicycle	
No e-bicycles	0.0	60.6	89.0	60.2	-	
E-bicycles	0.0	37.6	75.8	51.7	44.0	
	[0.0 - 0.0]	[28.6 - 37.6]	[67.9 - 75.8]	[41.7 - 51.7]	[36.2 - 46.3]	

*The modal split of mixed trips amounts to more than 100%, since multiple modes can occur in one single trip. The numbers can be interpreted as the percentage of the mixed trips that contain a certain mode.

Table 4.6: Modal split (distance) with and without shared e-bicycles, including sensitivity results between brackets

	Modal split [%]					
	Car	Transit	Bicycle	Walk	E-bicycle	Multimodal
No e-bicycles	43.6	0.9	46.6	0.0	-	8.8
E-bicycles	26.9	0.6	25.6	0.0	41.0	6.0
	[24.2 - 28.9]	[0.3 - 0.7]	[23.6 - 29.6]	[0.0 - 0.0]	[35.7 - 45.2]	[5.5 - 7.7]
	Modal split of multimodal trips [%]*					
	Car	Transit	Bicycle	Walk	E-bicycle	
No e-bicycles	0.0	3.1	5.1	0.6	-	
E-bicycles	0.0	1.3	2.5	0.4	1.8	
	[0.0 - 0.0]	[0.7 - 1.6]	[2.1 - 3.8]	[0.3 - 0.5]	[1.5 - 2.4]	

e-bicycles, but depends on the level of service that shared e-bicycles have when they are introduced on the roads.

The results in this study are plausible in the sense that the e-bicycle mainly replaces car and bike trips. This is in line with the findings in (Sun et al., 2020). They used a longitudinal dataset from the Netherlands Mobility Panel to analyze the modal shift effects of people who bought an e-bicycle. However, the potential modal share of shared e-bicycles is slightly higher than the study of (Sun et al., 2020) shows. For trips of about 15 kilometres, they found a modal share of 33-36%. This might be explained by the relatively high share of normal bicycles in the reference situation for this specific origin-destination pair and the fact that a multinomial logit model is used to determine

Table 4.7: Average speed, distance, and duration with and without shared e-bicycles, including sensitivity analysis results between brackets

	Average speed [km/h]	Average distance [km]	Average duration [min]
No e-bicycles	23.64	15.40	43
E-bicycles	24.01	15.56	41
	[22.09 - 25.99]	[15.52 - 15.61]	[38 - 45]

the next node for each agent, which does not account for the overlap ('red/blue-bus paradox'). Depending on the exact configuration of shared electric bicycles, the overestimation due to possible overlap between modes could be estimated to be between 0 and 4 percentage points when comparing the maximum modal share of (Sun et al., 2020) and our results.

4.5 Conclusions and recommendations

This study successfully demonstrated how an agent-based unlabelled multimodal supernetwork-based traffic assignment model can be used to assess the effects of future modes such as shared electric bicycles on the modal split for an example origin-destination pair Delft- Rotterdam. This is done by using a supernetwork framework, where each available mode is modelled as a specific layer within this supernetwork with nodes and edges, where the edges' resistances are described by a set of attributes without a mode-specific constant. The mode-specific layers are interconnected to a neutral layer with edges representing transfer resistances, also described with a set of attributes. The unlabelled approach, i.e., without mode-specific parameters and constants, makes it possible to add any future mode.

The results show plausible modal-shift effects from cars and bicycles to shared electric bicycles. However, the absolute modal share seems slightly overestimated because overlap is only partly considered. To account for overlap in routes (and similar modes) completely, it is recommended to explore grouping layers of similar modes and overlapping routes into one 'nest' by using a path-overlap factor. A path size correction logit model (PSCL) in combination with a multiplicative MNL is expected to work well on real networks (Bovy et al., 2008; Smits et al., 2018). PSCL models exist, for transit only, based on the shared number of transfer nodes, edges and travel times, which have higher accuracy for transit, but these models cannot be applied to car transport (Dixit et al., 2023). However, since both transit and car modes are used, this method is not trivial to implement on a multimodal supernetwork and is therefore proposed as a topic for future research.

The modular approach of this supernetwork allows for further explorations of other future modes, more scenarios, and other network configurations. Recommended options to explore further are to include other future modes, pricing policies, adding a time-based transit schedule, and changing the availabilities and stops of transit or other modes. Further, no disruptions (e.g., weather conditions, accidents) have been analyzed in this study yet. Disruptions could be implemented by temporarily increasing the edge resistance in some places. This could be an approach to give insight into how a future mode changes the travel time reliability of a system. Finally, it is recommended to integrate this multimodal supernetwork in a land-use-transport interaction model to see how higher-order aspects, such as activity patterns, change over the years as a result of the introduction of new transport modes.

Chapter 5

Finding the ultimate future mode in Delft using a supernetwork model with transit lines

Chapter 2 demonstrates how an unlabelled mode choice model can be used to calculate future modal split. Chapter 3 implements the unlabelled mode choice model of Chapter 2 in a traffic assignment model with a supernetwork and demonstrates how this supernetwork model can be used to calculate future modal split and the changes in other mobility effects when future modes are introduced. The current chapter extends the supernetwork model of Chapter 3 with explicitly modelled transit lines and uses this supernetwork model to present a 2-step approach to find an optimal combination of mode attributes which minimises the travel resistance of the Delft network. First, by varying the future mode attributes disregarding cost and travel speed to minimise the generalized travel resistance of the mode. And second, by using the outcome of the first step in simulations where (realistic) cost and travel speed are included.

Section 5.1 contains the abstract. Section 5.2 introduces the problem and main goal of this chapter. Section 5.3 explains the methodology of how the Delft network, including public transit, is implemented in an aggregated manner using equivalent edges, where the capacities of the equivalent edges are estimated using an existing OmniTRANS model of Delft, and how the ultimate future mode in Delft can be found. Section 5.4 contains the results, including changes in modal splits, resistance, and travel times. This chapter finishes with discussions and conclusions in Sections 5.5 and 5.6 on the methodology and findings of how the ultimate future mode can be found using this traffic assignment model with a multimodal supernetwork.

This chapter is currently under review at a journal.

5.1 Abstract

Future modes are emerging and expected to change mode and route choice but which future mode would reduce the generalized travel resistance of a current transportation network the most? We answer this question by using a supernetwork model extended with the option to add explicit public transit lines to find the ultimate future mode (the mode that minimises the generalized travel resistance of the network) in Delft based on solely its attributes without mode-specific bias. First, we identify the ultimate combination of mode attributes by minimizing the travel resistance for all mode attributes and types of travellers. This results in an active mode with weather protection, luggage carrying options and a driving task. Next, the cost and the average speed of the ultimate mode are varied within realistic limits to simulate the effect on the overall travel resistance, modal share, and total travel times. The results show that the ultimate combination of mode attributes results in a reduction of the average travel time of up to 20% and a reduction of generalized travel time resistance of up to 4.7%.

Keywords: agent-based modelling; future modes; multimodal transportation systems; unlabelled mode choice; supernetwork; traffic assignment

5.2 Introduction

Several future modes, ranging from autonomous vehicles to the hyperloop, are being developed and some of these have been introduced in varying degrees – from test implementations to local initiatives – in urban areas. These future modes could when fully deployed, completely change the way our societies function in terms of accessibility, livability and equity (Fagnant & Kockelman, 2015; Shaheen et al., 2019; Milakis et al., 2017). But how can we know which future 'ultimate' mode should be introduced to reduce the (generalized) travel resistance of a mobility system as much as possible?

To assess the impacts of a future mode on the generalized travel resistance, the attractiveness of the mode and the mode choice effects needs to be determined first. Mode choice is typically determined based on the utility for each mode using discrete choice models. The utility function for each mode consists of mode attributes and mode specific parameters (i.e., travellers' valuation) and constants. The travellers' valuations of existing mode attributes can be estimated using revealed preference research. For future modes this is not possible, because data for these modes is not yet available. Stated preference research can be used for estimating the travellers' valuations of existing and future mode attributes.

In literature, stated preference research is often used to assess the mode choice impacts of future modes (Arentze & Molin, 2013; Smit et al., 2019). Correia et al. (2019) specifically researches the impact of automated driving on the value of time while performing other activities in the car using a stated preference survey. The main advantage is that these studies give good insight into how these future modes will probably be used, but the main limitation these studies mention is that travellers will still probably behave differently once these future modes are actually introduced (revealed preference) compared to when they state their preferences in a controlled environment.

To assess the impact of future modes on the modal split and generalized travel resistance, traffic and transport models can be used. Future modes, such as (shared) autonomous vehicles, electric steps, and other modes have been analyzed in different types of models. For instance, Snelder et al. (2019) looked at the mobility impacts of connected and automated vehicles and automated (shared) taxis and vans using an iterative traffic assignment model that uses an elasticity model for destination choice, a multinomial logit model for mode choice and a network fundamental diagram to assess traffic impacts. The authors made expert based assumptions of mode-specific parameters and constants for these future modes. Stevens et al. (2022) used an agent-based model to assess the financial viability of autonomous mobility-on-demand systems in Rotterdam, the Netherlands with alternative specific constants based on stated preference data. System dynamics have also been used to analyze the impacts over time of automated driving and with(out) communication between vehicles (Puylaert et al., 2018). To find the ultimate future mode, it is necessary to model the impacts of a large set of potential future modes. However, setting up stated preference research for any potential future mode is infeasible.

To overcome above mentioned shortcomings of revealed and stated preference research, an abstract, or unlabelled, mode modelling approach has been developed to assess the modal share of any future mode for unimodal trips (Chapter 2). The unlabelled mode modelling approach was first introduced by Quandt & Baumal and describes a method to formulate a discrete choice model by describing the utility of each mode with the same mode attributes for each mode and by leaving out mode-specific constants and parameters (Quandt & Baumal, 1966). For unimodal mode choice, we have demonstrated that any future mode can be modelled using the unlabelled mode modelling approach as long as the future mode can be described as a (new) combination of existing attributes of which the relative importance can be estimated based on revealed preference data (Chapter 2). In those cases, the utility function of the future mode can be defined and thus the future mode can be added as an option in the choice set of a discrete choice model.

However, next to unimodal mode choice it is also necessary to model multimodal trips, since future modes can also specifically serve the first- and/or last-mile parts of a trip (Van Eck et al., 2014). Supernetworks can model multimodal trips without predefining multimodal mode/route-choice combinations. In general, a supernetwork can be defined as a network with subnetworks/layers each representing a different category (i.e., in the context of this study: transport modes and services) (Sheffi, 1984; Nagurney & Dong, 2002; Arentze & Timmermans, 2004; Lozano & Storchi, 2002; Bovy & Hoogendoorn-Lanser, 2005). These supernetwork models only need to know where people are allowed to switch between modes (Arentze & Timmermans, 2004; Nagurney et al., 2003). For instance, such models are applied to model the effects of fleet size, spatial availability of floating shared modes and parking fees on the use of shared cars (Li et al., 2018). In one study by Vo et al. (2021), a multimodal supernetwork is used to explore the effects of the interaction between private cars and transit modes on the activity-travel choices of individuals defining the locations where individuals can switch modes without predefined route sets.

Although multimodal supernetworks are an attractive option to analyse how travel patterns change in different scenarios, a downside is that simulations are computationally intensive, which can lead to long simulation times requiring the use of high-performance computers (Van Eck et al., 2014). Also, these models are usually developed only with modes with available choice data, including mode-specific parameters and constants, and cannot be applied to analyse the effects of future modes as long as mode-specific constants are used.

In Chapter 3 and 4, it was demonstrated that the unlabelled mode modelling approach can be used in a supernetwork model. This approach allows to analyse the mobility effects of future modes, which is demonstrated for two examples of future modes: autonomous vehicles and shared electric steps.

In this chapter, we apply the same combination of unlabelled mode choice and a supernetwork to determine which attributes of a future mode would actually minimise the total generalized travel resistance in a network in 2 phases. First, by varying the future mode attributes, while disregarding cost and travel speed and assuming the ultimate future mode is using a separate infrastructure, to minimise the generalized travel resistance of the mode. And second, by using the outcome of the first step in simulations where (realistic) cost and travel speed are included. Since this approach uses no mode-specific biases, we hypothesize that the ultimate future mode can be determined by optimizing the values and combinations of attributes describing such a mode rather than by starting from a preconceived design. This can be done as long as the future mode is described by a combination of mode attributes that are also used to describe the current modes in the dataset. Furthermore, the ultimate future mode uses the existing infrastructure and shares this infrastructure with the other modes (car, carpool and bicycles in this study). Lastly, it is assumed that the demand remains the same (the OD-matrix is not adjusted).

This explorative approach is taken because mobility providers and governing bodies have the need to understand which future modes can improve mobility in urban areas without a (possibly limited) predefined set of future modes to be considered. To the best of the authors' knowledge, no studies were found where the ultimate future mode has been established without determining beforehand what the attributes of this ultimate future mode should be. The second contribution of this chapter is the implementation of multiple public transit lines in one layer (i.e., 'nest') in the supernetwork to enable the modelling of explicit transit lines. The method to find an ultimate future mode that improves the mobility system the most is demonstrated for the city of Delft.

The next section describes the research approach to finding the ultimate future mode in the city of Delft. Section 5.4 shows the results and the discussion section interprets the results and explains the shortcomings. Knowledge gaps and possible future research directions to research methods to find the ultimate mode of urban areas are identified in Sections 5.5 and 5.6.

5.3 Research approach

This section is divided into three parts. The first part gives a description of the supernetwork model and its assumptions. The section thereafter summarises how a supernetwork model is applied to find the ultimate future mode in a computationally feasible approach consisting of two subsequent phases; 1) attribute combination enumeration and 2) a supernetwork application. Finally, the last part describes how the case-study of the city of Delft has been set up, including explicit modelling of public transport lines.

5.3.1 Supernetwork model

To understand how a supernetwork model can be applied to find the ultimate future mode based on its attributes alone, we need to briefly explain the setup of this model. Trip generation and distribution are considered exogenous. Given a certain OD-matrix, the supernetwork model assigns agents on edges (mode and route choice) in the network.

Several assumptions are made to develop the case-study. One assumption that has to be made is that travellers are already fully familiar with the future mobility system, the initial adoption has occurred and that the travellers' valuation of the mode attributes does not change with the introduction of a future mode. Furthermore, it needs to be assumed that the revealed preference data is assumed to contain a complete and coherent set of mode attributes that can describe current and future modes adequately.

A multinomial logit model (MNL) is used to determine the route choice through the multimodal supernetwork based on the route resistance (i.e., utility based on all mode attributes) and thus implicitly and simultaneously the mode choice. In this multinomial logit model, overlap between routes is considered by using an en-route route choice model that continuously looks for distinctive routes. A route is composed of a succession of edges. The total resistance per route is defined as the sum of the edge resistances in that route. Edge resistances are the sum of a series of products of mode attributes and the valuations of these attributes by agents. For the modelling approach, homogeneous groups of agents are combined in clusters. This means that the resistance of each edge is different for agents from different clusters. Multiple types of travellers, based on a cluster analysis using k-means and the elbow method (Chapter 3), are identified in this analysis to account for an approach that can map the effects for different trip purposes and types of travellers. A certain mode/route could be attractive for agents in one cluster, whereas, for an agent with the same OD-pair from another cluster, the same mode/route could be much less attractive. The resistance of an edge changes if use (intensity) increases for all modes, except transit. Note that it is possible that different options in the final route set in the MNL can have overlapping edges.

There are two categories of mode attributes; one category which is addable over the route regardless of the length of each edge and the length of the route (e.g., travel time, costs) (see Eq. 5.1) and one category which is not addable over the route (e.g., weather protection) (see Eq. 5.2). The attributes within this last category need to be weighted with the length of each edge within the route to come to a weighted average value for those attributes (e.g., weather protection on 70% of the total length of the route (Eq. 5.3)). These two edge resistance calculations are combined in Eq. 5.4, where the resistances of all edges in one route are summed and divided by the length of that route to get the ratio of the mode attributes of each edge respective to their share in the total route. Note that the resistance is calculated with the network (i.e., density) conditions at timestep t, even though the agent might encounter other network conditions at a later timestep while travelling through the network. Further, note that the value of χ is different for each mode.

$$E^{addable}_{i,t,a} = \sum_{c\in C}\sum_{k\in K} \beta_{c,k}\gamma_{a,c}\chi_{k,i,t}, \forall i \in I_r, \forall t \in T, \forall a \in A \tag{5.1}$$

$$E^{non-addable}_{i,t,a} = len_i * \sum_{c\in C}\sum_{m\in M} \beta_{c,k}\gamma_{a,c}\chi_{m,i,t}, \forall i \in I_r, \forall t \in T, \forall a \in A \tag{5.2}$$

$$L = \sum_{i=1}^{I_r} len_i \tag{5.3}$$

$$U_{r,t,a} = \sum_{i\in I}(E^{addable}_{i,t,a} + \frac{E^{non-addable}_{i,t,a}}{L}), \forall r \in R, \forall t \in T, \forall a \in A \tag{5.4}$$

where;

$E^{addable}_{i,t,a}$ = edge resistance addable component [-];
$E^{non-addable}_{i,t,a}$ = edge resistance non-addable component [-];
$U_{r,t,a}$ = route resistance for agent a travelling on route r at time t [-];
β = cluster valuation of mode attribute [-];
$\gamma_{a,c}$ = dummy variable indicating if agent a belongs to cluster c [-];
χ = value of mode attribute [-];
len = length of edge [km];
L = length of route [km];
i = edge index of edges within route [-];
k = addable mode attribute index [-];
m = non-addable mode attribute index [-];
t = timestep [-];
a = agent index [-];
c = cluster index [-];
r = route [-];
I_r = set of edges in route r;
K = set of addable mode attributes (e.g., travel time);
M = set of non-addable mode attributes (e.g., weather protection);
T = set of timesteps;
A = set of agents;
C = set of clusters; and
R = set of routes.

The resistances for the edges as described from Eq. 5.1 till 5.4 are determined based on Chapter 2, in which it was shown that any future mode can be modelled using the unlabeled mode modelling approach as long as the future mode can be described as a (new) combination of existing attributes of which the relative importance can be assessed based on revealed preference data describing trips including personal, trip, and mode information (Centraal Bureau voor de Statistiek, 2017).

