# Is Telecommuting Our New Mode of Transportation?

## A System Dynamic Approach Into The Mobility Impacts Of COVID-19

## MSc. Thesis Transport, Infrastructure & Logistics

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MOBILITEIT BEWEEGT ONS

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## A System Dynamic Approach Into The Mobility Impacts Of COVID-19

by

T.G. van Tol

in partial fulfilment of the requirements for the degree of
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# Preface

This thesis in front of you marks the end of my study at the Delft University of Technology. Several years ago, when I started as a Technology, Policy and Management student, I certainly did not expect that I would be graduating as a civil engineer.

This thesis is the result of the research I have conducted over the past 8 months towards the mobility impacts of the COVID-19 pandemic. The subject of COVID and mobility was of specific interest to me, as my master's degree almost entirely took place during the pandemic. During this time, I was familiarised with the aspects of studying from home myself and not being able to go to the campus for more than a year.

Throughout this project, I was able to learn a lot and develop my research and modelling skills. I would like to express my gratitude to a few who helped me during this thesis.

First, I would like to thank Martijn Legêne for introducing me to this thesis subject and Goudappel. I am also grateful for your guidance throughout this project that helped me through the challenges I encountered along the way. You were always available to answer any questions I had and provided me with direction when I lost the overview.

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My gratitude also goes to Goudappel for providing me with this opportunity and the people I met during my internship. I would like to thank several of my colleagues for their support and for helping me achieve this final result.

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*T.G. van Tol*
*Rotterdam, October 2022*

# Executive summary

## Introduction

The COVID-19 outbreak has affected various aspects of people's daily lives. It has caused people to adapt their overall behaviour including their travel moments. As a result, activity patterns have changed and a shift in travel behaviour can be perceived. Whether these abrupt changes will have a continual effect on our travel behaviour is still uncertain. Therefore the following research question was formulated:

*What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?*

Exploratory modelling of the future mobility impacts presents a first look at the potential magnitude and direction of the impacts of the pandemic in the long term. The objective is to explore the mobility impacts in the near and distant future on a macroscopic level. Our mobility system is a complex system which consists of feedback between our destination choice, route choice and mode choice that influence our travel behaviour. System Dynamics (SD) can provide an understanding of the dynamic complexity of such systems. Moreover, system dynamics enables the exploration of this system's behaviour under changing input uncertainties. By means of this, the uncommon combination emerged of transport modelling in a system dynamic environment.

## Model

This research developed a system dynamics model to explore the mobility impacts of COVID. The 4-step model is used as a guideline for the structure of the model. The four steps consist of (i) trip generation, (ii) trip distribution, (iii) mode choice and (iv) route assignment. As previous studies suggest potential effects within the mode attractiveness, the focus is on the mode choice. Implementing a choice model in the system dynamics model enables the exploration of change in travellers' choices and, thus, travel behaviour after the pandemic. The other phases in the 4-step model are included to ensure the SD model's complete transport modelling structure. Trip generation provides an input of trips and is combined with the trip distribution. The assignment is subsequently simplified because detailed route assignment can be problematic in a system dynamics environment.

Furthermore, the model consists of sub-components that simulate (behavioural) changes such as fewer trips due to COVID, different attitudes towards modes of transport, and remote working. These factors were identified throughout prior COVID research and the literature. In the model, there is a distinction made in trip types to observe mobility impacts at a detailed level. The implementation of different trip types is performed by the vectorisation of variables for trip purposes, distance classes and area types. In other words, a copy of the model structure is created to enable the exploration of detailed travel behaviour alongside general nationwide travel behaviour. In this research, the model outcomes of interest are primarily *modal split* and *number of trips*. Finally, the effect of remote working is implemented by introducing a new alternative to the mode choice. The addition of a tele-activity alternative, in other words, an option to not travel at all, enhances the dynamic aspect of remote working. It provides insight into the attractiveness of remote working under changing input conditions.

## Results

The COVID-19 pandemic undoubtedly has an impact on mobility in the Netherlands. The impact of remote working is visible in all cases. The number of telecommuting trips in the near future decreases from the maximum level during the pandemic and reaches a stable state in the distant future. The stable state that the number of telecommuters reaches, remains at an increased level compared to pre-pandemic telecommute behaviour. The increase in people working remote leads to a decrease in the use of primarily public transportation (PT). In a post-COVID-19 era, the pandemic has directed some public transport travellers towards other alternatives; the car, telecommuting and cycling. With the design of extreme scenarios, the attitude train travellers have regarding public transport was discovered as a substantial effect in the forthcoming years. Substantiated by scenario discovery, the attitude towards public transport needs to improve to reach pre-pandemic levels of PT attractiveness. The development of travellers' positive attitudes towards public transport strongly influences the recovery time. If the improvement in positive attitude is not stimulated, recovery to the initial pre-pandemic prognosis of public transport is significantly delayed. Furthermore, it was shown that the attractiveness of working from home increases again in the future if the variable cost of driving a private car continues to rise. This demonstrates the dynamic aspect and the subsequent benefit of including working from home as an alternative.

## Conclusion and discussion

The general attitude of travellers regarding public transport faced a setback, which is concerning. The focus within mobility over the past years has been to establish a positive modal shift to push travellers from private to public modes. The impacts of the COVID pandemic resulted in a setback. In order to stimulate travellers, policy interventions such as lower ticket prices and increased supply can be implemented to raise the attractiveness of public transport. Nonetheless, to improve travellers' willingness to use public transport, thus improving their positive attitude, the general image of public transport services should be stimulated. A combination of interventions is required to improve the general image of public transport services. The implementation and simulation of policy in the developed model are outside the scope of this thesis, nevertheless highly recommended for future research. In addition, attention should be paid to the implementation of measures or guidance in the system to prevent potential opposing effects. The results indicated that conflict emerges between stimulating remote working and stimulating public transport. The inclusion of telecommuting as a contending alternative in the mode choice of travellers illustrated telecommuting travel behaviour over time. The novelty of modelling telecommuting as a new alternative results in a simplification regarding travellers' motives to work from home. Future research can expand the knowledge of the motives for working from home.