Table 5.1: Mode attribute assumptions

Mode attribute	Source and determination
Initial cost (€)	Car, carpool, walk = 0; transit = 1; bicycle = 100 purchase (4 trips/day for 5 years)
Variable cost (€)	Car = 0.19 per km; transit = 0.20 per km; walk = 0; carpool = 0.19 / 2 per km
Time (min)	Car, carpool, transit, bicycle and walk from OViN (Centraal Bureau voor de Statistiek, 2017)
Driving task (-)	Car, bicycle = 1; carpool, transit, walk = 0
Skills (-) (i.e., drivers' license)	Car = 1; carpool, transit, bicycle, walk = 0
Weather protection (-)	Car, carpool, transit = 1; bicycle, walk = 0
Luggage (-)	Car, carpool = 1; transit = 0.5; bicycle, walk = 0
Shared (-)	Car, bicycle, walk = 0; carpool, transit = 1
Availability (-)	Car = 1; carpool = 0.1; transit = 0.5; bicycle = 1, walk = 1
Reservation (-)	Car, carpool, bicycle, walk = 1; transit = 0
Active (-)	Car, carpool, transit = 0; bicycle, walk = 1
Accessible (-)	Carpool, transit = 1; Car, bicycle, walk = 0

This study uses the same 12 attributes to define the resistance in the edges for all modes, as used in Chapter 3: Initial cost (€); Cost/trip (€); Time (min); Driving task (-); Skills (-) (i.e., drivers' license); Weather protection (-); Luggage (-); Shared (-); Availability (-); Reservation (-); Active (-); Accessible (-). The mode attribute assumptions per mode are shown in Table 5.1.

The supernetwork consists of one layer for each mode, with all public transit lines nested in one layer, subdivided in sub-layers each describing one line/service. This is done to account for similarity of all public transit lines to prevent overestimation of the modal share of public transit. All transit lines are frequency-based and are considered a 'service' using a different infrastructure than the other modes. This implies that adding a (future) mode also means adding a layer (with sub-layers if necessary) to the supernetwork, assuming that the future mode can be described with the same attribute set as the current modes. Edges represent aggregated road segments, transit (with specific lines that are modelled as separate 'sub'-layers in the transit layer/'nest') segments and dummy transition edges from and to a neutral layer. The transport mode edges have a length and a number of attributes (representing the mode and link attributes), whereas for some modes the 'time' attribute can change with the use of the edge (i.e., the traffic intensity).

Mode and route choice are determined simultaneously based on the resistance per edge. Subsequently, per timestep, trips are assigned to the supernetwork using a mesoscopic dynamic traffic assignment approach and the travel time aspect of the generalized resistance of edges on edges is calculated using a triangular fundamental diagram with the intensity on an edge using passenger car equivalent (PCU) factors. The dynamic approach is used to give insight into how intensity changes (over time; in different time steps) and might change the edge resistance and consequently the route choice, and, thus affect modal split. For an extensive description of the supernetwork definition, the simultaneous mode and route choice model and the network loading model, refer to the methodology section of Chapter 3.

Table 5.2: Assumed time to switch modes, including switching transit lines

Mode	Neutral to mode	Mode to neutral
Car	5 min (get in car)	2 min (parking)
Carpool	10 min (wait for driver)	2 min (get out of car)
Transit	7.5 min (waiting and walking time, assumed interval: 4x hour)	5 min (walking time)
Bicycle	1 min (get on bike)	1 min (parking)
Walk	0 min	0 min

When agents want to switch modes or transit lines, the resistance in the considered route also contains the time it takes to disembark from one mode, and embark to the other mode (see Table 5.2) and the 'initial cost' of a mode (see Table 5.1), the other attributes are considered 0 when switching modes. The times in these edges are multiplied by 3 to represent the extra effort it takes for users to switch modes and wait for the next mode (Wardman, 2004).

A timestep of 40 seconds is used to honour the minimum timestep to include all effects (an agent will spend at least one timestep on the shortest link (0.375 km) considering the highest free flow speed in this model (50 km/h)) in the model properly. The simulated time period in the model is 4 hours representing a morning peak hour from 6 AM till 10 AM. Note that this leads to a lower number of travellers with a trip purpose going 'home' and a higher number of travellers going to work. The same seed number is used in all simulations to compare different scenarios. The number of transfers between modes in the multimodal networks is limited to 2 (first-mile, main, and last-mile). All transit is modelled as one layer and contains all BTM transit in sublayers each presenting one line. Switching between transit lines does not count towards these modal transfers. This maximum of two transfers is assumed to be realistic.

5.3.2 Finding the ultimate future mode

This section explains how a supernetwork model is applied to find the ultimate future mode in the city of Delft. The total resistance of the network is the sum of the travel route resistances (see Eq. 5.4) that each agent encounters during their trip. The ultimate future mode is defined as the set of mode attributes that minimizes the resistance of the network (see Eq. 5.5). Note that Eq. 5.5 does not mention the route r and the timestep t. These two elements are relevant when calculating the route resistance at a certain timestep (see Eq. 5.1 till 5.4). The agent experiences a certain resistance throughout their trip as a result of the route resistance calculations. It is the agents' encountered resistance that is used in Eq. 5.5.

$$\min U_{network}(\chi^{future,non-addable}, \chi^{future,addable}) = \sum_{a \in A} U_a(\chi^{future,non-addable}, \chi^{future,addable}) \tag{5.5}$$

s.t.

$$\chi^{future,non-addable}\{0,1\}$$
$$\chi^{future,addable} \geq 0$$

where;

$U_{network}$ = network resistance [-];

U_a = resistance encountered by agent a [-];

$\chi^{future,non-addable}$ = vector containing the values of non-addable future mode attributes [-];

$\chi^{future,addable}$ = vector containing the values of addable future mode attributes [-]; and

A = set of agents.

The ultimate future mode is defined in two subsequent phases; 1) attribute combination enumeration and 2) a supernetwork application. The first phase minimizes the network resistance by enumerating through all non-addable (length-independent) mode attributes of the future mode, disregarding the addable (cost and travel speed) mode attributes. The second phase uses the ultimate mode attribute values of the first phase to make assumptions about the PCU-value and (dis)embark times for the ultimate future mode by adding one layer to the supernetwork with the future mode attributes. These conditions are used to run simulations using the supernetwork in which cost and travel speed of the ultimate future mode are varied to find feasible ultimate future mode attributes. Finally, these simulations are used to analyze mobility effects. Both phases are described in more detail below.

The ultimate mode can be found by looking at the attribute values of the DCM, see Table 5.3, which are calibrated using the unlabelled mode choice modelling approach in Chapter 2.

In the first phase, a calculation where the travel resistance for the ultimate future mode is minimized by enumerating through the trip-length independent attributes of the future mode is set up. For cost and travel times, these values are negative for all clusters, so a higher cost or a higher travel time is negative for the modal share of any type of future mode. This is not trivial for the other attributes, since those values are positive for some clusters and negative for others (see values in Table 5.3 for Delft). To find the best combination of attributes for a given cost and travel speed, the travel resistance of the ultimate future mode is minimized by enumerating through each combination of the trip-length independent attributes, where cost and travel speed can be disregarded, since these two attributes will only increase the travel resistance. This

Table 5.3: Mode attribute valuations per cluster

Cluster	1	2	3	4
(Initial) Cost	-1.53	-0.0846	-0.0932	-0.196
Time	-0.156	-0.4608	-0.0441	-0.03036
Driving task	-0.25	2.11	-0.0327	0.694
Skills	-0.0606	2.36	0.924	-2.69
Weather protection	0.107	-0.471	0.486	-0.959
Luggage	0.193	-0.755	-1.11	-0.384
Shared	-0.137	-1.21	-1.07	1.75
Availability	0.205	-4.22	0.395	-1.65
Reservation	0.186	-1.34	-1.9	1.91
Active	0.293	0.131	-0.666	1.39
Accessible	0.213	-1.07	-0.248	0.848

means that the rerouting due to a change in density on edges is excluded at this stage for the ultimate future mode. This travel resistance calculation contains all current modes, the future mode, cluster sizes and trip-length independent attributes. This makes the enumeration computationally feasible for all (512) combinations of the 9 trip-length independent ultimate future mode attributes.

After the intermediate results (i.e., values of the 9 trip-length independent attributes) are defined, the cost and travel time can be added (second condition of Eq. 5.5) and simulated in the second phase. To find a feasible ultimate future mode, it is assumed that the ultimate future mode is using the existing infrastructure (assuming mixed traffic with car, carpool, and bicycles). Furthermore, it is assumed that the ultimate mode is not a scheduled service (like public transit). To find tipping points and changes in modal share, travel times and travel resistance, the costs are varied from 0 to 0.50 €/km in steps of 0.10 €/km and the travel speeds (inverse of travel times) are varied from 5 to 60 km/h in steps of 5 km/h. These 72 configurations will result in how the modal split, travel times and travel resistance change with different costs and travel times for the ultimate future mode such that insight into the change in the use of current and future modes can be created.

5.3.3 Case-study: Delft

To illustrate the approach of finding the ultimate future mode, we want to analyse an urban area where revealed preference data was available, has several transit lines and where the future mode will use the existing (historical) infrastructure shared with other modes and has enough trips that one expects rerouting of travellers and some congestion to occur. This is to ensure that we can contribute to the literature of supernetwork model implementations by modelling explicit transit lines in the supernetwork. Furthermore, we aim to implement the shared infrastructure using PCU-factors to calculate density and speed on edges. Delft in the Netherlands has all those properties and is, therefore, used in this study. Note that the ultimate mode will not be transit based (with a schedule and lines), but will be implemented as a 'regular' mode as an extra layer in the supernetwork sharing the infrastructure with other modes. These conditions are used to keep this study physically within realistic boundaries.

Travel data for the Delft Case is derived from the OViN dataset describing personal, trip, and mode information for five modes (car, carpool, transit (BTM), bicycle and walk) (Centraal Bureau voor de Statistiek, 2017). The dataset is enriched with mode attributes (see Table 5.1) and clusters of travellers where the optimal number of clusters was determined using k-means clustering and the elbow method using trip and personal characteristics for the OViN dataset (Chapter 2).

The cluster-specific valuations of mode attributes of the four clusters appearing in the Delft case-study are depicted in Table 5.3. Cluster 1 (8.5% of trips) has trips where the purpose is other and there is no car ownership, cluster 2 (46.6% of trips) contains all trips where the trip purpose is work and business, cluster 3 (43.6% of trips) contains all trips where the trip purpose was to go home, and cluster 4 (1.3% of trips) contains all trips where the trip purpose is other and they own a car. Observe that for some mode attributes the sign for all clusters is the same (e.g., cost and time: all clusters have a negative valuation of cost and time, albeit in different degrees). However, some attributes show different signs for different clusters (e.g., 'Active'), indicating that some groups attach a negative value to 'Active', whilst others attach a positive value. This observation forms the background of the approach for finding the ultimate future mode.

An OD-matrix from an existing OmniTRANS model of Delft is taken. The OViN dataset and zonal population data are used to create the OD-matrix with the population of the 4-digit postal code zones in Delft and the number of trips per OD-pair in Delft. The final dataset contains 358,823 trips.

The Delft network is visualized in Figure 5.1 and Figure 5.2, with zones largely based on 4-digit postal codes with equivalent edges representing aggregated road segments, and without centroid feeders. These equivalent edges are a network representation of a group of actual roads and road segments. This model assumes sufficient availability of all modes (e.g., shared modes). This means that it is assumed that a future shared mobility provider can always plan and allocate sufficient vehicles to the nodes. In Delft, (BTM) transit uses the existing infrastructure in some locations, but also has its own lanes in some parts of the city (suburbs and campus). In this study, it is assumed that all transit is using a separate infrastructure, so transit is not taken into account in the congestion calculation. Intrazonal trips are not considered. This might lead to an underrepresentation of walking (and possibly) biking in the modal split of the OmniTRANS model.

The capacities of the equivalent edges are calibrated using the existing OmniTRANS model of Delft (same model used to generate the trips dataset) by varying the traffic intensity between each OD-pair with steps of 500 from 0 to 10000 to find the travel time per km per link for each traffic intensity. These data points are used to fit a BPR-function (Ortuzar & Willumsen, 2011) (see Eq. 5.6) with a preloaded network and an empty network, which is the same method used in OmniTRANS. Both

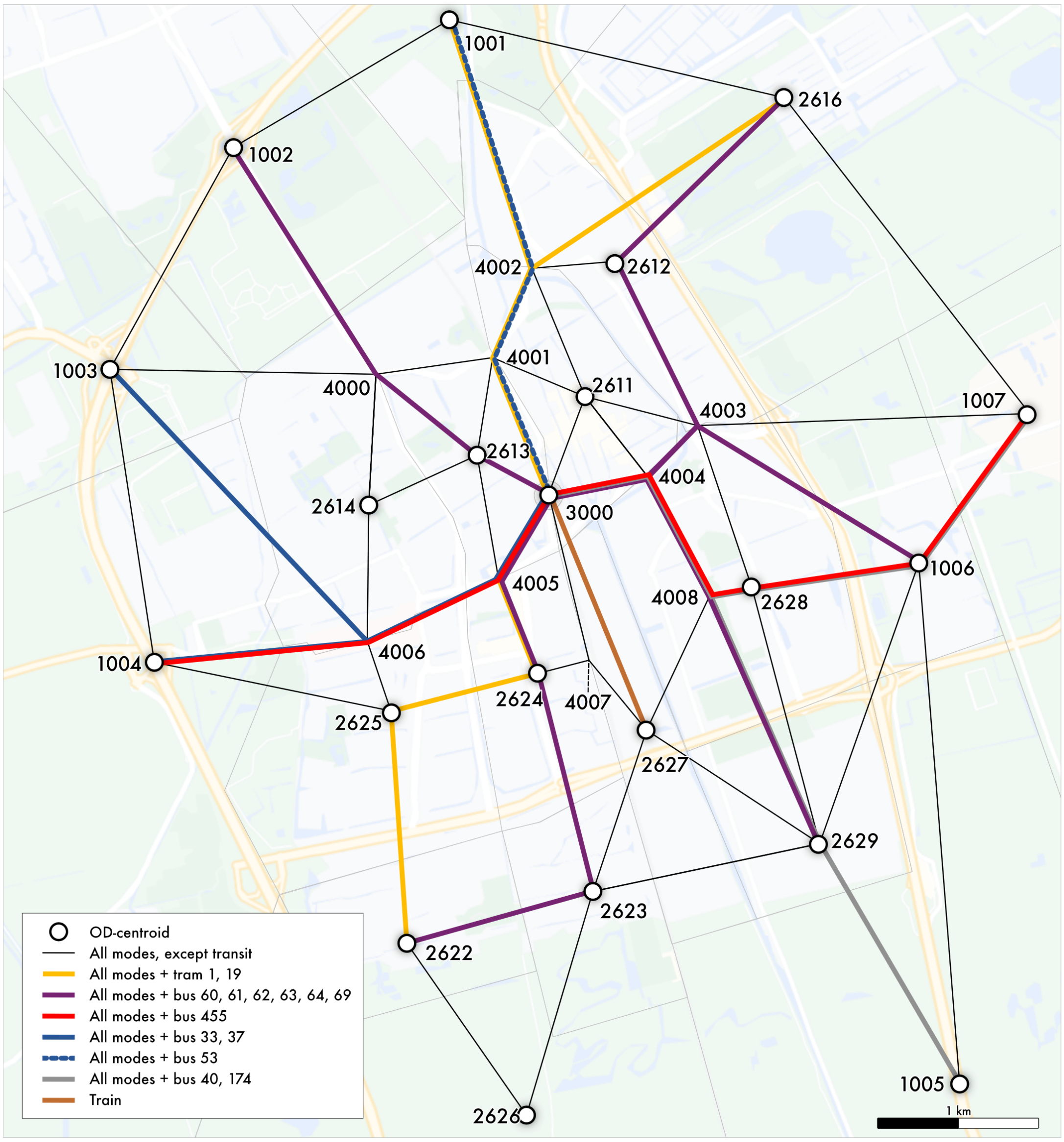

Figure 5.1: Simplified network configuration superimposed on a map of Delft. The numbers are the Origin and Destination centroids.

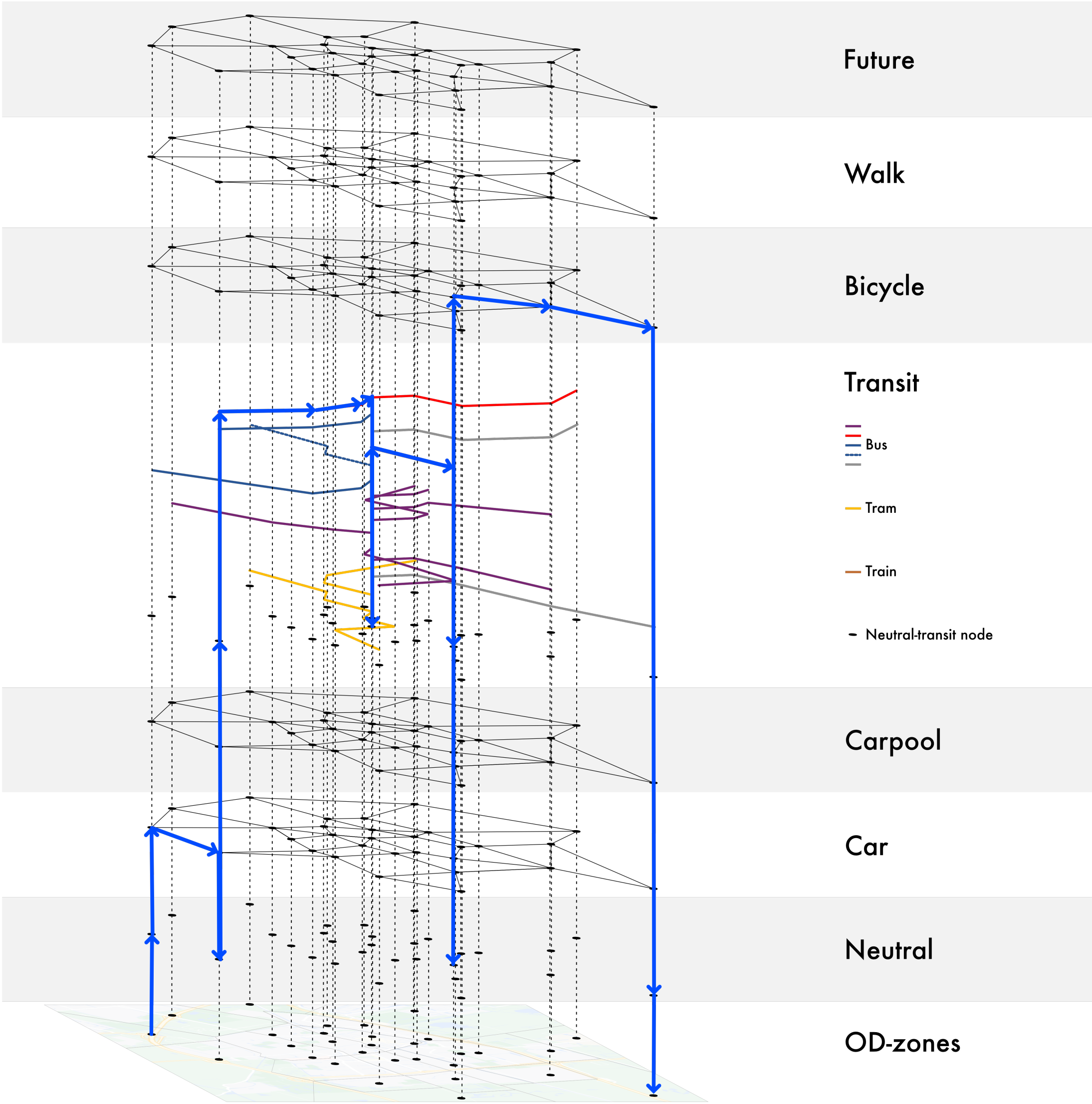

Figure 5.2: Supernetwork of Delft with 6 modes with transition links between modes through a neutral layer. One possible multimodal route is visualized in blue. Note that the transit layer contains sub-layers and a 'neutral'-transit layer, which works the same as the neutral layer depicted right above the OD-zones, but only for changing transit lines. Agents travel to this neutral-transit layer when they want to disembark from one transit line and enter another transit line.

networks are used to compare the capacities of the equivalent edges and to take the 'conservative' lowest capacities of the edges for this study. It has to be noted that the OmniTRANS model only describes the main roads in Delft.

The alpha and beta from the BPR-function are assumed to be 0.87 and 4 respectively, which are the same as in the OmniTRANS network. The RMSE is minimized to find the capacity of the equivalent edge. This calibration is done for each combination of Origin and Destination centroids that represent an equivalent edge in the supernetwork. The found capacities vary between 2717 and 6899 PCU/hour. The travel times per km on the preloaded network generally start increasing around the preload + 1500 PCU/hour for the considered equivalent edge of the Origin and Destination centroids and the average capacity for all equivalent edges is 4564 PCU/hour. The increase of travel times per km on the empty network starts happening around 2500 PCU/hour and the average capacity for all equivalent edges is 4639 PCU/hour. The capacities are comparable, where it makes sense that the average capacity is slightly higher for the equivalent edges in the empty network, since the agent in an empty network has more attractive (read: empty) alternatives compared to the agent in a preloaded network. It was chosen to use the capacities of the preloaded network to be on the conservative side (slight underestimation) for calculating congestion. The car, carpool and bicycle layers are assumed to use the same infrastructure with PCU values of 1.0, 1.0, and 0.2 respectively. To estimate the capacity of an (equivalent) edge with a certain traffic intensity, the following equation (Ortuzar & Willumsen, 2011) was applied:

$$T_V = T_0 * (1 + \alpha * \frac{q^\beta}{C}) \tag{5.6}$$

where;

T_V = travel time on edge with certain traffic intensity [hour];
T_0 = travel time on edge with traffic intensity of 0 PCU/hour [hour];
α = parameter [-];
β = parameter [-];
q = traffic intensity [PCU/hour]; and
C = capacity [PCU/hour].

The estimated capacities of the aggregated edges in the multimodal supernetwork model are used to calculate travel times following Daganzo's triangular fundamental diagram approximation (Daganzo & Geroliminis, 2008) (see Eq. 5.7 till 5.11). Travel times for cars, carpoolers and cyclists are based on the free-flow velocity, critical density, jam density, number of lanes, PCU values of each agent, and the number of agents present on that edge. In this study, the critical density (k_{crit}) and the jam density (k_{jam}) are assumed to be 125 PCU/km and 25 PCU/hour.

$$k < k_{crit} \Rightarrow v = v_{ff} \tag{5.7}$$

$$k_{jam} \geq k \geq k_{crit} \Rightarrow v = \frac{k_{jam} - k}{k} \frac{q_{crit}}{k_{jam} - k_{crit}} \tag{5.8}$$

$$k > k_{jam} \Rightarrow v = 0 \tag{5.9}$$

$$q_{crit} = v_{ff} * k_{crit} \tag{5.10}$$

$$k = \frac{\sum_{a \in A} pcu_a}{len} \tag{5.11}$$

where;

v = current velocity [km/hour];
v_{ff} = free flow velocity [km/hour];
k = current density [PCU/km];
k_{crit} = critical density [PCU/km];
k_{jam} = jam density [PCU/km];
q_{crit} = capacity (i.e., critical intensity) [PCU/h];
pcu_a = PCU-factor for agent a [PCU]; and
len = length of edge [km].

5.4 Results

As described in the previous section, the results consist of two parts: the results of the first stage with all (except cost and time) the mode attributes of the ultimate future mode and the final results, including cost and time. The results of the first stage of finding the ultimate mode are found when iterating through each combination of attribute values for all trip-length independent attributes and running these in 512 calculations and have the values as depicted in Table 5.4. The found ultimate future mode in the city of Delft will have a driving task, requires skills, has weather protection and luggage can be carried with this mode. Furthermore, this mode is not shared and thus has 100% availability and does not need a reservation. It is active and is not made explicitly accessible (for less mobile people). In preparation for the second phase of finding the ultimate future mode, an assumption about using the existing infrastructure must be made. Based on the attribute values, a lower PCU-value than a car can be assumed (active mode with driving task) and it has been assumed this mode will use the existing infrastructure. We decided to use the same PCU-value and (dis)embarking times as a bicycle for the second phase of this approach. The PCU-value is assumed to be 0.2 and the (dis)embarking time is assumed to be 1 minute.

Table 5.4: Mode attributes of the ultimate future mode

Attribute	Value
Driving task	1
Skills	1
Weather protection	1
Luggage	1
Shared	0
Availability	1
Reservation	1
Active	1
Accessible	0

Table 5.5: Modal split

Type of modal split	Future mode	Car	Carpool	Transit	Bicycle	Walk	Future	Mixed
% of trips	-	16.4	8.1	12.3	9.4	6.3	-	47.3
	Yes	[12.3 – 15.8]	[5.5 – 8.5]	[9.9 – 12.2]	[6.6 – 8.9]	[4.6 – 6.0]	[3.6 – 9.6]	[45.5 – 50.7]
% of distance	-	8.6	3.5	5.0	3.6	2.6	-	76.7
	Yes	[6.0 – 9.3]	[2.1 – 3.7]	[3.4 – 5.2]	[2.3 – 3.6]	[1.7 – 2.6]	[1.5 – 4.7]	[74.1 – 80.1]

Table 5.6: Modal split of multimodal trips

Type of modal split	Future mode	Car	Carpool	Transit	Bicycle	Walk	Future
% of trips*	-	63.2	45.3	61.9	51.8	42.8	-
	Yes	[54.6 – 59.6]	[37.0 – 42.8]	[53.0 – 58.3]	[41.2 – 46.5]	[33.7 – 38.5]	[31.5 – 53.1]
% of distance	-	28.6	19.1	22.3	18.2	11.8	-
	Yes	[22.5 – 27.4]	[13.6 – 16.8]	[17.0 – 22.2]	[13.5 – 17.1]	[8.7 – 10.3]	[9.3 – 21.7]

*The modal split of mixed trips amounts to more than 100%, since multiple modes can occur in one single trip. This number can be interpreted as a certain percentage of the mixed trip contains a certain mode.

Table 5.7: Average speed, distance, trip duration and resistance

Future mode	Average speed [km/h]	Average distance [km]	Average duration [min]	Average normalized (to base scenario without the ultimate mode) resistance [-]
-	14.4	11.3	60.3	100
Yes	[15.7 – 20.2]	[12.9 – 15.2]	[48.1 – 57.3]	[95.3 – 98.7]

Table 5.8: Normalized trip duration and resistance (default is 100 for base scenario without the ultimate mode) for each cluster

Indicator	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Trip duration [-]	[79.5 – 104.6]	[73.3 – 91.8]	[98.3 – 110.0]	[82.0 – 132.9]
Resistance [-]	[93.5 – 102.7]	[94.9 – 98.4]	[96.8 – 100.2]	[98.5 – 102.7]

For the second phase, the ultimate mode attributes are used to set up 72 simulations, where the cost and average speed of the ultimate mode are varied. The modal splits for all scenarios are shown in Table 5.5 and Table 5.6. With an average speed of the ultimate mode of 60 km/h, the modal share of the mode can be up to 9.6%. The share of multimodal trips including the use of the future mode is similar in all scenarios ranging between 45.5 and 50.7%.

The modal share of the ultimate mode – based on different indicators - is also given in Table 5.5 and Table 5.6. The average trip duration, the average speed, the average trip distance and the resistance in the network are depicted in Table 5.7 and Figure 5.3. Figure 5.3 till Figure 5.5 can be interpreted as a surface plot with projections for each dimension on each plane. The surface plot (blue) gives an indication of how both varying speed and cost of the ultimate mode affects the performance in terms of modal share, trip duration, average speed and distance respectively (depicted in the z-direction). The projections (yellow-green) on the planes give an indication of how a performance (z-direction) varies when you vary only speed or cost. The yellow-green gradient of the projection on the x-plane can be used to understand the z-value for both speed and cost of the ultimate mode. It can be observed that increasing the speed of the ultimate mode results in a higher modal share for this mode. The average trip duration for all travellers on all modes varies between 48 and 57 minutes, with the shortest trip durations observed when the speed of the ultimate mode is higher (as expected). This is a reduction of the average trip duration of 60 minutes in the base scenario without a future mode. The average distance travelled increases from 12.9 km up to 15.2 km compared to the base scenario (11.3 km) when the speed of the ultimate mode increases. Observe that the average travel times and distance travelled seem to be high for the network of Delft. This can be explained by the rerouting of travellers due to congested edges. Further note that the peaks between different scenarios. These peaks can be explained by the randomized set-up of agents choosing the next edge, which leads to variations in density on edges and different results, mainly variations in travel times and travel resistance.

The average speed of all modes in the network increases compared to the base scenario when the speed of the ultimate mode increases from 15.7 to 20.2 km/h. The average speed of all modes in the network decreases slightly when the cost of the ultimate mode increases. Note that the modal share is significantly higher when the cost is 0.40 €/km or less compared to higher costs of 0.60 €/km. Average trip duration and travelled distance do not show a trend with varying costs. When combining both speed and cost, it can be observed that the modal share increases with increasing speed and decreasing cost of the ultimate mode. Table 5.5 shows that most distance is travelled in multimodal trips.

Furthermore, Table 5.8, Figure 5.4 and Figure 5.5 depict the normalized travel time and resistance per cluster of travellers. We can observe that the trip duration varies for each configuration of speed and cost of the ultimate mode, where cluster 2 (trip purpose work or business) travellers always have an improvement in their travel times and the other clusters do not always have an improvement in travel times. Looking at Figure

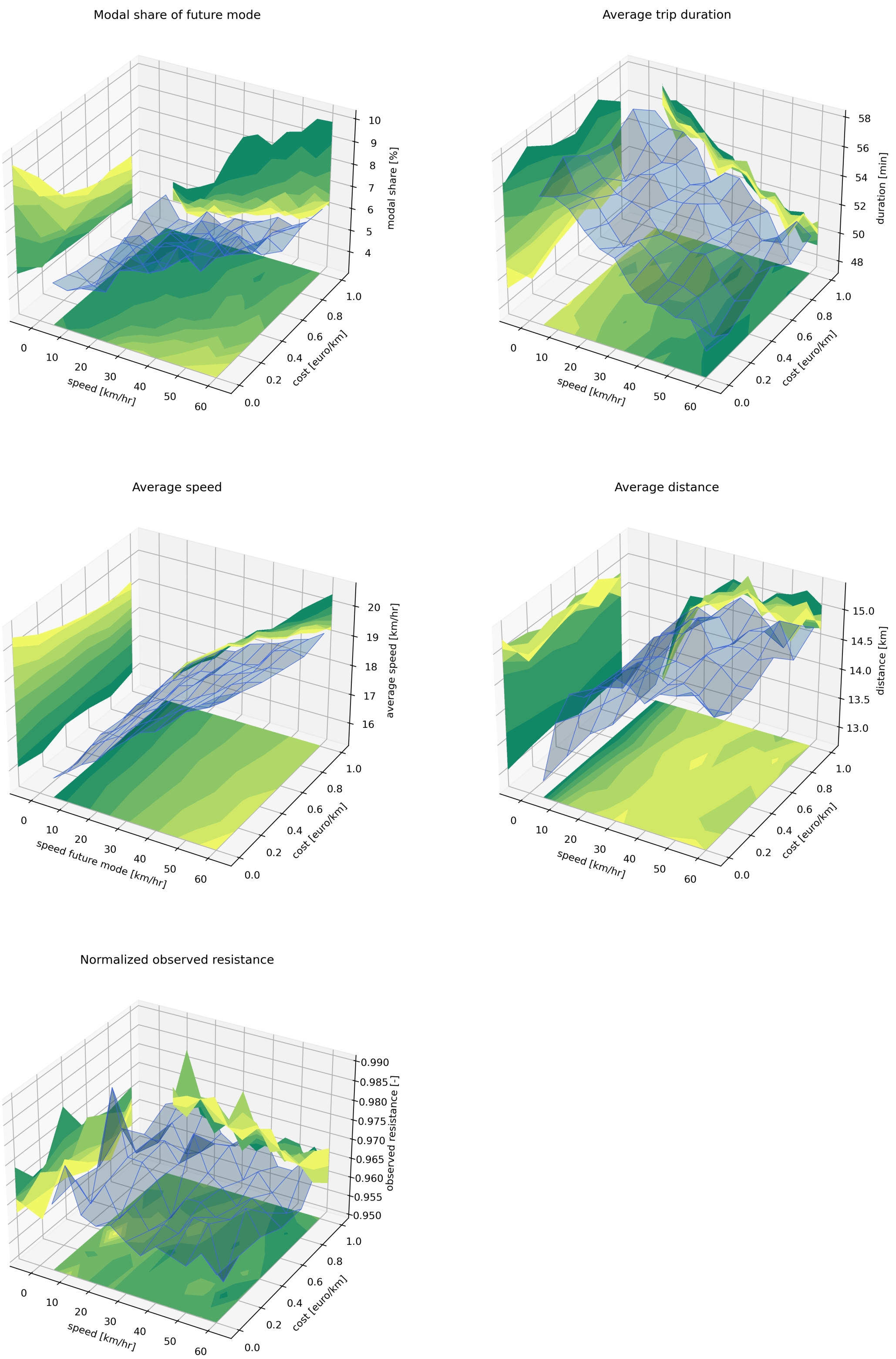

Figure 5.3: Modal share of ultimate mode, average trip duration in network, average speed in network, average distance travelled and total resistance (normalized with scenario without ultimate mode) in network with varying cost and speed for the ultimate mode

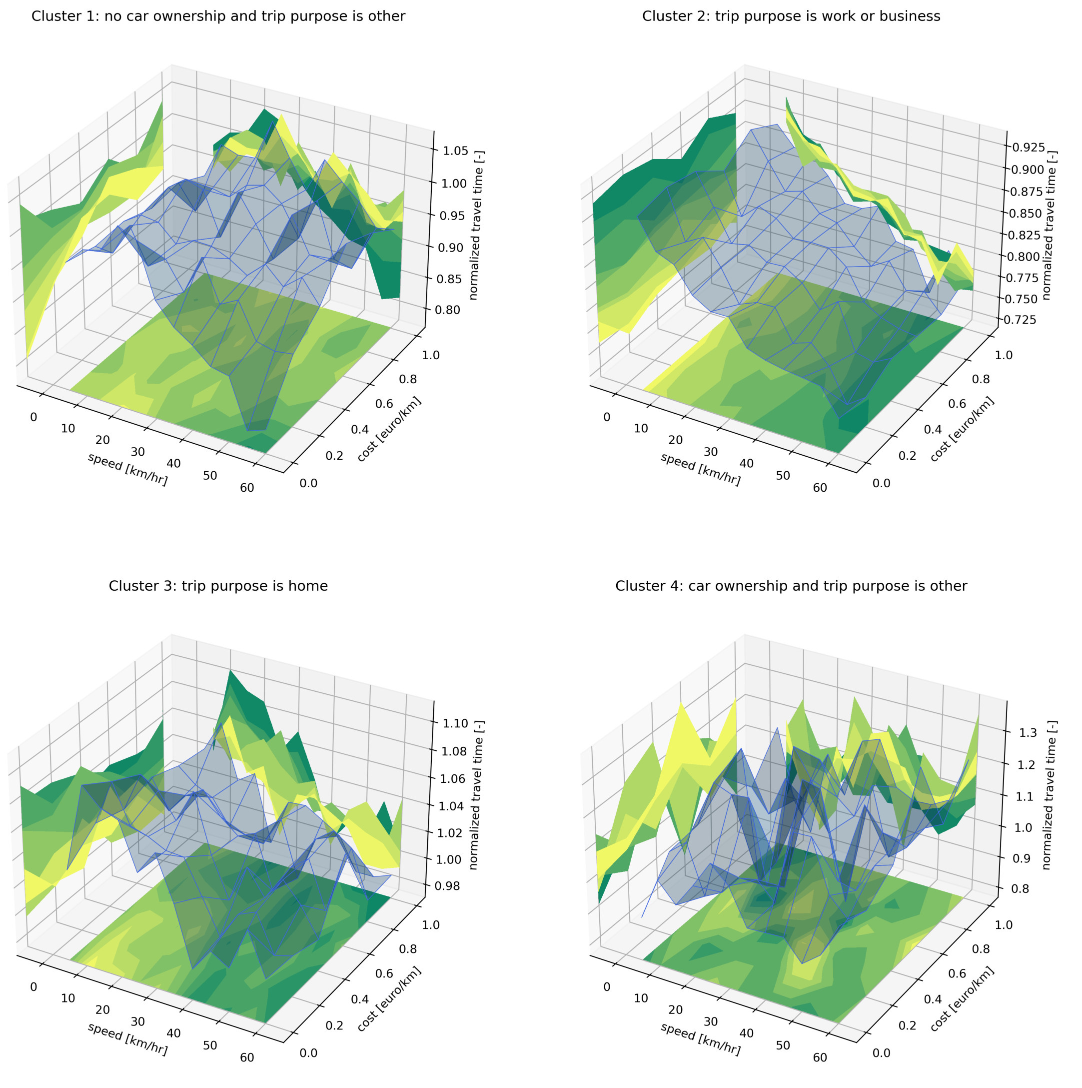

Figure 5.4: Normalized travel time (normalized with scenario without ultimate mode) per cluster (type of traveller) with varying cost and speed for the ultimate mode