To conclude this thesis contributed to prior scientific work and society in two ways. First, the research on the future effects of the COVID-19 pandemic was extended. This thesis identified *new relations between COVID-19 mobility impacts (i)* by emphasising the conflict that arises between stimulating telecommuting and public transport. Furthermore, *Specified the impact of uncertainties in the system (ii)* by addressing the importance of public transport attitude not only during the pandemic but also in the forthcoming years. At last, *delivered new insights by providing additional explanations for known effects (iii)*, using the behaviour of telecommuting throughout the years, in addition to the estimates in the literature.

Second, the approach chosen in this thesis differentiates itself from other transport modelling approaches by studying mobility disruptions in an explorative way. The developed SD model and its application to the case study of COVID illustrated that the behaviour of mobility impacts over time could be observed with system dynamics modelling. This is not achievable with traditional mobility models due to their microscopic focus and inability to adjust input parameters quickly. The need for alternative approaches and methods towards observing travel behaviour is required due to the changing demand for transportation in the coming years. The consequences of COVID, the mobility transition and smart mobility are examples of how our demand for transport and our mobility system will change.

# Contents

# List of abbreviations

| Abbreviation | Definition |
|---|---|
| BTM | Bus, Tram, Metro |
| CBS | Centraal Bureau voor de Statistiek |
| CLD | Causal Loop Diagram |
| COVID-19 | Novel Coronavirus (SARS-CoV-2) |
| CPB | Centraal Planbureau |
| DCM | Discrete Choice Model |
| EMA | Exploratory Modelling Approach |
| EV | Electric Vehicles |
| ICE | Internal Combustion Engine |
| KiM | Kennisinstituut voor Mobiliteitsbeleid |
| KPI | Key Performance Indicator |
| LMS | Landelijk Model Systeem |
| LUTI | Land- use/Transport Interaction |
| MNL | Multinomial logit |
| MPN | Mobiliteitspanel Nederland |
| NVP | Nederlands verplaatsingspanel |
| ODiN | Onderweg in Nederland |
| PBL | Planbureau voor de Leefomgeving |
| PRIM | Patient Rule Induction Method |
| PT | Public Transport |
| RUM | Random Utility Maximisation |
| SD | System Dynamics |
| SFD | Stock Flow Diagram |
| SSD | Sub System Diagram |
| WLO | Welvaart en Leefomgeving |

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# 1
# Introduction

## 1.1. Background & Research Context

COVID-19 has significantly impacted people's lives, activities and travel behaviour. On average a person in the Netherlands makes 2,9 trips per day (MuConsult, 2021). In March 2020 the number of trips reduced with 55% (De Haas et al., 2020b). As a result, empty highways and an unforeseen positive solution for the rising congestion problems were witnessed. In public transportation, a decrease in travellers of 90% was seen, leading to a drop in transit demand (Translink, 2022; CBS, 2021). At the time of writing (2022), the end of the 5th COVID wave in the Netherlands is considered to mark the end of a COVID era (RIVM, 2022; Murray, 2022). In a post-COVID era, expectations towards the future impacts in transport and mobility can be formed (MuConsult, 2021). The changes in our travel behaviour can result in potential lasting effects (Van Wee and Witlox, 2021). A lot of travel preferences change back to old travel patterns. Nonetheless, the mobility disruptions might have changed parts of our travel behaviour. It is uncertain what the future impacts regarding, for example, the recovery of public transport (Tirachini and Cats, 2020) and the future effect of remote working (Hamersma et al., 2021) will entail.

The changing circumstances result in an unexpected discontinuity of past travel trends and mobility behaviour (Chatterjee et al., 2021). These trend breaks contribute to the already increasing uncertainty in the future of travel demand (Marchau et al., 2010). COVID has created a new layer of uncertainty on the current existing levels of uncertainty (Papakatsikas et al., 2021). Moreover, it is unknown how long future disruptions and trend breaks will last.

Uncertainty in the transport sector is a phenomenon that has occurred to an increasing extent over the past years (Chatterjee et al., 2021). COVID is not the only factor that caused the increasing presence of uncertainty. The rise of changes in travel behaviour and activity patterns is not entirely new. For instance, changes in the work environment pre-COVID, an increase in flexible working and companies that switched to a permanent hybrid or remote work environment (Andreev et al., 2010). Moreover, other substantial changes in oil and gas prices have resulted in travel mode shifts (Van Cranenburgh et al., 2012). According to Frondel and Vance (2008), the fuel-price elasticity of households and individuals ranged between 35% and 41% during the oil crisis in 2008. As a result, the influence of COVID and other developments contribute to our mobility system's uncertainty and enhance the system's complexity.

**Research problem**

To prepare for the future, policymakers must know which changes in passenger mobility could happen. If new developments or trends are observed too late, the effects could lead to undesirable situations in the transport system. In the literature, various assumptions are made about future COVID travel transitions and their subsequent effect on mobility. The role of uncertainty is, therefore, vital. Data and predictions of pandemic mobility changes are highly valuable as input for policy-making (Van der Drift et al., 2021).

The long-term impact on mobility and the general uncertainties compose a risk for the existing predictions and their accuracy. Current traditional transport models have difficulties implementing uncertainties such as COVID-19 (MuConsult, 2021). These models lack the exploratory nature to cope with quickly arising events and changes. A new approach is required to explore the long-term impacts of COVID-19, which is more suitable for quantifying the potential effects of rapid emerging transitions in mobility. Moreover, the development of the impacts over time is of interest. This enables the observation of the complete dynamics of coherent mobility impacts in the complex system. For these reasons, this requires a research method that can observe and simulate the mobility consequences of the pandemic and its dynamics on a macroscopic level. Thus, a mathematical modelling method that uses causal relations between variables to enable quantitative exploration of system behaviour.

The pandemic creates opportunities to steer travel behaviour in the desired direction. Several future policy interventions use the impact of COVID to positive influence transitions (De Winter et al., 2021). Specifically, the Dutch government is interested in taking this opportunity to direct travel behaviour, in specific mode choice, in the desired direction (Olde Kalter, 2022). In addition, the pandemic can provide opportunities for a faster rise of sustainable mobility (Kanda and Kivimaa, 2020; Griffiths et al., 2021). However, the future impact of mobility should be explored to achieve all of the mentioned above. Producing meaningful results implies using qualitative research to observe the direction of impacts. As well as quantitative research to translate direction into measurable outcomes under various uncertainties.