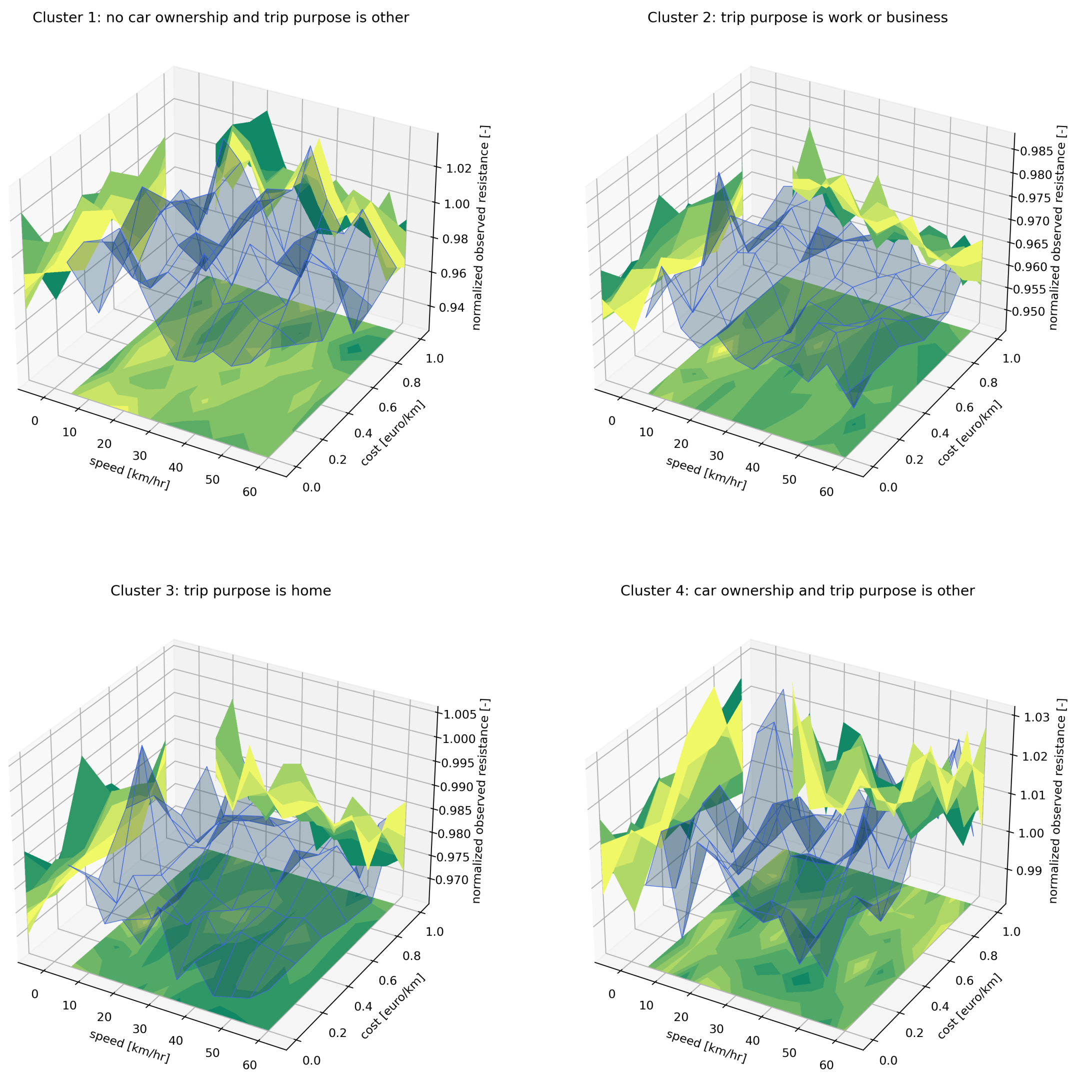

Figure 5.5: Normalized resistance (normalized with scenario without ultimate mode) per cluster (type of traveller) with varying cost and speed for the ultimate mode

5.4, it can be observed that generally, the travel times for clusters 1 (no car ownership and trip purpose is other), 2 (trip purpose is work or business) and 3 (trip purpose is home) show an improvement compared to the base scenario (without a future mode) when cost is lower and speed is higher (as expected). Cluster 4 (car ownership and trip purpose is other), however, does not always show an improvement in their travel times. When 'zooming out' and looking at the resistance (all mode attributes and not just travel times) in Figure 5.5, cluster 2 (trip purpose is work or business) and 3 (trip purpose is home) always experience a lower resistance for each configuration of speed and cost of the ultimate mode. Cluster 1 (no car ownership and trip purpose is other) is experiencing a lower resistance in most of the configurations, but cluster 4 (car ownership and trip purpose is other) is not experiencing a lower resistance compared to the base scenario without future mode. This can be explained by the fact that when the ultimate mode is introduced there is a modal shift from modes that do not use the road network (e.g. public transport) to modes that do use the road network. This causes an increase in total PCU values on the edges of the shared infrastructure, which leads to an increase in resistance on the same routes. Agents then have to choose the same or another longer (in length, not in resistance) route, which then leads to an increase in travel times and resistance for these agents.

Computational complexity

Finally, the Delft network was simulated on the Delft Blue supercomputer (a high-performance computer with up to 218 2x Intel XEON E5-6248R 24C 3.0GHz with 48 cores and 192GB of RAM) (Delft High Performance Computing Centre, 2022). Due to setting up simulations in a parallel manner, one run (this study has 72 runs) simulating 4 hours takes up to 6 hours with the Delft Blue supercomputer using 4 CPUs with 32GB per CPU reserved.

5.5 Discussion

This study presents an approach to finding the ultimate future mode in the Delft network using a supernetwork model based solely on mode attributes without defined mode-specific biases. The ultimate future mode is the mode that reduces the overall network resistance the most. It is assumed that the future mode is described by a combination of mode attributes that the ultimate future mode uses the existing infrastructure and shares this infrastructure with the other modes (car, carpool and bicycles in this study) and that the demand remains the same (the OD-matrix is not adjusted). Note that the network of Delft has been aggregated to manage computational complexity. Furthermore, the public transport lines in Delft have been modelled explicitly and the ultimate future mode is assumed to not be part of these public transport lines. Note that these assumptions limit the notion of the ultimate future mode in Delft, as some types of future modes (e.g., as part of public transport, and on a completely new separate infrastructure) are excluded. These assumptions are assumed to be sufficient to demonstrate the supernetwork model with explicit transit lines and develop an approach to find the ultimate future mode in the case of Delft but are limited when considering precise mode attribute values (e.g. cost/km or initial cost) of the ultimate future mode.

The ultimate mode attributes can generate an idea of how such an ultimate mode would look and function like. It is tempting to interpret the ultimate attributes and come up with a system description that fits the attribute values. To give one illustration (i.e., interpretation) of how the ultimate mode could look like; the ultimate mode attributes in Table 5.4 could translate into a product that is comparable to a small electric cargo bike ('bakfiets' in Dutch) with a roof. Note that the ultimate future mode in each area can be different compared to the Delft case in this study, since the type of travellers, their preferences and the presently available transport modes differ.

The two-phase approach was set up to manage computational complexity. We ran the calculations disregarding cost and travel speed in the first phase and congestion in the network was not taken into account. Only in the second phase a PCU-factor and congestion in the network was taken into account. It needs to be highlighted that the same (9) attributes will be the outcome of the first phase approach, since these are all attributes that are trip-length independent (non-addable), meaning that these attributes will stay the same when rerouting and congestion is included and a different PCU-factor is used for the ultimate future mode.

Two attribute values stand out: the ultimate mode is not shared and not accessible for travellers with special accessibility needs. When the ultimate mode is not shared it indicates that people do not want to use ride-sharing modes yet. This might change when people can get more used to shared (ownership) modes where there is enough availability. Note that it was assumed that the PCU of the future mode is 0.2 and that the dis/embarking time is 1 minute. When translating the mode attributes to an actual product/service design these values might not be feasible. For instance, a higher PCU will lead to different congestion conditions and that will lead to different mode and route choices. Also, the analysis results in an ultimate mode which does not need to be accessible for travellers with special accessibility needs. This can be explained by the fact that travellers with special accessibility needs are a small part of all travellers, and this outcome is the direct effect of the chosen generalized approach.

This highlights the idea that an ultimate transport mode does not stand on itself, but forms a transportation system together with other modes, such as transit. The combination of these modes should provide a complete service for all types of travellers (i.e., enough accessible options). This also highlights the need for proper analysis of how any future mode serves different people. In this case, it could be assumed that transit and carpool do cover the travellers with special accessibility needs. In other networks, this might not be trivial and a basic level of service needs to be guaranteed for all travellers.

Looking into the effect on travel times per cluster highlights that not each cluster experiences an improvement in travel time compared to the base scenario. A similar trend can be observed for the resistance for each cluster. In most instances, the resistances go down, but cluster 4 (trips where the purpose is other and the traveller owns a car) seems to experience a higher resistance for most configurations of the ultimate mode. This introduces the question of how the approach to finding the ultimate future mode should be set up and create an improvement for all travellers. Is the future mode using the existing infrastructure? Are the ultimate mode attributes optimized for the majority of travellers increasing the travel resistance for a small part of travellers from another cluster? In the case of this study, it clearly shows that one cluster is not experiencing an improvement, whereas all the other clusters do experience an improvement.

When policy-makers look into stimulating the use of a mode that is close or equal to the ultimate mode, they can influence cost and regulate speed and availability. Speed and availability have the largest influence on the modal share of the ultimate mode, whereas cost has less influence in the case of Delft within the analysed ranges. For instance, from this perspective, lowering the average trip duration (where the overall resistance still is lowered) is not achieved by subsidizing this ultimate mode and it could be more effective to invest in sufficient capacities of transit or adjust the road network itself, whilst ensuring a similar or improved resistance for travellers in cluster 4.

Further, no disruptions are modelled in the scenarios. This modal aims to calculate the modal split and the travel time change for the ultimate future mode. In theory, random disruptions could be modelled by increasing the edge resistance in some places. This could be done to see how an ultimate future mode can change the resilience of a transport system. For a detailed analysis of how a future ultimate mode can affect resilience, the duration of disruptions on edge resistances and interaction between agents (modelling, i.a., headways, spillback, and lane-switching) on the edges will need to be added to the presented supernetwork model.

Finally, the Delft network is an intracity network with intracity traffic. There is likely an underrepresentation of intrazonal traffic (mostly walking and cycling), since the network is aggregated. The scale of the Delft network is not large enough that intercity traffic can be captured within the network topology, since it covers one city centre. A network with multiple city centres could create insight into intercity traffic and in those types of networks, other ultimate modes could emerge when following the same approach as in this study.

5.6 Conclusions and future research

This study successfully explores how a supernetwork model can be used to find the ultimate future mode in Delft. This exploration is done by controlling all ultimate mode attributes, except travel time and cost, and optimizing for travel resistance in the network. After the ultimate combination of attributes is found, the cost and the average speed of the ultimate mode are controlled to simulate the mobility effects (e.g., travel resistance, modal share, and travel times). It can be concluded that the ultimate future mode in Delft can be found by using this two-phased approach. In this section, methodological conclusions and recommendations are given and are finalized with recommendations for researchers, policy-makers and companies.

Note that the travel resistance is more than just cost and travel time, it consists of all attributes in this study. This means that the ultimate mode is not one where just cost and travel time are low, but one which complements the existing network the best, such that the resistance per OD-pair and for different types of travellers (i.e., clusters) goes down as much as possible. However, clusters are not affected the same, some profit more, others less (or even experience a higher total resistance). This highlights the need for separate analyses for each type of network, since there is no such thing as a one-size-fits-all ultimate mode. Rather, a discussion should be held about reducing the resistance of a transport network in an equitable manner and which ultimate transport mode can reduce this resistance in the most effective way.

A first step in this discussion is presented in this chapter, but future research could look more into testing a combination of (cluster-specific) ultimate modes serving different travellers and OD-pairs from the perspective of reducing resistance for all travellers within each cluster. It is recommended to also vary the PCU-factors, the embark and disembark times, the initial costs and whether the ultimate mode is using a (partly) shared or separate infrastructure in a sensitivity analysis. The final mode attributes might look different as a result.

Not just a combination of ultimate modes can be interesting to look at, but also the availability (in certain locations and as a capacity of carriages or shared (rented) modes) of the ultimate mode in the network. Future studies can look into adding a development and construction cost element to the presented approach. This can help to find trade-offs for policy-makers between finding the ultimate mode and making it available everywhere or at certain points in the network with the goal of reducing resistance.

Furthermore, it is recommended to expand this approach with other mode attributes to improve the approach of how to find the ultimate future mode and to add conditions such that travellers from all clusters experience a reduction in travel resistance. For instance, air and noise emissions could be included in the mode attributes to (partially) include sustainability and livability in this approach as well.

To further include livability, it is also recommended to look at the land use of modes. For instance, scheduled traditional public transport services (e.g., BTM) can be one of the most space efficient modes for high density urban areas but was not considered in this case-study as a possibility for an ultimate mode. So depending on the case-study, it is recommended to look into how the 2-phased approach might need to be adjusted to include an optimisation of existing public transport services and then adding an 'ultimate' future mode using the current infrastructure whilst considering land use.

This model uses a trip-based approach, but can be extended to an activity-based approach where transport modes used for multiple activities throughout the day can be considered as well (e.g., work trips with a car in the morning will return home in the evening with a car as well). It is recommended to look into how the approach of this study can be combined with the approach of Liao et al. (2014). They explored how full daily multi-activity travel patterns can be modelled using a so-called multistate supernetwork with space-time prisms to simulate the opening and closing times of certain travel options to explore how full daily multi-activity travel patterns can be simulated.

Note that this approach in this study is different from other studies where mode-specific constants are estimated or assumed and specific future modes are considered instead of finding the mode attributes that would benefit the network performance. A downside of this approach is that it is dependent on the set of mode attributes included in the original dataset because the attributes relevant for decision-making can change over time. Future research could look into how to account for changing travel preferences when new decision-making mode attributes are introduced to people's travel options.

As was mentioned before, the ultimate mode is context-dependent, and therefore, should also be analyzed in different scenarios to come up with a 'robust' ultimate mode. These different scenarios can factor in changes in population, travel patterns, certain policies or different travel preferences.

The presented approach can be used by researchers, policy-makers and companies. Researchers can use and extend this approach to generate insight into multimodal trips of future modes without having revealed preference data of future modes available. Furthermore, they can extend existing models in such a way that mode-specific biases do not have to be included anymore. Also, policy-makers can use this approach to stimulate the introduction and use of this ultimate future mode (given it is available) to reduce travel resistance with the goal of improving equity. And, finally, companies can use this to develop the ultimate future mode to gain a large market share.

Chapter 6

Conclusions & recommendations

The current chapter combines the main findings, discussions, answers to the research questions, societal relevance, and recommendations of Chapter 1 till 5 and can be read in Sections 6.1, 6.2, 6.3, 6.4, and 6.5 respectively.

6.1 Main findings

This section is divided into two parts: the discrete choice model and the supernetwork model. The main findings for each of these two parts can be found in the two sections below.

6.1.1 Discrete choice model

Chapter 2 explores an approach for calculating the mode choice and modal split of any new transport mode in a future situation when such a mode is well established. The modal split of two future modes (shared autonomous car and electric step) is calculated. The modal splits are calculated using a multinomial logit model and a nested logit model without alternative specific constants and parameters, demonstrating that the unlabelled mode choice modelling approach can be used to calculate the modal split of any future mode. Note that the main attributes influencing mode choice (such as travel time and cost) of the future transport modes are already experienced in current transport systems. Further, it should be highlighted that clusters based on personal and trip characteristics are used to capture the heterogeneity of travellers and trip purpose. In Chapter 2 it was demonstrated that using a utility function without any alternative specific constants or parameters resulted in a rho-squared of 0.828 and an overall accuracy of 0.758 when using clusters grouping similar people and similar trips. The approach is applied to a dataset based on empirical data (OVIN (Centraal Bureau voor de Statistiek, 2017)) with 5 existing modes and 2 future modes, where each future mode is analysed separately.

For currently known modes, it is demonstrated that using an alternative specific constant in the utility function does not give significantly different results than our approach. Therefore, it can be concluded that the unlabelled mode choice modelling approach can be applied when using this dataset.

When predicting the modal split of a future mode using a multinomial logit model, it might be concluded that an overestimation of the future modal split occurs due to the partial similarities between different transport modes. Removing the overestimation of similar modes was done by implementing a nested logit model. In the nested logit model, the future mode was automatically nested in a nest with the ‘most similar’ existing mode using the normalized multidimensional distance between the future mode and an existing mode. It can be concluded that a nested logit model is better suited for estimating the potential modal split of a future mode than a multinomial logit model.

6.1.2 Supernetwork model

Chapter 3 explores how the effects of any future mode on the modal split and on the travel times of an urban area can be estimated by developing a mesoscopic multimodal supernetwork model. This is done by describing each available mode as a specific layer within a supernetwork with nodes and edges, where the edges’ resistances are described by a set of attributes without a mode-specific constant. The mode-specific layers are interconnected to a neutral layer with edges representing transfer resistances, also described with a set of attributes. This allows researchers to automatically cover all multimodal options without defining mode and route choice sets. The attributes have weights attached to them, which are estimated using the same method as with the multinomial logit model as described in Chapter 2.

This approach is verified in Chapter 3 with 3 small yet exemplary network configurations while varying the network edge lengths, available modes, and multimodal trips enabled and disabled. From this, it is concluded that the simulated agents’ travel behaviour is logical. Furthermore, this approach is implemented on a Sioux Falls network (Chapter 3) and the travel behaviour simulation on this network configuration also seems logical. This method is also applied in Chapter 4 on an OD-pair between Delft and Rotterdam and the results on modal shifts are comparable with another study (Sun et al., 2020). It is concluded that this approach can calculate the mobility effects of any future mode using a multimodal supernetwork model.

Chapter 5 extends the supernetwork model approach to find the ultimate future mode in Delft. This is done by varying all ultimate mode attributes and optimizing for the resistance. After the ultimate combination of attributes is found, the cost and the average speed of the ultimate mode are varied to simulate the mobility effects (e.g., resistance, modal share, and travel times). It can be concluded that the ultimate future mode in Delft can be found by using this two-phased approach. It has to be noted, however, that finding the ultimate future mode is context-dependent. Network specifications, available modes, and travellers’ perceptions of mode attributes determine which attributes and scenarios should be considered as discussed in the Section 6.2.2.