**Research questions**

To achieve the research objective and identify the mobility impact of COVID-19, the following main research question is proposed:

> ***What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?***

To support the main research question, the following sub-questions are designed. Likewise, these sub-questions guide the further structure of this research.

To observe the future impact of COVID-19 within the mobility sector, exploring the current knowledge regarding travel behaviour before and during COVID-19 is of added value. The use of existing knowledge and research into the (future) effect of the pandemic on travellers' behaviour and patterns supports the scientific strength of this research. Subsequently, it reduces the workload by focusing on the scoped set of mobility and COVID-19 elements. This results in the first sub-question:

*1: What are the current known developments/trends in mobility resulting from COVID-19?*

Translating the uncertainties of COVID-19 into measurable variables requires a quantitative approach. An exploratory research approach is proposed, to explain the mobility impacts and observe the behaviour that causes the impacts. To define why this is a suitable approach and to elaborate on the best techniques within an exploratory approach, the following sub-question is composed:

*2: How can the mobility impact of COVID-19 be quantified and explained?*

To determine the impact of the pandemic on mobility, the mobility system must be defined and delimited first. By defining the scope of the mobility system and the scope of COVID-19, a system representation can be represented in the form of a model. Qualitative modelling results in the first outline of the impacts on the mobility system. Hence the following sub-question is defined:

*3: How can the uncertainties originating from the pandemic be implemented and modelled?*

The qualitative conceptual model can be translated into a quantitative model. A simulation model is developed by formulating the qualitative model, describing the system's behaviour, as defined in sub-question 3. Moreover, this presents a model that can determine the mobility impacts on specific key performance indicators (KPIs) under certain input values. The sub-question below is composed to answer this.

*4: What are the quantified mobility impacts of COVID-19?*

Finally, due to the high degree of uncertainty, exploratory modelling analysis can be used to observe and analyse the outcomes under various conditions and scenarios. The alteration of input values creates multiple future post-pandemic scenarios, to explore alternative future directions. This way, the research is substantiated more, and the main research objective can be achieved. This leads to the last sub-question:

*5: What is the role of uncertainty in the future impact of COVID-19 on mobility?*

## 1.2. Theoretical framework and methodology

This section introduces a theoretical framework to establish a scientific perspective. Furthermore, the alternative research approach and methodology are described.

### Uncertainty

In transport and mobility planning, the goal is to cope with the presence of uncertainty. To produce accurate predictions regarding travel behaviour and transport planning, uncertainty needs to be accounted for (Marchau et al., 2010). Because uncertainty is not merely the lack of knowledge; uncertainty needs to be defined. The general definition of uncertainty by Walker et al. (2003) is "*Any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system.*" This can be either due to the absence of knowledge or variability inherent to the system under consideration. In the case of the COVID pandemic, a substantial change (Van Cranenburgh et al., 2012) is the cause for uncertainty and subsequent change to the transport system as a consequence.

The transport policy-making process has several aspects where uncertainty can arise. Different elements affect the policy-making process within the framework of model-based policy analysis (Walker, 2000). Uncertainty can often arise through external factors or forces. Besides the more evident external forces, such as changes in demography, economy and technology (Marchau et al., 2010), COVID can be seen as a new external force. According to Papakatsikas et al. (2021), transportation planning in the short- and mid-term future must cope with an added layer of uncertainty as a result of COVID.

Uncertainty is currently dealt with in various ways concerning predictions for the future of passenger mobility. On an overall level, the use of *Welvaart en Leefomgeving* (WLO) scenarios is a common future exploration tool which is used for high and low scenarios in mobility forecast/ transport planning (Snellen et al., 2015). The general WLO scenarios are updated once in 5 years. However, for the mobility scenarios, the WLO scenarios are updated annually due to their implementation in, among others, Cost-benefit analyses and the *Landelijk Model Systeem (LMS)* (Renes and Romijn, 2015). This yearly update of the WLO scenarios results in accurate predictions for the near future. The distant future remains difficult to predict due to the unknown uncertainties.

Nevertheless, sudden changes cause additional uncertainty, which is not accounted for in future exploration, such as WLO scenarios. Marchau et al. (2010) stated, for example, that WLO scenarios for 2040 do not contain oil prices higher than the prices during the 2008 economic crisis. The authors argued that possible abrupt external forces could lead to scenarios that do not always reflect the actual situation accurately. In combination with the pandemic, Ritsema van Eck et al. argued in 2020 if the current WLO scenarios for 2030 and 2050 are sufficient to cope with the large-scale changes within the economy and living environment. The authors mentioned, in particular, the effect of mobility behaviour and their added uncertainty to the scenarios in place.

Current times are undeniably full of uncertainty and lack knowledge about the future of mobility. Where COVID-19 could be accountable for a potential lasting significant shift in passenger mobility. Together with the ongoing trends such as sustainable mobility and increasing car costs, the current circumstances provide an optimal opportunity to direct passenger mobility in the desired direction (De Graaf et al., 2020).

**Alternative transport modelling approach**

In transport modelling, there is often worked with the concept of predict and provide; predicting the future of transport based on extrapolating historical trends and providing the necessary supply. Because following earlier trends is not always the desired future situation, the concept of 'predict and provide' is no longer sufficient if the deviation from historical trends is the goal (Jones, 2016). With the current developments and transitions in mobility, travel behavioural changes and policies are more relevant than ever. Therefore, decision-making based on 'vision and validate', introduced by Jones (2016), is more suitable for the circumstances mentioned above. Where *vision* refers to outlining and planning what the future goal in mobility entails. *Validate* is putting that vision to the test, using exploration and experimental forecasting techniques (Frisby, 2021). On top of that, the COVID pandemic and associated travel disruption have abruptly ended several trends, which creates the opportunity to steer travel behaviour in the desired direction, creating an opportunity for vision and validate (Frisby, 2021).