6.2 Discussion

This section discusses the methodologies of, first, the approach of the discrete choice model using the unlabelled choice modelling approach and, second, the development of this approach using a supernetwork model. Finally, attention is given to the computational challenges of the discrete choice model and the supernetwork model.

6.2.1 Discrete choice model

Chapter 2 presents an approach for calculating the mode choice and modal split of future transport modes in a future situation in which such modes are well established using a discrete choice model without alternative specific constants, of which the parameters are estimated based on revealed preference data.

When applying the estimated utility logit function to predict future mode choice, it can be observed that the future modal shares of the future modes seem to be relatively high when using a multinomial logit model due to a possible overestimation caused by a violation of the Independence of Irrelevant Alternatives (IIA) assumption, i.e., some modes in the model are regarded as being completely different while in fact there are partially overlapping characteristics. Due to its formulation, the model tends to overestimate the mode choice of such overlapping modes.

To overcome the similarity issue, a nested logit was implemented as well; using that approach, the future modal shares seem to be more modest with up to 9 and 4 percentage points lower modal split for shared autonomous cars and electric steps respectively. The nest in this nested logit model consists of the future mode and the most similar existing mode, which is determined by calculating the multidimensional distance of each pair of modes (Baikousi et al., 2011). Knowing from the 'red/blue bus paradox' that an overestimation of the future modal split occurs when using a multinomial logit model, it can be concluded that the nested logit is the preferred discrete choice model in this case.

What should be noted as well is that the attributes (values) that can be derived from empirical data from the current modes do not necessarily properly represent the attributes for future systems (e.g., what is shared exactly?) and new attributes might become significant which are not measured currently (e.g., fear of autonomous driving). Moreover, preferences are changing over time, one example would be the changing trend that people prefer to lease rather than own a car.

Some of these preferences might also be correlated to the novelty of a mode, such that it affects people's mode choices. It can be argued that it is hard to define when modes are not considered 'novel' any longer by travellers and the effect of a 'new' mode becomes insignificant. Note that this effect does not need to be taken into account when modes are well-established (as in this dissertation). Also note that this approach assumes that the marginal utility for future modes remains the same compared to existing modes, which can be debated. For instance, mode choice habits and attitude towards new or more sustainable modes can change over time. Note that this would also be a challenge in other discrete choice models, since parameters are also assumed to stay the same over time. Furthermore, it needs to be highlighted that the alternative specific constant captures habitual behaviour (regardless of the novelty of a mode) after people got used to all modes in the option set. The effect of leaving out alternative specific constants and parameters in regards to habitual behaviour can be researched further.

Further note that the mode attributes in the utility function are considered linear additive, this might not always be the case for some attributes. For example, if a mode is active, the valuation might be dependent on the distance in a non-linear manner (longer distances tire people substantially, whereas shorter distances might not tire people at all). This should be taken into account when interpreting these results and extrapolating these results to other (future) modes or changing traveller preferences.

6.2.2 Supernetwork model

Chapter 3 presents an approach for calculating the modal split and travel times of future transport modes for uni- and multimodal trips using a supernetwork model. This is done by using a supernetwork where each layer represents a mode and multimodal trips can be simulated by transferring from one layer to another. Nodes and edges are used to describe the network. The resistance of edges is are expressed as generalised values, and consist of a weighed sum of a set of resistance factors as derived from analysis of empirical data. The weighing factors depend on mode characteristics and the user-group (cluster) specific preferences and are based on Chapter 2 where a discrete choice model is estimated using revealed preference data. Both Chapter 2 and Chapter 3 use the examples of an electric step and a shared autonomous car to explore this approach.

The results in Chapters 3, 4, and 5 show logical results, where longer edge lengths and larger distances between origin and destination show a shift towards faster modes (if all other attributes are kept the same). Multiple routes/modes are chosen in a logical manner and show logical results when looking at average travel times, average distance and average speed.

In Chapter 2 a discrete choice model (DCM) was calibrated using a similar method where a nested logit (NL) model was preferred over an MNL to reduce overestimation of the future mode with partially similar characteristics (attributes, routes) compared to already existing modes. This effect has been partly taken into account in the super-network model by using each next node only one time in the MNL to find the shortest route options. However, Chapters 3, 4, and 5 conclude that it is still possible that future modes are overrepresented in the modal split due to the MNL of the mode and route choice model without accounting for similarities between the modes (i.e., layers).

For the purpose of finding the best multimodal route sets, this model decides on the next nodes for agents to travel to en-route. Route searching is done during each timestep for each agent that reaches a node and needs to decide on the next edge to travel on. This means that closer to the agents' destination, the total route resistance changes, consisting of fewer edges, this might change the mode and route choice.

It is good to note that transit has fixed routes and stops, which differs from other modes, where agents do not have to leave the mode to change the route. Chapter 3 does not explicitly model transit lines, whereas the modelling approach for transit in Chapter 5 is extended to include explicit transit lines each with their own characteristics. The network is set up in such a way, that all transit options are modelled as one 'nest'/layer in the supernetwork to prevent an overestimation of transit in the shortest route function. This nesting approach can be generalised for other similar modes as well. One can define which modes should be put together in one layer in the supernetwork using a similarity index as described in Chapter 2.

Chapter 5 extends the supernetwork model to find the ultimate future mode in Delft. The ultimate mode attributes can generate an idea of how such an ultimate mode would look and function like. It is tempting to interpret the ultimate attributes and come up with a possible solution. It was decided to give some examples of how to go about translating the ultimate mode attributes to mode concepts that could be introduced in the transport network of Delft. Please note that it is important to realise that the examples are probably biased interpretations of an ultimate mode. We invite the reader to also take a look at the ultimate mode attributes and try to translate those into their own idea of an ultimate mode.

To give some illustrations of how the ultimate mode in Chapter 5 could look like, Dr. Euiyoung Kim, at the Industrial Design faculty at Delft University of Technology, was interviewed to share his expertise on future modes. He translated the ultimate future mode attributes into a potential product design. He philosophises that in the near-term (<5 years) private (active/manual) water boats could play a larger role in Delft. Furthermore, I would like to propose that the ultimate mode attributes in Chapter 5 could also translate into a product that is comparable to an electric cargo bike ('bakfiets' in Dutch) with a roof. Note that the ultimate future mode in each area can be different compared to the Delft case in this dissertation, since the type of travellers and the presently available transport modes differ.

Chapter 5 highlights the idea that an ultimate transport mode does not stand on itself, but forms a transportation system together with other modes, such as transit. The combination of these modes provides a complete service for all types of travellers (i.e., enough accessible options). This also highlights the need for proper analysis of how any future mode serves different people and if it indeed actually improves, for instance, accessibility for everyone. In this case, transit and carpool are assumed to help people with special accessibility needs and reduce the pressure on transit. In other networks, this might not be trivial and a basic level of service needs to be guaranteed for all travellers. Looking into the travel time changes per cluster when a future mode is added show the importance of looking into the improvement per type of traveller, since not all type of travellers experience an actual improvement.

When policy-makers look into stimulating the use of a mode that is close or equal to the ultimate mode, they can influence cost and regulate speed and availability. Speed and availability have the largest influence on the modal share of the ultimate mode, whereas cost has less influence in the case of Delft. For instance, from this perspective, lowering the average trip duration is not achieved by subsidizing this ultimate mode and it could be more effective to invest in sufficient capacities of transit or adjust the road network itself. Looking at results from this approach calls for context-dependent interpretation when trying to come up with policies to improve the ultimate mode.

The previous section can be seen as an introduction to the idea of looking at the total 'resistance' instead of a few dimensions, such as travel times. This resistance can be described as the total resistance in the network observed by the traveller. This total resistance is comprised of all encountered modal attributes in the network and is more than cost and speed, but comprised of all elements that a traveller uses to make a decision. So, when improving the mode, it is interesting to look at the full resistance rather than only looking at specific metrics to get a holistic picture if people will have an improved experience or not. This philosophy can be extended to include other quality-of-life dimensions, such as emissions.

Finally, the Sioux Falls and Delft networks are intracity networks with mostly intracity traffic. There is likely an underrepresentation of intrazonal traffic (mostly walking and cycling), since the network is aggregated. The networks are not large enough that intercity traffic can be captured within the network, since they cover one city centre. A network with multiple city centres could create insight into intercity traffic and in those types of networks, other ultimate modes could emerge when following the same approach as in this dissertation.

6.2.3 Computational complexity

Calculating the future modal splits using a discrete choice model for all presented combinations in Chapter 2 requires a lot of calculations and can take a lot of computation time (up to 7 days) on a Macbook Pro with a 2,4 GHz Quad-Core Intel Core i5 and 8GB of RAM. For the presented future modes, a selection (by selecting a set of cost, travel time and availability with a variation of $\pm 20\%$) of mode attribute value combinations (125) are tested and the computation times remain relatively limited (up to 30 minutes). To use this approach in workshops with policy-makers or stakeholders, in which results ideally should be available within minutes, it is recommended to implement a Monte Carlo simulation to reduce the computation time even more.

The simulations for the example networks (2-4 nodes per layer, max. 6 modes) (Chapter 3) and the Delft-Rotterdam network (4 nodes per layer, max. 5 modes) (Chapter 4) were run on a personal computer and both took approximately 1 minute to finish per simulation run. The simulations for the Sioux Falls network (24 nodes per layer, max. 6 modes) (Chapter 3) and the Delft network (30 nodes per layer, max. 6 modes (with transit lines modelled explicitly)) (Chapter 5) were run on a high-performance computer and took approximately 6 hours to finish per simulation run. Due to the nature of the shortest route function, the computational complexity increases with the power of 3 when the number of nodes, edges, modes, or agents increases. This means that for complex/real-life networks, a powerful computer needs to be used and for simple smaller networks (estimated to be up to 8-10 nodes per layer) a less powerful personal computer can be used. When using a high-performance computer, parallel computing should be applied to keep total simulation time manageable.

6.3 Answer to research questions

In this section, the main research question is answered by answering each sub-research question.

Main research question:

How can the ultimate future mode of a mobility system be determined before it is available?

The ultimate future mode can be defined as the mode that adds most value to the mobility system. In this study, we define the ultimate future mode as the mode that can be added to the transport system that reduces the (generalized) travel resistance the most. But how can we know which future ultimate mode should be introduced to minimize the travel resistance of a mobility system?

This dissertation presents an approach that gives insight into how future modes could change mode and route choice and as a result can affect travel times and resistance (experienced travel resistance for travellers).

To assess the impacts of a future mode on the generalized travel resistance, the attractiveness of the mode and the mode choice effects needs to be determined first. Mode choice is typically determined based on the utility for each mode using discrete choice models. The utility function for each mode consists of mode attributes and mode specific parameters (i.e., travellers' valuation) and constants. The travellers' valuations of existing mode attributes can be estimated using revealed preference research. For future modes this is not possible, because empirical data for these modes is not yet available.

To overcome the lack of revealed preference research, an unlabelled mode modelling approach has been developed to assess the modal share of any future mode for unimodal trips (Chapter 2). The unlabelled mode modelling approach was first introduced by Quandt & Baumal and describes a method to formulate a discrete choice model by describing the utility of each mode with the same mode attributes for each mode and by leaving out mode-specific constants and parameters (Quandt & Baumal, 1966).

Mode choice affects the use of modes and routes, leading to changes in travel times and route choices. In order to understand which future mode attribute values minimizes the travel resistance, the network effects of mode choice needs to be simulated in a mobility system. To achieve this, a mesoscopic multimodal model with a supernetwork with the unlabelled mode choice modelling approach to describe the edges in the network is developed (Chapter 3 and 4). After, a method using the supernetwork model to find the ultimate future mode based on solely its characteristics without mode-specific constants and parameters of a mobility system is presented in Chapter 5. As mentioned before, the ultimate future mode can be found by minimizing the resistance (for all considered attributes) of the transport network, such that a reduction in total resistance can be observed. This is done by enumerating all mode attributes and finding the mode attribute combination that reduces the resistance of the network as much as possible. The presented approach in Chapter 5 analyses the mobility effects for each type of traveller in the network and presents guidelines to find the ultimate future mode in other networks to reduce the travel resistance for all travellers considering the future mode uses the current infrastructure. Using the supernetwork model in this dissertation, the ultimate future mode of a mobility system can be determined before it is available based on its attributes alone without the need of empirical data of future modes.

Sub-research questions:

1. *How can the modal split of unimodal trips with any future mode be determined?*

   The modal split of any future mode can be estimated using a discrete choice model when using the unlabelled mode modelling approach where alternative specific parameters and constants (ASCs) are excluded in the utility function (Chapter 2). Furthermore, each mode should be described using the same attributes, such that revealed preference data can be used to estimate the effect of solely the modes' attributes on mode choice. In this way, the modal share of any future mode can be estimated using revealed preference data with a discrete choice model, since no ASC is needed. Note that relevant mode attributes might change in the future, since new attributes might become dominant in the decision-making process of travellers. The approach presented in this dissertation cannot capture this possible change in dominant attributes, since the calibration of the choice parameters is done based on a revealed dataset with the currently dominant mode attributes.

2. *How can the modal split and network effects of multimodal trips with any future mode be determined?*

   To assess the mobility effects of future modes on an urban area, a supernetwork model has been developed in which mode choice and route choice are simultaneously modelled including transfer possibilities at mobility hubs. Any future mode can be added to the supernetwork model based on its characteristics and the resulting mobility changes can be observed. Chapter 3 answers this sub research question and contributes to the literature by explaining how the mobility effects can be assessed by using a neutral layer in the supernetwork model and by implementing a novel shortest path function determining the mode and route choice for each agent by minimizing their resistance. The distinction of mode attributes into length-independent (e.g., initial costs) and length-dependent (e.g., cost per km) attributes is useful to model the resistance in the supernetwork and is used in the before-mentioned shortest path function.

Chapter 4 also helps to answer this sub research question and contributes to the literature by demonstrating how a supernetwork model can be applied to one OD-pair between Delft and Rotterdam to analyse the effects of shared electric bicycles. The network layout and OD-flows need to be determined and at least two scenarios, with and without shared electric bicycles, need to be set up to analyse the effects of shared electric bicycles on one OD-pair between Delft and Rotterdam.

3. *How can the ultimate future mode be determined?*

   A supernetwork model is applied to find the ultimate future mode in Delft based on solely its characteristics without mode-specific biases in Chapter 5. The ultimate future mode is found by minimizing the resistance (for all considered attributes) of the transport network, such that an improvement in total resistance can be observed. Note that not all clusters (types of travellers) automatically experience a reduction in resistance when adding a future mode. This approach gives insight into the mobility effects of adding a future mode and helps to create policies or define the ideal mode attributes as such that it benefits all clusters. This chapter contributes to the literature by demonstrating how a supernetwork model can be used by policy-makers and mobility providers to improve mobility in an area or know of which mode(s) its use needs to be stimulated.

6.4 Societal relevance

This dissertation demonstrates an approach in which the transport system of an urban area can be improved effectively by looking at the resistance of travellers. This approach of looking at reducing the resistance by optimising several attributes is flexible and can be extended with other attributes and parameters relevant to the case-study at hand. The presented approach in this dissertation can be used by, inter alia, researchers, policy-makers and companies.

Researchers can use and extend the unlabelled mode modelling and supernetwork approach to generate insight into multimodal trips of future modes without having revealed preference data available. They can also use this method to scrutinize which mode attributes add 'most value' to the transport system. Furthermore, they can extend existing modelling approaches in such a way they do not have to generate mode and route choice sets beforehand.

Also, policy-makers can use this approach to assess the use of this ultimate future mode to reduce the travel resistance for all travellers in the network. As presented in Chapters 3, 4 and 5, this can be achieved by using different clusters (i.e., travel preferences) for each type of traveller. It can be specifically relevant when a future mode is going to use the current infrastructure, but is only used by a certain group of travellers (e.g., high-income). The introduction of an extra transport mode on the current infrastructure can influence the congestion in certain parts of the transportation network for existing modes and travellers that do not have the option to use the future mode.

For example, subsidies and tax reductions can be analyzed for existing and future modes by reducing, e.g., the value of the cost attribute for future autonomous cars, increasing the cost for conventional cars or calculating the needed capacities for (future) modes and their infrastructure. Several combinations of policies and available modes can be analyzed and combined into multiple scenarios to help policy-makers make effective policies.

Finally, companies can use this to develop the ultimate future mode to gain a large market share. These companies would only want to develop transport modes that have added value. In this dissertation, this added value is captured in a reduction of the resistance (i.e., mode attributes).

6.5 Recommendations

This section describes the recommendations relevant to this dissertation. Again, the recommendations are also divided into two parts: one going into the recommendations relevant to the discrete choice model and the other one going into the recommendations relevant to the supernetwork model.

6.5.1 Discrete choice model

Mixed logit models can overcome the methodological shortcomings (assumption of IIA, unobserved preferences, and individual preferences over time) of both MNL and NL. The main aim of Chapter 2 is to demonstrate that revealed data preference can be used to calculate the potential modal share of a future mode using a discrete choice model without a mode-specific constant. The distributions for each mode attribute valuation would need to be assumed in order to cope with the open-form expression of a mixed logit. Future studies can implement a mixed logit model and compare its performance with the multinomial and nested logit models.

Further exploration can be done with other types of discrete choice models (e.g., cross-nested logit, paired combinatorial logit) to get a better grasp on the calculation of the modal split of future modes. The main challenge with modelling these discrete choice models is that multiple scaling parameters need to be simultaneously estimated for the future mode, which can result in mathematically underdefined functions.

6.5.2 Supernetwork model

Due to a possible overestimation of the total modal share of similar modes observed in Chapter 2 for the discrete choice model, it might be the case that an overestimation of the total modal share of similar modes is occurring in the studies with the supernetwork as well. Note that the mode/route choice function already partly accounts for the similarity between routes by reconsidering the route at each node. It is recommended to look into grouping layers of similar modes and routes into one ‘nest’ by using a path-overlap factor to normalize this possible overestimation as is currently implemented for public transport lines in Chapter 5 in the case of Delft. It is also recommended to look into how a PSCL model can be implemented with different types of modes in a multimodal supernetwork to account for a overlap in mode/route in available options.

Furthermore, intersections are not modelled explicitly, in the supernetwork model agents cross from one edge to another without resistance in the nodes. Spillback and queueing are also not taken into account yet. It is recommended to implement spillback, queueing and explicit modelling of intersections in nodes to increase the level of detail to assess the mobility effects of future modes on the network.

The supernetwork approach is computationally expensive for larger networks. It is recommended to research how the computational load can be reduced, whilst still maintaining the agent-based approach and output consisting of modal split and travel times. Special attention to the shortest route-seeking function should be given, as more than 80% of the time the computer was using this specific function.

Note that the resistance in Chapters 3, 4 and 5 is more than just cost and travel time, it consists of all (11) attributes. This means that the ultimate mode is not one where just cost and travel time are low, but one which complements the existing network the best, such that the resistance per OD-pair for all types of travellers (i.e., clusters) goes down as much as possible within realistic and physical constraints. This highlights the need for separate analyses for each type of network, since the ultimate mode depends on the characteristics of the existing network and the type of travellers.

Rather, a discussion should be held about reducing the resistance of a transport network in an equitable manner and which ultimate transport mode can reduce this resistance in the most effective way. Future research could look more into testing a combination of multiple ultimate modes serving different travellers and OD-pairs from the perspective of reducing resistance.

Not just a combination of ultimate modes can be interesting to look at, but also the availability (in certain locations and as a capacity of carriages or shared (rented) modes) of the ultimate mode in the network. Future studies can look into adding availability (e.g., number of shared bicycles at certain locations) to the presented approach. This can help to find trade-offs for policy-makers between finding the ultimate mode and making it available everywhere or at certain points in the network with the goal of reducing resistance. This also ties in with another recommendation, which is to use this approach in an activity-based model instead of a trip-based model.

Furthermore, it is recommended to expand this approach with other mode attributes to broaden the idea of what an ultimate mode is and how to go about improving a mode. For instance, air and noise emissions could be included in the mode attributes to (partially) include sustainability and livability in this approach as well.

The ultimate mode is context-dependent, and therefore, should also be analyzed in different scenarios to come up with a 'resilient' ultimate mode. These different scenarios can factor in changes in population, travel patterns, certain policies or different travel preferences.

Finally, it is recommended to model the change in accessibility, land use and activities as depicted in Figure 1.1 to further the understanding of how future modes change urban areas and which future mode can most effectively improve the accessibility and livability of urban areas.

Appendix A

Software architecture, implementation and computational aspects of a supernetwork model in Python

The traffic assignment model with a supernetwork introduced in Chapter 3 was implemented in Python and can be used to calculate future modal split and the changes in other mobility effects when future modes are introduced. This appendix explains how the supernetwork model can be implemented and what the computational aspects of the supernetwork model are. In order to add complexity to the network and to analyze multiple scenarios, whilst limiting computation time, two main things were done: 1) the development of a shortest path function limiting the number of routes (max. 600 routes) whilst keeping the feasible routes available and 2) the implementation of parallel CPU computing on the DelftBlue computer (high performance computing). These implementations allowed for a feasible computational time and made it possible to analyze multiple scenarios to find the ultimate future mode attributes as described in Chapter 5.

Section A.1 shows the abstract of this appendix. Section A.2 introduces the problem and main aim of this software appendix. Section A.3 explains the implementation and architecture of the software package. Section A.4 goes into the computational aspects of this framework and Section A.5 explains the quality control that has taken place during development. Finally, the availability and the reuse potential are discussed in Sections A.6 and A.7. Read this appendix in conjunction with Chapter 3 and the software available on GitHub as described in Section A.6.

A.1 Abstract

This software package contains a newly-developed, complex, and computationally-expensive multimodal supernetwork traffic assignment model to estimate the potential modal split and travel times of any future mode. Modes can be described with a set of attributes without the need to define mode-specific constants and parameters. Therefore, this software package can be used to assess the impact of future modes, where data on its use cannot be known yet. The model output consists of the modal split of each mode and travel times of each trip. It can be reused for different networks and with each type of mode. The only condition is that the user defined a complete and coherent set of mode attributes that can describe the choice behaviour of travellers without the need for mode-specific constants and parameters. This appendix describes the software architecture, implementation and computational aspects of the supernetwork model in Python. The software is available on GitHub.

Keywords: agent-based modelling; future modes; multimodal; python; unlabelled mode choice; supernetwork

A.2 Introduction

Several future modes with different characteristics, ranging from shared electric steps to autonomous vehicles, have been developed and some of these have been introduced in varying degrees – from test implementation to local initiatives – in urban areas. These future modes will, for instance, affect the level of sustainability and accessibility of urban areas (Fagnant & Kockelman, 2015; Shaheen et al., 2019; Milakis et al., 2017; van Arem et al., 2019).

The goal of the model in this appendix is to understand how the introduction of future modes affects the modal split, travel times and travel resistance (i.e., 'generalized' travel time) and the effect on first- and last-mile mode choice. Unlabelled discrete choice models can be used to estimate modal split of future modes for unimodal trips (Quandt & Baumal, 1966; de Clercq et al., 2022). Traffic assignment models can be used to simulate travel times and travel resistance for unimodal trips. This software architecture appendix describes the software architecture, implementation and verification of a mesoscopic multimodal supernetwork traffic assignment model, which combines an unlabelled discrete choice model and simultaneous mode and route choice assignment model using a supernetwork to assess mobility effects, such as changes in travel resistance and travel time, of *any* future mode. The model calculates mode and route choice simultaneously based on the resistance per edge and then assigns agents (travellers, not vehicles) to the multimodal supernetwork. This approach enables the analysis of both uni- and multimodal trips, as is necessary to understand the mobility effects of future modes, also for the first- and last-mile parts of a trip.

A multitude of studies discuss the types of traffic assignment models and distinguish between static, quasi-dynamic, and dynamic modelling approaches. A static model assumes that traffic conditions do not change within the simulated period. A dynamic model assumes that edge conditions (i.e., edge resistance) change dynamically over time within the simulated period, which allows for more accurate congestion and spillback modelling and dynamic route choice behaviour. (Quasi-)dynamic models can capture emergent effects, such as congestion and spillback (Ortuzar & Willumsen, 2011; Van Eck et al., 2014; van Wageningen-Kessels et al., 2015).

To assess the modal share of future modes it is necessary to include multimodal trips which can capture first and last-mile modes (e.g., shared bicycles available at train stations are especially valuable as a last-mile mode) (Van Eck et al., 2014). This can be done by developing a microscopic or mesoscopic dynamic multimodal supernetwork, as opposed to a macroscopic static unimodal model, enabling the simulation of multimodal trips without the need to predefine the combinations of modes and routes (Van Eck et al., 2014; Liao, 2016). These supernetwork models only need to know where people are allowed to switch between modes (e.g., where the mobility hubs are located). For instance, such models are applied to model the effects of fleet size, spatial distribution (read: availability) of floating shared modes and parking fees on the use of shared cars (Li et al., 2018). In one study (Vo et al., 2021), a multimodal supernetwork is used to explore the effects of the interaction between private cars and transit modes on the activity-travel choices of individuals defining the locations where individuals can switch modes without predefined route sets.

The literature shows that multistate supernetworks can be developed to analyse how travel patterns can be simulated without predefining mode and route choice sets. Liao et al. (2014) explored how full daily multi-activity travel patterns can be modelled using a so-called multistate supernetwork with space-time prisms to simulate the opening and closing times of certain travel options to explore how full daily multi-activity travel patterns can be simulated.

This software package uses a mesoscopic dynamic assignment that models individual agents with aggregated link travel time computations. The agent-based approach makes it possible to trace all individuals over time. Modes can be described with a set of attributes without the need to define mode-specific biases. Therefore, this software package can be used to estimate the use of future modes, where data on its use cannot be known yet. It can be reused for different networks and with each type of mode. The only condition is that the user defined a complete and coherent set of mode attributes that can describe the choice behaviour of travellers without the need for a mode-specific bias. The supernetwork assignment model is set up using Python 3.10.2 and the NetworkX package (Hagberg et al., 2008).

This appendix focuses on the software architecture. Read Chapter 3 for the application of this model on three small, but exemplary networks and the Sioux Falls network. The code is available on GitHub (see details in Section A.6 Availability). It is recommended to first read this appendix and then look at the code.

A.3 Implementation and architecture in Python

This software package is developed as a stand-alone package using Python. Generally, the architecture is structured as visualized in Figure A.1. Parallelograms are data objects, which are fed into several functions (squares). First, the model is initialized, which is based on the discrete choice model from Chapter 2. Note that all elements with a grey background are defined in Chapter 2 and not altered. In this phase, all inputs, parameters, clusters (type of travellers), and network definition ((a) in Figure A.1) are initialised for the simulation. The inputs needed to run a simulation specifically are:

- OD-matrix,
- Revealed preference data (OViN data in this study),
- Modes + mode attributes, and
- Network definition.

Furthermore, some parameters can be set before starting simulations. The main parameters to be set are:

- number of timesteps,
- stepsize,

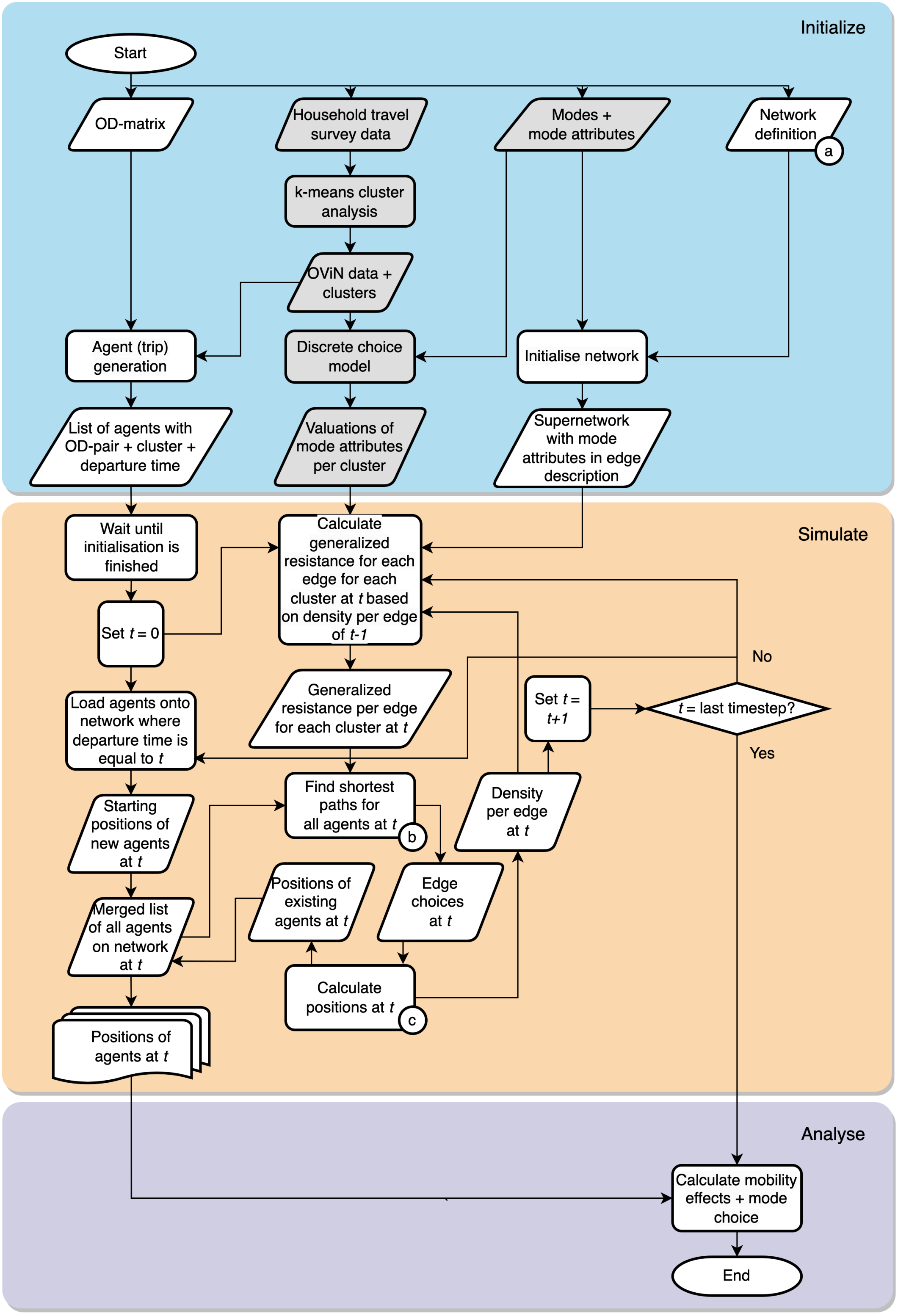

Figure A.1: Model structure of multimodal supernetwork. The grey background indicates the components originating from our parameter estimation study about unlabelled mode choice modelling (Chapter 2). (a) refers to the network definition (see A.4.1), (b) to the combined mode and route choice model (see A.4.2), and (c) the network loading model (see A.4.3).

- scaling factor of trips (this scales the OD-matrix and the Fundamental Diagram function), and
- unimodal or multimodal trips.

Second, the simulation takes place. In this phase, all inputs are used to set up a simulation where the combined mode and route choice model is used ((b) in Figure A.1), and the network loading model ((c) in Figure A.1) is used. Generalized resistances for each edge for each cluster (type of traveller) are calculated and fed into a shortest-path function. This function is used to determine which edges agents will travel to when they are 1) entering the network or 2) reaching a node and need to determine their next step. At each timestep, the positions of each agent, the edge densities and resistances per cluster are saved in binary (.pkl) and dictionary (.json) files. These data are retrieved in the next timestep and during the last part of the code where the data is processed to calculate KPIs.

After simulating all timesteps, the third and last phase starts, which is the analysing phase. The results are stored in the data folder under resultsSummary.csv. In this phase, mobility effects are calculated based on the locations of each agent, duration of each trip, edge densities, and resistance (the resistance agents experience when they travel through the network). All this information can be retrieved for different OD-pairs and for each type of traveller. The following output can be retrieved:

- Average trip duration
- Average velocity
- Average distance travelled
- Average trip duration per cluster (type of traveller)
- Total resistance
- Resistance per cluster and OD-pair
- Modal split (% of trips) including multimodal trips
- Modal split (% of distance travelled)

A.4 Computational aspects of supernetwork model

This section describes the computational aspects of the main components in this software package. It aims to create an understanding of the implementation and trade-offs such that the computational complexity is kept at a feasible level. It also aims to give insight into how these aspects could be improved upon in future versions. Three computation aspects are highlighted and are the same three aspects as in Figure A.1; (a) the network definition (see A.4.1), (b) the combined mode and route choice model (see A.4.2), and (c) the network loading model (see A.4.3).

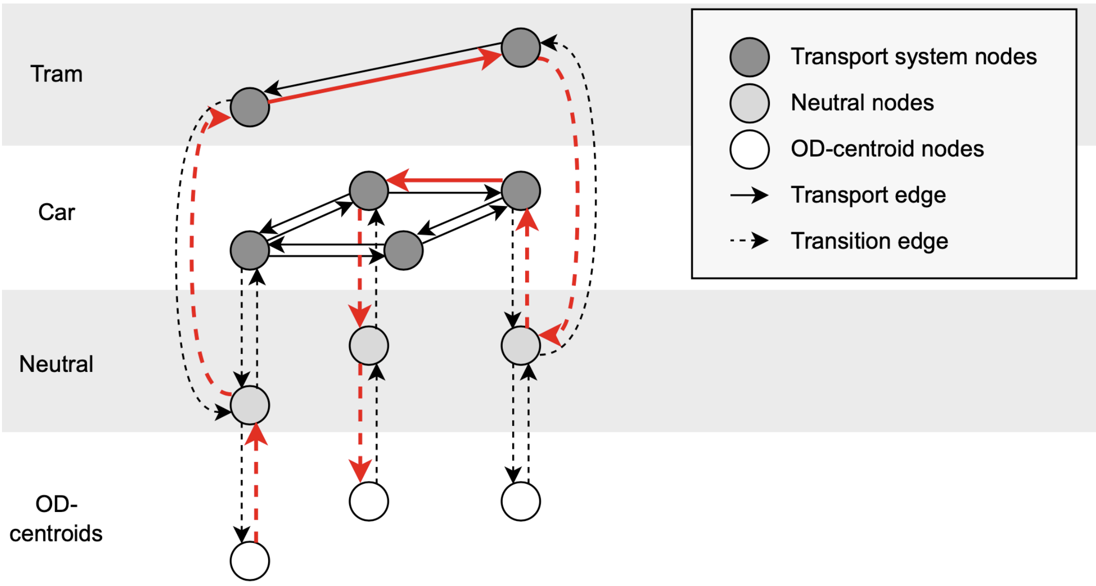

Figure A.2: Supernetwork example with 2 modes (upper two layers) with transition edges between modes through a neutral layer. One possible multimodal route is visualized in red.

A.4.1 Network definition

The supernetwork consists of one layer for each mode (see the 2 example modes in Figure A.2). Edges represent aggregated road segments, transit segments (representing aggregated/abstract transit lines) and dummy transition edges from and to a neutral layer. The transport mode edges have a number of attributes (representing the mode and edge attributes), whereas for some modes the 'time' attribute can change with the use of the edge (i.e., the intensity). The dummy transition edges have a length of 0, but with a resistance equal to the effort it requires to get on or off the mode (including parking, waiting for PT, etc.). This supernetwork uses a neutral layer which serves as a 'hub' for agents to switch modes. Nodes only have a function in defining the network topology, but have no further attributes: all attributes and thus resistance factors are defined in edges.

In the scientific case-studies, we have defined only aggregated networks to keep computational complexity limited. The software framework can handle non-aggregated networks, but then it needs more time to finish a simulation (3 to 4 hours for a simulation period of 4 hours when using a high performance computer for a network with 30 nodes per layer (240 nodes in the whole network) and 6 modes).

A.4.2 Mode and route choice

Agents start and end their trip in OD centroid nodes. Agents move from one (transition) node to another via edges, thereby creating the route that results from the combined mode and route choice model. A 'route' in the model is defined as a specific sequence of edges (could represent one or more transport mode edges) and one or more transition edges (if the route includes one or more switches between modes). Routes are determined en-route. When an agent reaches a node, the next node for this agent is determined by calculating the total resistance of all possible next edges.