Systems thinking connects with the process of vision and validate and the demand for an alternative research approach as identified in the research problem. The transportation system is a complex system according to Sussman et al. (2009) that, as indicated above, encounters several layers of uncertainty. System Dynamics (SD) enables the observation of the development of the impacts over time and the observation of complete dynamics of coherent mobility impacts in the system. SD is a mathematical modelling method that uses causal relations between variables to enable quantitative exploration of system behaviour. With an SD approach, an alternative research approach is chosen, resulting in a better fit for the research problem.

## 1.3. Thesis outline

The remainder of this thesis report is structured according to the research questions. Chapter 2 analyses the current mobility developments throughout the pandemic. Thereafter, Chapter 3 provides the reasoning for the applied methods. Chapter 4 is the model design chapter, where the developed model is explained, and the application of the model to the situation in the Netherlands is discussed. Subsequently, Chapter 5 presents the outcomes of the mobility effects and the role of uncertainty. Chapter 6 discusses the results, implications and recommendations. Finally, the conclusions are drawn in Chapter 7. All produced models, code and data can be found in the online repository on GitHub[1].

[1] https://github.com/ThomasvTol/MSc-Thesis.git

# 2

# COVID-19 developments in mobility

This chapter presents an overview of the known developments and trends in mobility due to the COVID pandemic. With the use of the literature, the scope is narrowed, and the current developments are structured. The different aspects of travel behaviour affected by the pandemic are outlined in Section 2.1. The effects are subsequently categorised in the attractiveness of modes (Section 2.2) and activity patterns (Section 2.3). In addition to scientific literature, this section is complemented with grey literature (technical reports by various research institutions) meant to fill the gaps and extend the situation in the Netherlands.

## 2.1. Travel behaviour

It is a known fact that travel behaviour changed due to the COVID-19 pandemic. Shortall et al. (2021) described various changes during the pandemic due to the lockdowns and measures. Research carried out by De Haas et al. (2020b) indicated that changes in travel behaviour also applied to the intelligent lockdown which was in place in the Netherlands. The fact that travel behaviour changes occurred during lockdowns is not surprising based on the general limitation of movements. The changes during COVID were, however, unanticipated.

Predictions towards the future of travel behaviour are not based on abrupt changes. Therefore, lasting changes in behaviour are more challenging and generally based on estimations. Nonetheless, several studies (Van Wee and Witlox, 2021; MuConsult, 2021; Hamersma et al., 2021) have indicated that the aspects of travel behaviour are subject to a degree of change. The level of change is yet to be determined.

To gain a better understanding of the changes in travel behaviour, a subdivision of the elements within travel behaviour is made. With this division, the effects are categorised, and the scope of the research is defined around travel behaviour elements impacted by COVID. The elements of travel behaviour taken into account in this research and hence subject to sizeable change are the latter four presented in Figure 2.1. Among these factors, COVID-19 can impact all four. Within **Change of departure time** COVID impacts the time of departure choice. With the introduction of remote working, the traditional 9-5 workweek is no longer self-evident (Hamersma et al., 2021). **Change of destination** affected by COVID is, among others, the choice to not travel at all. Due to COVID lockdowns or due to tele-activities (Taale et al., 2021). Remote working is also part of the change of destination. Working from home causes commuters to not travel to their work destination. For **Change of mode** a primary effect is the continuation of a potential mode shift trend caused by COVID (Van der Drift et al., 2021; De Vos, 2020). Finally, **Change of Route** are short-term changes in our travel behaviour that encounter little to no effect as a result of COVID.

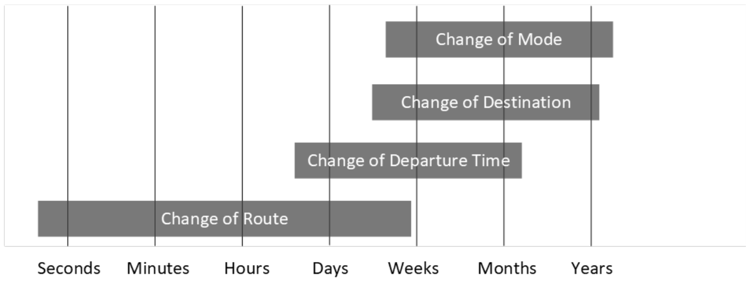



**Figure 2.1:** Response time to changed circumstances within travel behaviour (adapted from Brederode (2015))

## 2.2. Attractiveness of mode of transportation

It is shown that COVID-19 has changed the attractiveness of specific modes of transportation. They result in travellers choosing a different mode of transport to reach their destination. The attractiveness of a mode of transport is a measurement widely used in transport engineering and modelling. In the traditional 4-step model (Ortúzar and Willumsen, 1990; McNally, 2007) mode choice is the third step. The attractiveness of a specific mode is translated and quantified into a utility function within disaggregated transport models. To determine travellers' utility and, subsequently, their choice of a mode of transport, (Discrete) choice models (DCM) are used (Pel, 2018). The application of choice models can, under certain conditions also be utilised in aggregated models. When the attractiveness of a mode of transport changes, travellers' attitudes and preferences towards a particular mode adjust according and result in a mode shift (Olde Kalter, 2021). A mode shift is a phenomenon which is often desired by (transport) policymakers to push travellers from one mode to another (e.g. private car to public modes.)

### 2.2.1. Public transport decrease

A decrease in public transport is one of the main drivers causing a potential negative mode shift; travellers choose the car or (e-)bike instead of public transport. First of all, overall movements decreased as a result of COVID measures. Second, when travelling, people choose more often for a private mode of transportation; this could be either bike, car or walking (Van Wee, 2020; De Haas et al., 2020a). This shift was due to people limiting their moments of contact; the effect was especially discernible during the first lockdowns. Public transport ridership decreased significantly, leading to empty vehicles (Gkiotsalitis and Cats, 2020). The change in modalities results in a model split where Bus/Tram/Metro (BTM) and train are less represented. According to a study from the Dutch *Kennisinstituut voor Mobiliteitsbeleid* (KiM), travellers rate public transport more negative compared to the situation before COVID-19 (De Haas et al., 2020a). This is an understandable effect during a pandemic where people try limiting their contact moments. However, future exploration of CROW regarding the long-term effects concluded that in some scenarios, the train, bus, tram and metro are permanently less attractive for travellers. This is mainly due to sunk investment cost in other alternatives, the changing of modes is perceived as positive or avoiding crowding (CROW, 2021a).