A multinomial logit model (MNL) (see Eq. A.1) (Smits et al., 2018) is used to determine the mode/route choice based on the route resistance. The result of the MNL is an overview of the probabilities of each of the routes (for each edge connected to the current mode). Shortest routes are found using Bellman-Ford (Bellman & Kalaba, 1960). The next edge is chosen in three main steps. First, the route resistances of a maximum of 100 routes per next possible edge are calculated. To perform this step, each next possible edge is temporarily removed from the network to avoid being considered multiple times. These 100 shortest routes are based on the length of the route and are assumed to cover the reasonable routes that should be considered by the agent when determining the next edge. Note that the 100 *shortest* route in length are taken to calculate the *travel resistance* of these 100 routes. The shortest route in length is different than the travel resistance, since the travel resistance is determined by the parameter estimation and all mode attribute values. Second, the lowest total travel resistance of these 100 routes is taken as the resistance of the considered edge. Third, after the lowest possible total resistance of all possible next edges is determined, the MNL is used to calculate the chances that each of the possible edges is chosen. Then, from a uniform distribution, a pseudo-random value between 0 and 1 is extracted (to account for the heterogeneity in agents) and used to determine which next edge each agent chooses. Note that this algorithm is repeated for each agent in each cluster at a certain timestep when the agent needs to consider their next edge. The result of each agent is combined into a list of edge choices, which is the output of (b) in Figure A.1. These steps are visualized in the flowchart in Figure A.3.

The computational complexity is limited by considering up to 600 routes (maximum of 6 next edges and up to 100 routes per edge considered). This is assumed to be sufficient as there are roughly up to $6^3 (= 216)$ combinations of multimodal trips (first, main and last-mile) to be considered. Assuming all these combinations are practical considerations of an agent, about three routes per combination of modes are considered.

When an agent reaches the next node, this process is started again. If congestion is becoming too high on one route, it is theoretically possible that an agent goes 'back' to a previous node to find another route. To prevent endless theoretical back-and-forths from happening, the edge that an agent has travelled on previously is removed from

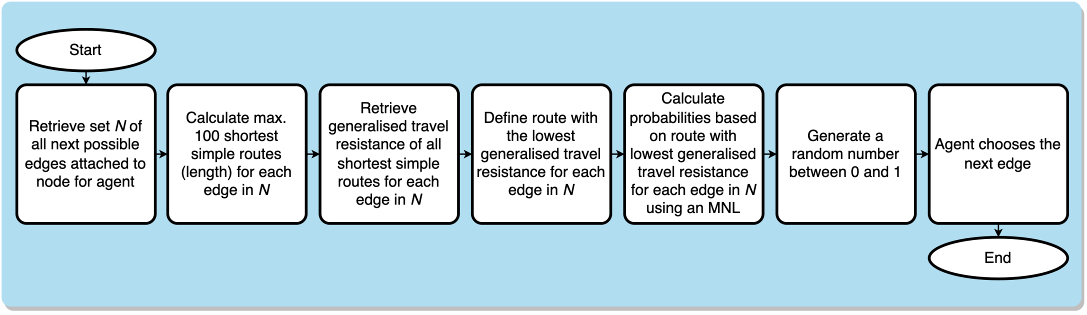

Figure A.3: Algorithm to determine the next node within edge set N for each agent

the options for this agent when considering the next edge to travel on.

$$P_{r,t,c} = \frac{e^{U_{r,t.c}}}{\sum_{p \in R} e^{U_{p,r,t,c}}}, \forall r \in R, \forall t \in T, \forall c \in C \tag{A.1}$$

where;

U_r = resistance of route r [-];
U_p = resistance of route p [-];
R = subset of shortest N (6) routes [-];
T = set of timesteps [-];
C = set of clusters [-];
r = selected route [-];
t = timestep [-];
c = cluster index [-];
p = route index of subset R for denominator; and
$P_{r,t,c}$ = probability that route r is chosen at timestep t, for cluster c.

A.4.3 Network loading

In this software package, a mesoscopic dynamic model is used for network loading with a strict weak order of agents (people) per edge (van der Gun, 2018). A strict weak order means that multiple agents can leave and enter the edge per timestep and agents have an order (read: ranking/position) on the edge. The number of agents already present on an edge at a certain timestep determines the travel times, which partly describes the edge resistance; therefore, this might affect route choice for agents considering entering the edge at a later time. A timestep of 0.01 hours is used to update the positions of all agents. This timestep is chosen such that an agent will spend at least two timesteps on the edge with the shortest free-flow time (0.02 hours) considering the highest free-flow speed in this model (64 km/h or 40 mph) (Bar-Gera et al., 2013). No iterations are carried out to assign all the agents to the network.

This supernetwork needs to account for the change in travel resistance when future modes are introduced and when the density on an edge changes. Daganzo's (Daganzo

& Geroliminis, 2008) triangular fundamental diagram (see Eq. A.2 till A.4) for car, carpool and bicycle is used to compute the speed of the agents on an edge based on the current density. Other interactions between agents on an edge (lane-switching, headway, etc.), spillback and queueing are not modelled. Travel times for cars, carpoolers and cyclists are based on the free-flow velocity, critical density, jam density, number of lanes, PCU values of each agent, and the number of agents present on that edge. The critical density (k_{crit}) and the jam density (k_{jam}) are assumed to be 125 pcu/h and 25 pcu/h. Density is calculated as the sum of all pcu values of all agents present on that edge, normalized for the length of that edge (see Eq. A.6). The capacity is calculated as shown in Eq. A.5.

$$k < k_{crit} \Rightarrow v = v_{ff} \tag{A.2}$$

$$k_{jam} \geq k \geq k_{crit} \Rightarrow v = \frac{k_{jam} - k}{k} \frac{q_{crit}}{k_{jam} - k_{crit}} \tag{A.3}$$

$$k > k_{jam} \Rightarrow v = 0 \tag{A.4}$$

$$q_{crit} = u_{ff} * k_{crit} \tag{A.5}$$

$$k = \frac{\sum_{a \in A} pcu_a}{len} \tag{A.6}$$

where;

v = current velocity [km/hour];
v_{ff} = free flow velocity [km/hour];
k = current density [pcu/km];
k_{crit} = critical density [pcu/km];
k_{jam} = jam density [pcu/km];
q_{crit} = capacity (i.e., critical intensity) [pcu/h];
pcu_a = pcu-factor for agent a [pcu]; and
len = length of edge [km].

A.5 Computational complexity

The computational complexity is high, like other supernetwork models, and equal to $O(KN^3)$, where K is the number of shortest paths and N is the number of nodes, from the so-called k-shortest path approach (Yen, 1971). Note that the total number of paths is dependent on the number of nodes, edges, and layers (i.e., modes). The implementation of multicore processing was necessary due to the extremely long computation time (more than 8 hours for the Sioux Falls network per timestep on a single core). This made the total script approximately 20 times faster when using 32 cores (4 CPUs with 8 cores with 32GB RAM in total) on a high-performance computer and 7 times faster on a personal computer with 8 cores (4 CPUs with 2 cores with 8GB RAM in total).

Even after the implementation of multicore processing, more than 80% of the computation time is spend on the shortest route function. The simulations for the example networks (2-4 nodes per layer, max. 6 modes) (Chapter 3) and the Delft-Rotterdam network (4 nodes per layer, max. 5 modes) (Chapter 4) were run on a personal computer and both took approximately 1 minute to finish per simulation run. The simulations for the Sioux Falls network (24 nodes per layer, max. 6 modes) (Chapter 3) and the Delft network (30 nodes per layer, max. 6 modes (with transit lines modelled explicitly)) (Chapter 5) were run on a high-performance computer and took up to 6 hours to finish per simulation run.

It is recommended that for complex/real-life networks, a powerful computer needs to be used and for simple smaller networks (estimated to be up to 8-10 nodes per layer) a less powerful personal computer can be used. When using a high-performance computer, parallel computing should be applied to keep total simulation time manageable.

A.6 Quality control

Quality control has been carried out by performing unit tests on the generalized resistance, shortest-path, and fundamental diagram functions. Furthermore, functional tests have been carried out for 36 simple exemplary networks, the Sioux Falls network and an aggregated network of Delft, the Netherlands. For details on the functional tests, please refer to Chapter 3 where this multimodal supernetwork traffic assignment model has been introduced.

In order to assess the validity of the results of the approach, the elasticity of the model can be compared with elasticity from the literature. The elasticity of the model is determined by increasing and decreasing the travel costs and travel times for cars and transit. Table 4.1 shows the elasticity of this study (for the example network with 4 nodes) and two reference studies. It can be observed that this study's elasticity falls within the guidelines of the Dutch Regional model (which is based on a multitude of other studies) except for the transit cost, which shows a slightly lower elasticity than the guidelines. The TNO study also shows a slightly lower cost than the guidelines and argues that the lower elasticity might come from the free and unlimited transit subscriptions that students have in the Netherlands and that they are therefore less price sensitive. Since all other elasticities fall within the boundaries of the guidelines and our value for transit cost is only slightly lower than the TNO study and falls just outside the guidelines of the Dutch Regional model, it is concluded that the elasticity with this study is sufficient.

On the GitHub of this software package, one can just run the code with one simple exemplary test network (see Figure A.4) to see how the software works with a synthetic OD-matrix, revealed preference dataset and considered modes and their attributes.

Table A.1: Elasticity of vehicle kilometres for car and transit (BTM) by varying travel times and costs with +-10%

Mode	Attribute	Elasticity		
		This study	Guidelines GM 2.4.0 of the Dutch Regional model (Snelder et al., 2021)	TNO study (Snelder et al., 2021)
Car	Cost	-0.24	-0.2 to -0.5	-0.40
	Time	-0.49	-0.3 to -0.7	-0.51
Transit (BTM)	Cost	-0.55	-0.6 to -1.2	-0.59
	Time	-1.30	-0.6 to -1.3	-0.75

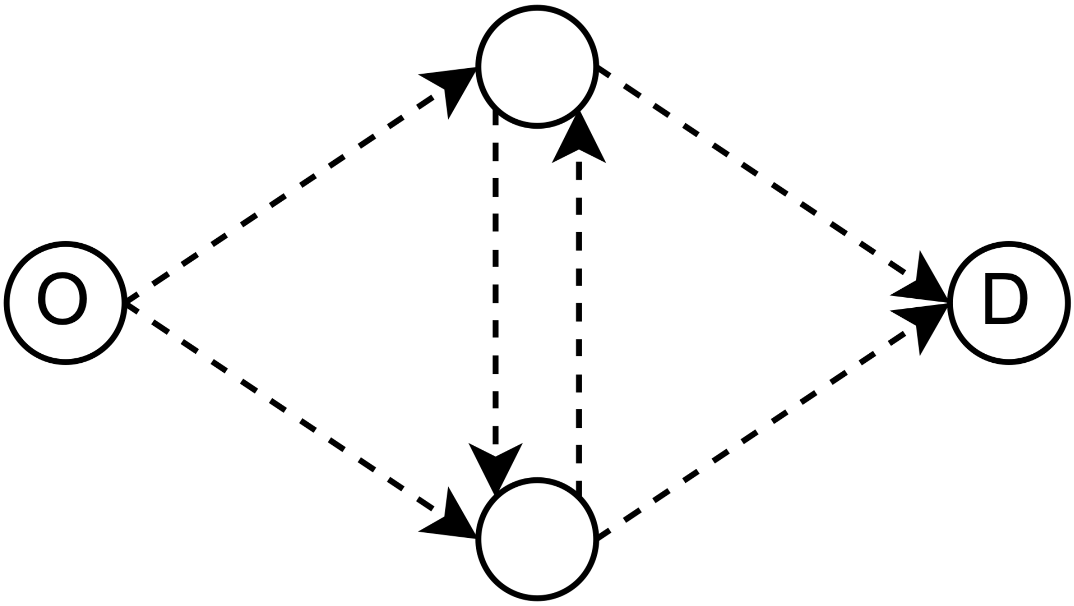

Figure A.4: Exemplary test network with O as Origin and D as Destination.

To select other networks and to include a future mode with a certain set of mode attributes, just follow the instructions in the main.py file. To implement another network, add a configuration by defining nodes and edges using the same logic as with all networks in the functions.py file at the function *initializeNetwork*.

A.7 Availability

Operating system
No specific operating system needed.

Programming language
Python 3.7 or higher

Recommended system requirements

For networks with a maximum of approximately 12 OD-centroids: 8GB RAM or more, 10GB free disk space or more, 2,4 GHz Quad-Core Intel Core i5 or faster
For networks with more than 12 OD-centroids: 32GB RAM or more, 10GB free disk space or more, 8-core 3Ghz or faster

Dependencies
Extra python packages:
ujson, min. version: 4.2.0
numpy, min. version: 1.21.2
pandas, min. version: 1.3.5
networkx, min. version: 2.6.3
matplotlib, min. version: 3.5.0
imageio, min. version: 2.9.0

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de Clercq, Gijsbert Koen; define, analyze, write, develop and test code
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Software location:
Code repository
Name: GitHub - Supernetwork
Identifier: https://GitHub.com/KoendeClercq/Supernetwork
Licence: GPL-3.0 Licence
Date published: 02/08/2023

Dataset, case-study and results location:
Code repository 4TU
Name: Supporting files for dissertation - On the mobility effects of future transport modes
Identifier: https://data.4tu.nl/datasets/e281d623-9d5b-4eda-ad85-7eebb9a9eee4
Licence: Restrictive Licence
Date published: 16/11/2023

A.8 Reuse potential

The software package can be used by researchers and policy-makers within and outside the transportation field. Within the transportation field, future modes, pricing policies, new utility functions, and networks can be implemented and analysed. In other fields, inspiration might be drawn from this approach: choice modelling behaviour using utility functions with a spatial element. This spatial element can be interpreted as ‘stocks’ (e.g., available housing stock) or ‘inventory’ (e.g., fast-moving consumer goods). The multimodal supernetwork approach can give insight into bottlenecks in any type of process (e.g., where is the housing stock too low?).

It is possible to set up large realistic networks with this multimodal supernetwork approach. As mentioned earlier, the computational complexity is high, like other supernetwork models, and equal to $O(KN^3)$, where K is the number of shortest paths and N is the number of nodes, from the so-called k-shortest path approach (Yen, 1971). Note that the total number of paths is dependent on the number of nodes, edges, and layers (i.e., modes). When reusing this software package, multicore processing is recommended. It is also recommended to look at a GPU implementation of the mode and route choice function (80% of computation time spent on this function), since a large number of the same function is called independently and can be implemented in a parallel manner (even more optimized than the current CPU implementation of this function). This GPU implementation also opens the possibility of implementing microscopic vehicle/agent interactions and more detailed networks and transit schedules without compromising on computation times. The current version does not iterate within one timestep to allocate agents again, a recommended improvement could be to take a portion of the allocated agents and use the new densities per edge and have these agents choose their next edge again until these results found an equilibrium.

Software can be reused and further developed as long as this article is acknowledged. Furthermore, it should be clear which components are adjusted and how they are adjusted.

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Summary

The accessibility and livability of urban areas are under pressure. That is why, in the last decades, numerous transport modes, such as shared bicycles, shared scooters, automated cars, ride-hailing services, electric bicycles, and other personal light electric vehicles have been developed. The use of such future modes could potentially change the way our urban areas function and look substantially in terms of spatial use, sustainability, health, equity, safety and economic opportunities. Analyzing how mode and route choice behaviour could change when future modes are available is challenging since potential users are not familiar with such systems yet, so current transport models with mode-specific constants and parameters, which are calibrated using empirical data, do not suffice for this purpose. Furthermore, it is challenging to know which mode attributes need to be implemented in a future mode to minimise the travel resistance (experienced by travellers) of the transport network. So, that brings us to the main research question: How can the ultimate future mode of a mobility system be determined before it is available?

This dissertation aims to answer this question in three steps. First, by developing an unlabelled modelling approach in a discrete choice model to estimate the modal split of unimodal trips of future modes without mode-specific constants and parameters. Second, by developing a new supernetwork model that applies the unlabelled mode modelling approach to model simultaneous route and intermodal mode choice. This approach gives insight into how future modes could change mode and route choice and as a result can affect travel resistance. In both steps, shared autonomous vehicles and electric steps are used as example modes. Furthermore, the supernetwork approach is used to demonstrate the influence of shared electric bicycles on the modal split between Delft and Rotterdam. Finally, in the third and last step, the supernetwork approach is used to find the ultimate future mode attributes in Delft by minimizing the network resistance, answering the main research question.

This dissertation successfully explores the unlabelled modelling approach in a discrete choice model and the supernetwork approach for calculating the mode choice and travel resistance for unimodal and multimodal trips of any future transport mode in a future situation. The main contribution of this approach to the literature is the implementation of an unlabelled modelling approach using revealed preference data to estimate the modal split of future modes rather than having to make use of stated

preference data and analysing existing modes for both unimodal and multimodal trips.

The potential modal split of any future mode can be estimated using a discrete choice model when using the unlabelled mode modelling approach where alternative specific constants and parameters (ASCs) are excluded from the utility function. A condition to be able to do so is that each mode should be described using a set of attributes from which the respective preferences can be derived from empirical (revealed preference) data. Implicit (or hidden) mode attributes in an ASC can be made explicit by defining a complete set of mode attributes, such that all mode attributes that describe mode choice behaviour are made explicit and ASCs become redundant. In this way, the modal share of any future mode can be estimated using revealed preference data with a discrete choice model since no ASCs are needed. The following attributes are included in the utility function that describe existing and future modes: Cost (€); Travel time (min); Driving task (-); Skills (-) (i.e., driver's license); Weather protection (i.e., roof) (-); Luggage (-); Shared (ownership or space) (-); Availability (-); Reservation (-); Active (-); Accessible (-). The performance of this approach is similar to the approach with an ASC, with a rho-squared of 0.828 and 0.823 for the unlabelled mode modelling approach and approach with an ASC respectively.

Note that the approach comes with some limitations. First, it should be possible to describe a future mode in terms of parameters for which the preferences are known. Second, relevant mode attributes might change in the future since new other attributes might become dominant in the decision-making process of travellers. The approach presented in this dissertation cannot capture this possible change in dominant attributes since the calibration of the choice parameters is done based on a revealed dataset with the currently dominant mode attributes.

When predicting the modal split of a future mode using a multinomial logit model it might be that an overestimation of the future modal split occurs due to the partial similarities between different transport modes. To reduce the overestimation, this study implemented a nested logit model. The nested logit model was realized by nesting the future mode in a nest with the most similar existing mode. The modal split using two of the same current modes in a multinomial logit model (simulating the modal share of when the red/blue bus paradox occurs) was compared with the modal split of the multinomial logit and the modal split of the nested logit model when introducing autonomous vehicles and electric steps. It was observed that the overestimation is indeed reduced when a nested logit model is used. Therefore, it was concluded that a nested logit model is better suited for estimating the potential modal split of a future mode than a multinomial logit model.