According to Gkiotsalitis and Cats (2020), the future impacts are hard to estimate; the behavioural responses and adaptation of passengers is the main incentive in the recovery of PT. In Shelat et al. (2021), the effect of crowdedness on train use is studied. Where a *Value of Crowdedness* is determined to capture the degree of acceptable crowdedness for travellers during and after COVID-19, this study is a working paper, hence the yet unknown outcome on travel behaviour. In recent research, De Haas and Faber (2022) evaluated the relationship between the attitude of PT users and their travel behaviour. De Haas and Faber (2022) measured the changes in attitude using survey data from *Mobiliteitspanel Nederland* (MPN). The observation of attitudes before and during COVID-19 provides estimates for attitudes and travel behaviour of PT travellers in a post-COVID era.

Currently, in 2022, a post-COVID era has started where the first lasting effects can be observed. In February of 2022, the *National Traveller Survey* (Dutch: *Landelijk Reizigersonderzoek*) demonstrated that PT ridership level is still around half of the passenger number in 2021, compared to 2019 (Taale, 2022). One of the highlights is also the differences between regional and national outcomes of the National Traveller Survey (MuConsult, 2022). Specific outcomes are still limited; it is suggested that recovery of PT in highly urban areas is seen faster.

Finally, besides public transport over land, the passenger aviation industry experienced a massive trend disruption. During the pandemic, the number of travellers decreased to extremely low levels. Nonetheless, the aviation industry is on the rise again, and passenger numbers are expected to be back at the pre-pandemic level around 2025 (Bakker and Moorman, 2021). However, aviation is outside the scope of this research due to the focus being on mobility and trips within the Netherlands.

### 2.2.2. Increase of private modes

*Car use and Car ownership*
A direct cohesive cause of the decrease in public transport use is the increased use of other modes. Travellers have switched from public modes of transport, mainly train, to private modes such as the car. In particular, increased car ownership could be dangerous for future public transport recovery (CROW, 2022c). Travellers who purchased a car during COVID will likely use that mode of transport for at least a few years into the aftermath of the pandemic. Which results in more private car users. According to Dicke-Ogenia (2022) private cars nowadays are almost similar to an investment. Cars currently have good value preservation, and the supply of new vehicles is low. The rapid increase in car ownership during and after COVID is endorsed by results from the national traveller survey, which stated that especially the number of leases and company vehicles increased (MuConsult, 2022). This effect could be due to attitude changes; employees choose the option of a lease car instead of a public transit membership. A different cause for increased car users could occur through travellers already possessing a private vehicle. The shift of these travellers can also lead to long-term effects; for example, people rediscover the benefits of private transport and are less likely to shift back to public transportation (De Haas and Faber, 2022).

*Individual shared modes*
With fewer users on buses, trams, metro and trains, there is a share of PT users that shifts to shared mobility. Mainly a change to individual shared mobility modes is present (De Vos, 2020). Individual shared modes of transportation are shared bicycles, e-mopeds, e-scooters, and cars. The magnitude of these effects is relatively unknown and is currently not expected to have a significant future impact. The Ministry of I & W endorses the rise of specific shared e-mopeds in the Netherlands (MuConsult, 2022). In addition, it is argued that increased shared mobility often comes at the expense of public transit ridership. However, there is not yet accurate quantitative research to support this claim.

*Active modes*
Besides the car, cycling is seen as a serious alternative mode of transport for PT travel. A Dutch study found with the use of data from *Nederlands Verplaatsingspanel* (NVP) an increase in cycling both during peak and off-peak hours (Van der Drift et al., 2021). Besides more leisure travel by (e-)bike, the (e-)bike is seen as a serious commuter mode of transport. The increase in (e-)bike use is a development not only seen in a cycling country such as the Netherlands. A study based on GPS data by Molloy et al. (2021) also mentioned the importance of the rise of bicycle users in Switzerland and the potential lasting effect. The attractiveness of walking also increased due to the pandemic, where recreational travel took a lift De Vos, 2020. The phenomenon of going for a stroll (dutch: een blokje om gaan) as a leisurely walk took a whole new turn during COVID-19.

## 2.3. Activity patterns

Second, activity patterns have changed immensely in general. Due to social distancing, activity participation has reduced substantially (De Vos, 2020). Moreover, the intelligent lockdown imposed by the Dutch government was mainly aimed at limiting the interactions, hence reducing movements, in general (De Haas et al., 2020b). One of the major consequences of the COVID-19 measures is the shift from onsite to online activities. This shift has a significant impact, specifically on commuter and educational travel. According to a study from Hamersma et al. (2021), commuter and educational travel could expect structural changes because of the lasting effect of working from home. These possible long-term effects of teleworking are endorsed by Van Wee and Witlox (2021), who, among other things, mention the importance of online tools and people becoming aware of those tools. Besides tele-activities, multiple other effects cause changes in activity patterns and activity behaviour. The degree of leisure travel increases, for example (De Vos, 2020). People spend more time on leisure activities when other trips are reduced. Something which can be explained by the concept of constant travel time budget (Mokhtarian and Chen, 2004; Mouratidis and Peters, 2022). However, this does not hold when all movements are restricted. The concept of constant travel time budget is likely to contribute, among other things, to the fact that the impact on future combined travel time is presumably limited (Van Wee and Witlox, 2021). This section further elaborates on the substantial changes in activity patterns.

*Fewer trips*
During the lockdown period in the Netherlands, the total number of trips decreased universally. According to De Haas et al. (2020b), the intelligent lockdown in the Netherlands caused a temporary decrease in outdoor activities for all trip purposes. The most considerable decrease was seen in travel purposes; shopping, sport, visits of family and friends,

volunteer work and other social and recreational activities (De Haas et al., 2020a). Government policy related to corona was accordingly aimed at limiting individual interactions, also known as social distancing (Ministerie van Volksgezondheid Welzijn en Sport, 2020). As a result, the number of trips inevitably decreased. Around half of the working population experienced a change in their work situation (Hamersma et al., 2021). This reduces half of the trips with a business or work-related purpose.

*Tele-activities*

The term telecommuting originates from the late 1980s. With the introduction of personal computers and telecommunication, the concept of remote working started (Haghani et al., 2003). The definition of remote working is: Work that is performed remotely from the employer or client using information and communication technology (ICT) (De Vries and Weijers, 1998). The rapid successive developments in communication possibilities caused telecommuting to be a hot topic in the 1990s (Van Reisen, 1997). Over the past 20 years, remote working has become an option for commuters with desk jobs. However, people tend to use the option not frequently. Before COVID, 65% of the working population never worked from home, and 20% worked from home 1-2 days per week (Hamersma et al., 2021).

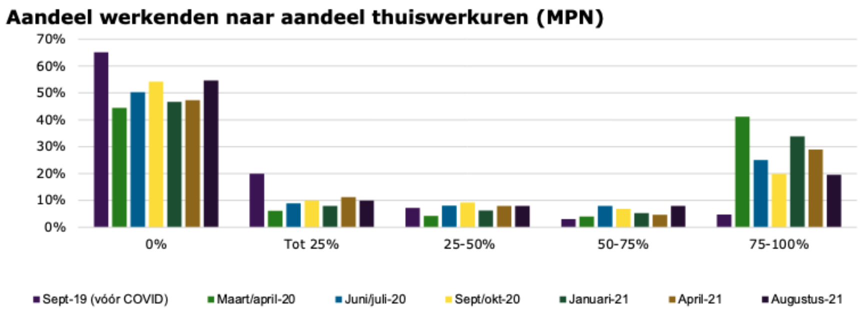



**Figure 2.2:** Development of telecommuting during COVID (Hamersma, 2022)

Figure 2.2 indicates that during the pandemic a maximum of 40% worked almost completely from home. In the subsequent COVID waves the number of telecommuters decreased, nevertheless the amount of telecommuters remains relatively high. 50-60 % of telecommuters expect to work more from home after COVID, compared to before COVID, according to survey results from *Mobiliteitspanel Nederland (MPN)* (Hamersma et al., 2021). Respondents indicated the desired future level of working at home is between 1-3 days.

In addition to working from home, telecommuting also includes remote studying for students. The majority of remote working for students occurs at higher education institutions. The more practical-oriented courses and education were limited to studying from home only during the pandemic. Their role in future remote working is negligible. A difference between telecommuting for educational and work purposes is the fact that students often lack the resources or study place to effectively work or study from home (Hamersma, 2022). Shifting to more online activities also results in less use of the train. As stated by Hamersma et al., 2021, the train as a mode of transport is significantly represented among commuting, business and educational travellers. This impact is also present but less visible in other public transport modes. If teleworking remains to a certain high degree, the impact on PT traffic is estimated to be higher than on car traffic. The higher decrease in PT trips compared to car trips during COVID supports this claim. In the context of reducing trips, both on the main road network and during the peak periods in PT, the Dutch government actively attempts to inform employers about the opportunities of partially working from home (Olde Kalter, 2022).

Finally, a surprising result is that the willingness to telecommute in the future increased over time during COVID (Hamersma, 2022). The annoyance of working from home has made way for the advantages such as less travel time and an improved home office.

*Other tele-activities*

Besides working from home for educational and work purposes, tele-activities are also seen in trips with a shopping purpose. Shopping behaviour has changed due to the pandemic. The closing of shops results in more people shopping online. The lasting effects for the e-commerce branch are hard to determine but could be expected to some degree (Mouratidis and Peters, 2022). Behavioural changes in consumer behaviour are the main cause of this effect.

*Residential location*

If people only travel to the office half of the time compared to pre-COVID, a shift in location attractiveness could occur. A longer commuting distance is less inconvenient than before COVID. Land use and the built environment might therefore be subject to changing travel behaviour in the long term (Mouratidis and Peters, 2022). It is unlikely that COVID-19 will result in less time spent travelling in the future. The concept of constant travel time budget (Mokhtarian and Chen, 2004) is a possible cause for this (Van Wee, 2020). In the future travellers accept for instance longer travel times if they only travel to work 3 out of 5 days. This might lead to people choosing their residential location further apart from their work location.

Changing a place of origin or residential location is a deeply embedded change in travel behaviour. Such a change is initiated by the combination of COVID, telecommuting and current difficulties in the housing market. When living in urban areas because of the short commute distance, telecommuting 2 to 3 days a week could initiate a preference for a more non-urban residential location. In addition, Mouratidis and Peters (2022) state that "Telework and virtual meetings increased to a greater extent in denser neighbourhoods than in lower-density neighbourhoods", meaning that a relocation shift from urban to non-urban areas is possible. The observation that telecommuting occurs more often in highly urban areas is endorsed by KiM (Hamersma et al., 2021). A possible explanation is the larger presence of office jobs in urban regions.

## 2.4. Chapter conclusion

This chapter has presented the current knowledge regarding mobility impacts as a result of the COVID-19 pandemic. The first sub-question can be answered.

*What are the current known developments/trends in mobility resulting from COVID-19?*

The knowledge gap that has presented itself in the literature is the difficulty of estimating the level of change due to a high degree of uncertainty. The main takeaway is that the direction in which travellers will adapt their travel behaviour is relatively unambiguous; travellers are less inclined to use public modes of transportation, and a rise in remote working is observed. However, the extent to which this will occur is uncertain. There are several yet unknown factors that will determine the level of change. Within telecommuting, for example, the expected number of people who will work remotely, to what degree people will work from home and how fast people return to on-site work. The fact that these travellers might or might not travel significantly affects the number of trips, resulting in changes in the planning of transport demand and supply. Furthermore, the valuation of modes of transportation has changed with a potentially lasting effect. The mode appreciation of travellers can be observed adequate in real-time. Nonetheless, the future valuation of travellers is difficult to determine. The developments of mode attractiveness over the years are currently a question.