The unlabelled modelling approach in a discrete choice model can estimate the effects of future modes on unimodal trips. In order to analyze multimodal trips and other mobility effects of future modes, besides modal split, such as a change in travel times and change in travel resistance as a function of the use (intensity) of the network, the unlabelled modelling approach is extended with a traffic assignment network using a supernetwork with one layer/subnetwork per mode.

To allow researchers to automatically cover all uni- and multimodal options without the need to define mode and route choice sets, the supernetwork model is defined in which each available mode is defined as a specific layer with nodes and edges, where the edges' resistances are described by a set of attributes without an alternative-specific constant and are dependent on its use (i.e., travel time depends on density on edge). To explicitly model (dis)embarking of modes, the supernetwork model uses a so-called neutral layer. The neutral layer is connected to all mode-specific layers with edges representing transfer (embarking and disembarking) resistances, also described with a set of attributes.

The main contributions of developing the supernetwork model to the literature are 1) the implementation of an unlabelled choice model in a supernetwork model enabling the analysis of multimodal trips, 2) the implementation of a novel shortest path function determining the mode and route choice for each agent in a simulation combining length-dependent (e.g., cost, speed) and length-independent (e.g., active, luggage) mode attributes, and 3) the use of a so-called neutral layer in the supernetwork to automatically capture all mode and route choice combinations for multimodal trips including the effort to embark and disembark transport modes.

This approach is successfully verified with 3 small yet exemplary network configurations and the Sioux Falls test network mimicking the availability of shared autonomous vehicles and electric steps next to the current modes: car, carpool, transit, bicycle and walk. The supernetwork approach is successfully applied to assess the effect of shared electric bicycles on the modal split on an OD-pair between Delft and Rotterdam.

The supernetwork model is applied to answer the main research question: find the ultimate future mode in Delft based on solely its characteristics without mode-specific biases. The ultimate future mode can be found by optimising the future mode attributes, such that an improvement in the total travel resistance of the transport network can be observed. This is done by, first, enumerating all mode attributes, except cost and travel time, and finding the mode attribute combination that reduces and, second, simulating the future mode attribute combination, including cost and travel time, reducing the resistance of the network as much as possible. We analyse the mobility effects for each type of traveller in the Delft network given the ultimate future mode attributes. This case study contributes to the literature by 1) implementing explicit transit lines in one layer and 2) successfully demonstrating how a supernetwork model can be used by policy-makers and mobility providers to improve mobility in an area or know which future mode should be developed and implemented. The found ultimate future mode in Delft is active, has the option to bring luggage and is not shared. The ultimate combination of mode attributes results in a reduction of the average travel time of up to 20% and a reduction of generalized travel time resistance of up to 4.7%.

It is concluded that the supernetwork model in this dissertation can be used to determine the ultimate future mode of a mobility system before it is available based on its attributes alone without the need for stated preference data on future modes. It is recommended to implement spillback and queuing in future versions. Furthermore, it is recommended to expand the supernetwork model with other mode attributes and add accessibility, liveability, land use and activities to further the understanding of how future modes change urban areas and which future mode can most effectively improve the accessibility and livability of urban areas.

Samenvatting

De bereikbaarheid en leefbaarheid van stedelijke gebieden staan onder druk. Om deze druk te verminderen zijn er de afgelopen decennia talloze vervoerswijzen ontwikkeld, zoals deelfietsen, deelscooters, geautomatiseerde auto's, taxidiensten, elektrische fietsen en andere persoonlijke, lichte elektrische voertuigen. Het gebruik van dergelijke toekomstige vervoerswijzen zou de manier kunnen veranderen waarop onze stedelijke gebieden functioneren en er uitzien met betrekking tot ruimtelijk gebruik, duurzaamheid, gezondheid, gelijkheid, veiligheid en economische kansen. Het analyseren van hoe vervoerswijze- en routekeuzegedrag zou kunnen veranderen wanneer toekomstige vervoerswijzen beschikbaar zijn is een uitdaging, omdat potentiële gebruikers nog niet bekend zijn met dergelijke systemen. Hierdoor zijn huidige keuzemodellen met vervoerswijze-specifieke constanten en parameters niet geschikt. Bovendien is het een uitdaging om te weten welke vervoerskarakteristieken in een toekomstige vervoerswijze moeten worden geïmplementeerd om de reisweerstand (die reizigers ondervinden) van het vervoersnetwerk te minimaliseren. Dit brengt ons bij de hoofdonderzoeksvraag: hoe kan de ultieme toekomstige vervoerswijze van een mobiliteitssysteem worden bepaald voordat deze beschikbaar is?

Dit proefschrift beantwoordt deze vraag in drie stappen. Ten eerste door een ongelabelde modelleringsaanpak te ontwikkelen in een discreet keuzemodel om de modal split van unimodale reizen van toekomstige vervoerswijzen te schatten zonder vervoerswijze-specifieke constanten en parameters. Ten tweede door een nieuw supernetwerkmodel te ontwikkelen dat de ongelabelde vervoerswijze-modellering toepast om gelijktijdige route- en intermodale vervoerswijzekeuze te modelleren. Deze aanpak geeft inzicht in hoe toekomstige vervoerswijzen de vervoerswijze en routekeuze kunnen veranderen en als gevolg daarvan de reisweerstand kunnen beïnvloeden. In beide stappen worden gedeelde autonome auto's en elektrische steps als voorbeeldvervoerswijzen gebruikt. Verder wordt de supernetwerkaanpak gebruikt om de invloed van elektrische deelfietsen op de modal split tussen Delft en Rotterdam te berekenen. Ten slotte wordt, in de derde en laatste stap, de supernetwerkaanpak gebruikt om de ultieme toekomstige vervoerswijze-attributen in Delft te vinden door de netwerkweerstand te minimaliseren, waarmee de hoofdonderzoeksvraag wordt beantwoord.

Dit proefschrift onderzoekt met succes de ongelabelde modelleringsaanpak in een discreet keuzemodel en de supernetwerkaanpak voor het berekenen van de vervoerswijze-en routekeuze en daarmee de modal split en verandering in reisweerstand voor uni- en multimodale reizen van elke toekomstige vervoerswijze in een toekomstige situatie. De belangrijkste bijdrage van deze aanpak aan de literatuur is de implementatie van een ongelabelde modelleringsaanpak waarbij gebruik wordt gemaakt van onthulde voorkeursgegevens om de modal split van toekomstige vervoerswijzen te schatten, in plaats van gebruik te moeten maken van verklaarde voorkeursgegevens en bestaande vervoerswijzen te analyseren voor zowel unimodale als multimodale reizen.

De potentiële modal split van elke toekomstige vervoerswijze kan worden geschat met behulp van een discreet keuzemodel met gebruik van de ongelabelde vervoerswijze-modelleringsbenadering waarbij alternatieve specifieke constanten en parameters (ASC's) worden uitgesloten van de nutsfunctie. Een voorwaarde om dit te kunnen doen is dat elke vervoerswijze beschreven moet worden met behulp van een set attributen waaruit de respectievelijke voorkeuren kunnen worden afgeleid uit empirische data (onthulde voorkeursgegevens). Impliciete (of verborgen) vervoerswijze-attributen in een ASC kunnen expliciet worden gemaakt door een volledige set vervoerswijze-attributen te definiëren, zodat alle vervoerswijze-attributen die het vervoerswijze-keuzegedrag beschrijven expliciet worden gemaakt en ASC's zodanig overbodig worden. Op deze manier kan de modal split van elke toekomstige vervoerswijze worden geschat met behulp van empirische data met een discreet keuzemodel, aangezien er geen ASC's nodig zijn. De volgende attributen zijn opgenomen in de nutsfunctie die bestaande en toekomstige vervoerswijzen beschrijven: Kosten (€); Reistijd (min); Rijtaak (-); Vaardigheden (-) (d.w.z. rijbewijs); Bescherming tegen weersinvloeden (d.w.z. dak) (-); Bagage (-); Gedeeld (eigendom of ruimte) (-); Beschikbaarheid (-); Reservering (-); Actief (-); Toegankelijk (-). De prestaties van deze ongelabelde aanpak zijn vergelijkbaar met de aanpak met een ASC, met een rho-kwadraat van 0,828 en 0,823 voor respectievelijk de ongelabelde vervoerswijze modelleringsaanpak en de aanpak met een ASC.

Houd er rekening mee dat de aanpak enkele beperkingen met zich meebrengt. Ten eerste moet het mogelijk zijn om een toekomstige vervoerswijze te beschrijven in termen van parameters waarvan de huidige voorkeuren bekend zijn. Ten tweede kunnen relevante vervoerswijzekenmerken in de toekomst veranderen, omdat nieuwe andere kenmerken dominant kunnen worden in het besluitvormingsproces van reizigers. De aanpak die in dit proefschrift wordt gepresenteerd kan deze mogelijke verandering in dominante attributen niet vastleggen, aangezien de kalibratie van de keuzeparameters wordt gedaan op basis van een onthulde voorkeursgegevens met de huidige dominante vervoerswijze-attributen.

Bij het voorspellen van de modal split van een toekomstige vervoerswijze met behulp van een multinomiaal logitmodel kan het zijn dat er een overschatting van de toekomstige modal split optreedt als gevolg van de gedeeltelijke overeenkomsten tussen verschillende vervoerswijzen. Om de overschatting te verminderen, heeft dit onderzoek een genest logitmodel geïmplementeerd. Het geneste logitmodel werd bewerkstelligd door de toekomstige vervoerswijze te nesten in een nest met de meest vergelijkbare bestaande vervoerswijze. De modal splits waarbij gebruik wordt gemaakt van twee van dezelfde huidige vervoerswijzen in een multinomiaal logitmodel (waarbij het modale aandeel wordt gesimuleerd wanneer de red/blue bus-paradox optreedt) werd vergeleken met de modale splitsing van de multinomiale logit en de modal split van het geneste logitmodel voor twee vervoerswijzen: autonome voertuigen en elektrische steps. Er werd waargenomen dat de overschatting inderdaad minder groot is wanneer een genest logitmodel wordt gebruikt in vergelijking met het multinomiaal logitmodel. Daarom werd geconcludeerd dat een genest logitmodel beter geschikt is voor het schatten van de potentiële modal split van een toekomstige vervoerswijze dan een multinomiaal logitmodel.

De ongelabelde modelleringsaanpak in een discreet keuzemodel kan de effecten van toekomstige vervoerswijzen op unimodale reizen schatten. Om multimodale reizen en andere mobiliteitseffecten, naast de modal split, zoals een verandering in reistijden en verandering in reisweerstand als functie van het gebruik (intensiteit) van het netwerk, van toekomstige vervoerswijzen te analyseren wordt de ongelabelde modelleringsaanpak uitgebreid met een verkeerstoewijzingsnetwerk dat gebruik maakt van een supernetwerk met één laag/subnetwerk per vervoerswijze.

Om onderzoekers in staat te stellen automatisch alle unimodale en multimodale opties mee te nemen in de analyse zonder de noodzaak om vooraf keuzesets voor vervoerswijze en route te definiëren, is het supernetwerkmodel gedefinieerd als een netwerk waarin elke beschikbare vervoerswijze wordt gedefinieerd als een specifieke laag met knooppunten en lijnen, waar de weerstanden van de lijnen zijn beschreven door een set attributen zonder een alternatief-specifieke constante en afhankelijk zijn van het gebruik ervan (dat wil zeggen dat de reistijd afhankelijk is van de dichtheid van de reizigers op de lijn). Om het in- en uitstappen van vervoerswijzen expliciet te modelleren, maakt het supernetwerkmodel gebruik van een zogenaamde neutrale laag. De neutrale laag is verbonden met alle vervoerswijze-specifieke lagen, waarbij lijnen de overdrachtsweerstanden (in- en uitstappen) vertegenwoordigen, ook beschreven met een reeks attributen.

De belangrijkste bijdragen van de ontwikkeling van het supernetwerkmodel aan de literatuur zijn 1) de implementatie van een ongelabeld keuzemodel in een supernetwerkmodel dat de analyse van multimodale reizen mogelijk maakt, 2) de implementatie van een nieuwe kortste-routefunctie die de vervoerswijze- en routekeuze voor elke reis bepaalt voor elke reiziger in een simulatie die lengte-afhankelijke (bijv. kosten, snelheid) en lengte-onafhankelijke (bijv. actief, bagage) vervoerswijze-attributen combineert, en 3) het gebruik van een zogenaamde neutrale laag in het supernetwerk om automatisch alle vervoerswijze- en routekeuzecombinaties voor multimodale reizen, inclusief de inspanning om bij een vervoerswijze in en uit te stappen.

Deze aanpak is met succes geverifieerd met drie kleine maar goed illustrerende netwerkconfiguraties en het Sioux Falls-testnetwerk dat de beschikbaarheid nabootst van gedeelde autonome auto's en elektrische scooters naast de huidige vervoerswijzen: auto, carpool, openbaar vervoer, fiets en lopen. Ook is de supernetwerkbenadering met succes toegepast om het effect van gedeelde elektrische fietsen op de modal split op een OD-paar tussen Delft en Rotterdam te beoordelen.

Het supernetwerkmodel wordt toegepast om de belangrijkste onderzoeksvraag te beantwoorden: vindt de ultieme toekomstige vervoerswijze in Delft op basis van uitsluitend de kenmerken ervan, zonder vervoerswijze-specifieke constanten en parameters. De ultieme toekomstige vervoerswijze kan worden gevonden door de attributen van de toekomstige vervoerswijze te optimaliseren, zodat een verbetering in de totale reisweerstand van het transportnetwerk kan worden waargenomen. Dit wordt gedaan door, ten eerste, door alle vervoerswijze-attributen heen te enumereren, behalve kosten en reistijd, en de toekomstige vervoerswijze-attributencombinatie te vinden die de toekomstige totale reisweerstand minimaliseert en, ten tweede, deze toekomstige vervoerswijze-attributencombinatie te simuleren, inclusief kosten en reistijd, waardoor de weerstand van het netwerk zoveel mogelijk wordt verminderd binnen praktisch haalbare reistijden en kosten. We analyseren de mobiliteitseffecten voor elk type reiziger in het Delftse netwerk, gegeven kenmerken van de ultieme toekomstige vervoerswijze. Deze casestudy draagt bij aan de literatuur door 1) expliciete OV-lijnen in één laag te implementeren en 2) met succes aan te tonen hoe een supernetwerkmodel door beleidsmakers en mobiliteitsaanbieders kan worden gebruikt om de mobiliteit in een gebied te verbeteren of te weten welke toekomstige vervoerswijze moet worden ontwikkeld en geïmplementeerd. De gevonden ultieme toekomstige vervoerswijze in Delft is actief, heeft de mogelijkheid om bagage mee te nemen en wordt niet gedeeld. De ultieme combinatie van vervoerswijze-attributen resulteert in een reductie van de gemiddelde reistijd tot 20% en een reductie van de algemene reisweerstand tot 4,7%.

Er wordt geconcludeerd dat het supernetwerkmodel in dit proefschrift kan worden gebruikt om de uiteindelijke toekomstige vervoerswijze van een mobiliteitssysteem te bepalen voordat het beschikbaar is, op basis van enkel de attributen, zonder de noodzaak van verklaarde voorkeursgegevens over toekomstige vervoerswijzen. Het wordt aanbevolen om spillback en queueing in toekomstige versies te implementeren. Bovendien wordt aanbevolen om het supernetwerkmodel uit te breiden met andere vervoerswijze-attributen en toegankelijkheid, leefbaarheid, landgebruik en activiteiten toe te voegen om het inzicht te vergroten in hoe toekomstige vervoerswijzen stedelijke gebieden veranderen en welke toekomstige vervoerswijzen de toegankelijkheid en leefbaarheid van stedelijke gebieden het meest effectief kunnen verbeteren.

About the author

Koen de Clercq was born in The Hague, the Netherlands on October 8th, 1992. He finished high school (gymnasium) in 2011 at the Stedelijk Dalton College in Zutphen, the Netherlands. After this, he pursued a mechanical engineering degree at Delft University of Technology. He joined the Honours Bachelor Programme and went for an exchange year at Chalmers University of Technology in Gothenburg, Sweden in 2014 for one year, where he followed courses on sustainability, robotics, and process management. After finishing his exchange programme, he went back to Delft to do his master's degree within mechanical engineering with a specialisation in BioRobotics. His master thesis was about the effects on pedestrian crossing decisions of external human-machine interfaces on automated vehicles, performed in collaboration with the Technical University of Munich in Germany and is published in Human Factors.

After obtaining his master's degree, he worked in a consultancy and an engineering firm for two years, developing CRM-applications for several organisations and performing dynamic calculations on the transport of monopiles (foundations) of offshore windmills. He decided to pursue a PhD after working in industry for two years. Following his interest in transportation, he started his PhD in 2020 on the mobility effects of future modes at the Transport and Planning department at Delft University of Technology, funded by NWO as part of the SUMMALab project (under Grant 439.18.460 B). He researched how future modes could influence mobility effects, such as modal split, travel times and resistance. He did this by developing an unlabelled mode choice model and a supernetwork model using revealed preference data to estimate the modal split of future modes.

Koen is interested in a wide range of topics from robotics and transportation to sustainability and economics. In the future, he will direct his career towards sustainability using his knowledge and skills of engineering, conducting research, and transportation.

Publications

Journal papers

1. **de Clercq, G. K.**, A. van Binsbergen, B. van Arem, M. Snelder (2022) Estimating the Potential Modal Split of Any Future Mode Using Revealed Preference Data, *Journal of Advanced Transportation*, 2022.

Under review

1. **de Clercq, G. K.**, A. van Binsbergen, B. van Arem, M. Snelder (2024) Assessing the Mobility Effects of Any Future Mode Using an Unlabelled Choice Model in an Agent-Based Multimodal Supernetwork.

2. **de Clercq, G. K.**, A. van Binsbergen, B. van Arem, M. Snelder (2024) Demonstrating how a multimodal traffic assignment model can be used to find the ultimate future mode in Delft.

Conference contributions

1. **de Clercq, G. K.**, M. Snelder, A. van Binsbergen, B. van Arem (2023) Analysing the Effects of Adding Shared Electric Bicycles as a New Mode on the Modal Split of Multimodal Trips between Delft and Rotterdam Using an Unlabelled Multimodal Supernetwork, in: *Proceedings of 11th symposium of the European Association for Research in Transportation*, Zürich.

2. Snelder, M., M. 't Hoen, **G.K. de Clercq** (2023) Automatisch rijden in de Welvaart en Leefomgeving Scenario's voor 2040 en 2060, in: *Proceedings of Colloquium Vervoersplanologisch Speurwerk*, Brussels.

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