# 3
# Methodology

This chapter provides an answer to sub-question 2: *How can the mobility impact of COVID-19 be quantified and explained?* Therefore, the research method to explore the mobility impacts is explained and argued. Section 3.1 provides a general introduction to the current demand for alternative modelling approaches. Subsequently, the methodology of system dynamics is elaborated on in Section 3.2 and its use in transport and mobility is discussed in Section 3.3. Thereafter, Section 3.4 describes the use of transport modelling elements. Finally, *Exploratory Modelling and Analysis* is introduced as an analysis method in Section 3.5.

## 3.1. Demand for alternative approach

In order to meet the research objective and observe the mobility impacts of COVID, the use of exploratory modelling is proposed. This is, however, not the only approach which is able to observe impacts on mobility. Nonetheless, an exploratory modelling approach is considered the best suitable option.

Since the start of COVID-19 in 2020 numerous studies regarding the future of passenger mobility in the Netherlands were conducted (De Haas et al., 2020b; MuConsult, 2021; Hamersma et al., 2021; and several more). With the majority having a qualitative research approach. Due to the existence of qualitative research, another literature study towards the mobility impacts of the pandemic does not make a significant contribution. Moreover, the direction of change is often observable, but the degree of change often is not. Therefore, a quantitative approach with a macroscopic level of detail is chosen. The advantage of this research approach is the fact that it can support possible predictions or estimations which were established throughout literature research. Furthermore, this approach enables the observation of the cohesive net effects.

Currently, there are some initial quantitative studies on the mobility impact of the pandemic. However, these studies often suggest the possible implementation of scenarios in a quantitative way. The actual quantification of the consequences of COVID-19 is often omitted and postponed to future studies and research. First of all, in a recent study Van der Drift et al. (2021) used survey data from the *NVP (Nederlands Verplaatsingspanel)* to evaluate primarily the changing activity and mobility patterns during the pandemic. The authors briefly consider the future impact, however not much is mentioned regarding the long-term impacts.

Second, MuConsult (2021) in cooperation with CROW studied the possible implementation of COVID-19 scenarios into the *Landelijk Model System (LMS)* commissioned by the Ministry of I & W. The LMS is a traffic and transport model managed by Rijkswaterstaat on behalf of the Ministry (Hofman, 2017). With the use of storylines created in an earlier study regarding a future exploration by CROW/MuConsult (CROW, 2021c), a first quantitative translation towards the future of passenger mobility in the Netherlands was made. The first exploration of MuConsult (2021) resulted in a possible setup for future calculation in the LMS. One of the drawbacks of this method is that the LMS is a rather large transport model which has relatively high computing time and cost. Therefore, this is not a possibility in this research. Furthermore, a traffic and transport model such as the LMS result in outcomes on a detail level which is far beyond the desired detail level of this research.

To conclude, a quantitative exploratory approach is chosen. The advantage of this approach is the fact that it can support possible predictions or estimations done throughout literature research. In combination with a high degree of uncertainty, an exploratory modelling approach is a suitable method (Walker et al., 2013, Chap 9.3.4, p. 239).

## 3.2. System Dynamics

System Dynamics (SD) is chosen as the best method to achieve the research objective. First of all, this research has a macroscopic scope and aims to model aggregated traffic instead of individual travellers or vehicles. SD has a macroscopic approach where the centralised system behaviour is the point of interest (Nieuwenhuijsen et al., 2018). Whereas, in a microscopic approach, the decentralised individual behaviour takes centre stage (Borshchev and Filippov, 2004). For that reason, the best way to explore the mobility impacts of COVID is by studying the behaviour on a macroscopic level.

Second, the fact that system dynamics is a useful method when a high level of uncertainty is present. The uncertainties in the future of passenger mobility are of a high magnitude. Therefore modelling with a system dynamic approach is a useful tool to model and simulate the current and future situation. The combination of system dynamics and uncertainty is not a given, according to Pruyt (2010) surprisingly few system dynamics studies refer directly to uncertainty. However, SD is often an exquisite method to handle uncertainty. Second, the dynamic complexity of the mobility system fits the objective of an SD approach, which is, among others to identify the dynamic complexity of a system (Sterman, 2000a). Furthermore, SD starts with the assumption that the behaviour of a system is largely caused by its own structure (Pruyt, 2013). This underlines the importance of feedback within the system. In the case of the long-term impacts on the mobility system, the behaviour is also partially influenced by its own structure. Feedback between the choice to travel, choice of mode and destination choice all influence each other and contributes to a complex mobility system.

System Dynamics was developed by Jay Forrester at the Massachusetts Institute of Technology in the 1950s (Forrester, 1958). With SD, causal relations of variables can be identified, which provides a better understanding of the relations between system elements and the behaviour of a system (Sterman, 2000b). Furthermore, the presence of feedback in a dynamic system is an essential element. Dynamic complexity occurs when the system structure is defined by closely coupled, non-linearly connected variables that form feedback loops (Sterman, 2000b). The concept of feedback originates from the control engineering theory (Auping, 2021).

**System dynamics modelling process**

The system dynamics modelling approach exists of five steps according to Sterman (2000b). The process can be divided into a qualitative modelling part and a quantitative modelling part. After the problem definition is defined, the conceptual model can be visualised. This can be accomplished through different types of diagrams (Pruyt, 2013). With the use of supporting diagrams, the model description is translated into the model structure. Causal Loop Diagrams (CLDs) are often used to visualise and communicate the feedback loops and direct causal relations between variables. In addition to the CLDs, Sub-System Diagrams (SSDs) are useful conceptual diagrams in the qualitative modelling stage. The system boundaries, variables and relations are also defined in the model conceptualisation phase.

The quantitative modelling part consists of *model formulation*, *model testing* and *policy design and evaluation*. First, in the *model formulation*, the conceptual model is translated into a simulation model. Before the model is operational, the relations between variables need to be quantified. The SD model consists of a set of integral equations that are numerically solved (Pruyt, 2013). The equations represent behaviour such as accumulation, feedback and delays. Stock Flows Diagrams (SFD) are an important quantitative principle in System Dynamics (Pfaffenbichler, 2011). With a stock-flow structure, these elements are modelled, and subsequent dynamic behaviour occurs when flows accumulate into stocks (Abbas and Bell, 1994). The concept of feedback is essential in this as it adds dynamic facets and prevents elements based only on linear behaviour (Auping, 2021). Examples of feedback in the model are found in the mode choice, the number of (car) trips, the impact of COVID on trips, telecommuting behaviour and appreciation of public transportation. In addition, delays in the system are for example witnessed between travellers' adoption time in switching modes of transport and the time it takes to create new travel behaviour habits. Finally, to operate the model and perform experiments, the model needs to be verified and validated.

## 3.3. System Dynamics and mobility

Implementations and the use of System Dynamics in the field of transport research are not common. Because the model-building phase starts from scratch, this section elaborates on the previous use of SD in transport research. This supports the development of a robust structure of the SD model.

**System Dynamics in transportation**

Transitions and developments within mobility are fast-evolving, with potentially significant implications for the future of transportation behaviour (Papakatsikas et al., 2021). System dynamics is an exploratory modelling methodology that can be applied in this case as argued in the section above. In the field of transportation and in particular personal mobility the use of SD is not a common choice as a research methodology (Shepherd, 2014). With the paper of Abbas and Bell (1994), the first link between transportation and SD modelling was done. With the subsequent work of Shepherd (2014), the use of SD in current transportation problems are evaluated. Which concluded that the use of SD was still not very common and the potential is regularly overlooked.

In 1994, Abbas and Bell first published their findings regarding the modelling approach of SD, compared to traditional Transport modelling. This was one of the first insights into the strengths and weaknesses of SD models applied for transportation. They highlighted among the strengths; dealing with externalities, policy analysis and support in the decision-making processes. Moreover, through SD simulation the short- and long-term behaviour of a transport system is observed and traced. This was particularly useful for gaining insight into the nature of transport problems. Around 20 years later Shepherd (2014) reviewed the use of SD models in transportation once again. The application of SD models in transportation was generally not used and traditional transport modelling is often the chosen alternative. Although, Shepherd (2014) argued that SD models provide the best approach and outcome under the above-mentioned conditions.

**Land- use/transport interaction System Dynamics models**

To make an SD model geographical specific, the model requires the implementation of zones or areas. By combining Land- use/transport interaction (LUTI) models with urban dynamics a geographical element is implemented. The original idea of *Urban Dynamics* by Forrester (1969) was to split an SD model up into two zones, urban environment and outside of this environment. In later additions, more spatial elements were added to the original urban dynamics model (Sanders and Sanders, 2004). Which eventually resulted in the possibility of implementing a complete zonal representation or an urban area (Swanson, 2003).

Partly due to the implementation of spatial elements, the use of SD in transport modelling increased in recent years. Starting with the development of the model MARS (Metropolitan Activity Relocation Simulator) by Pfaffenbichler et al. (2008). The MARS model is an SD model to model urban mobility. This model was developed in 2008 and is still in use today. The MARS model uses the feedback between mode attractiveness and simplified assignment through increased travel times (i.e. congestion) adopted from the 4-step transportation model. In urban mobility problems, the MARS model has proven its strengths and is validated through the application of the model in more than 15 cities and metropolitan areas worldwide (Pfaffenbichler, 2011). Nevertheless, the focus of the MARS model is primarily on urban areas, resulting in somewhat opposing objectives compared to this research.

The attractiveness of location is of importance within LUTI models. The pandemic influenced the way people perceive their ideal living situation (Bons, 2021). As a result, housing preference is subject to change (Buitelaar et al., 2021). The modelling of the housing market is an aspect researched a lot within SD modelling (Eskinasi, 2014). Therefore, the inclusion of location attractiveness can be explored.

**Mobility innovations**

Since the development of the MARS model, the use of SD modelling in transportation has increased. Studies where uncertainty plays a significant role, are in particular suited to apply an exploratory modelling approach. Hence, the emerging use of SD regarding new innovations, entries or trends in the mobility system. For example, the introduction and adoption of autonomous vehicles (AV) is an innovation within the transportation system that is studied with the use of SD. Gruel and Stanford (2016) studied the long-term effects of AVs based on an adapted conceptual model of Sterman (2000b). Furthermore, Legêne (2018) analysed the spatial impacts of the introduction of AVs by developing a geospatial disaggregated system dynamics model. This model was applied to a case study in the Copenhagen metropolitan area. It was one of the first geographically specific SD models using extensive sub-scripting to represent a network of zones.

Related to this, Puylaert (2016) assessed the mobility impacts of early forms of automated driving in the Netherlands. The research of Puylaert provides an approach similar to the approach in this study by developing an SD model to observe mobility impacts. Contrary to the study of Legêne et al. (2020), Puylaert et al. (2018) used categorised area types as zones.

The work of Puylaert (2016) is closely related to one the first transport-implemented SD models in the Netherlands. Heyma et al. (1999) used system dynamics as an exploratory method to predict the future of transport and mobility with their SD model: *De ScenarioVerkenner*. The Scenario Explorer model was developed by TNO on behalf of the ministry and Rijkswaterstaat in 1999 to develop a tool for long-term travel demand forecasting in passenger transport (Malone et al., 2001). The model from Puylaert adapted the use of travel demand in the same way and uses the same categorisation of area types. The inclusion of travel demand is also addressed in the model developed in this research. Hence, the model work from Heyma et al. (1999) & Puylaert (2016) is useful in the subsequent development phase of this research. Besides the introduction of autonomous vehicles, SD is also used in regard to other mobility trends to observe system behaviour (Papakatsikas et al., 2021). The authors of this paper likewise argued that SD could be a suitable method for further research on the effects of COVID on mobility.

## 3.4. Transport modelling

The system dynamics approach will be used in a combination with aspects of transport modelling. To answer the main research objective the SD model requires to include a form of travel data and travel behaviour. To stay within the proven transport modelling techniques the 4-step model (Ortúzar and Willumsen, 1990) is used as a guiding principle. Figure 3.1 illustrates briefly the 4 steps within this model. From the current developments of COVID, the mode attractiveness and activity patterns emerged as points of interest. The mode attractiveness can be linked to the third step in the 4-step model: *Mode choice*. Whereas activity patterns and change of those patterns can be linked to the first step: *Trip generation* and even a step before that. By travellers deciding to make a certain trip.

By using the 4-step model as a guideline, the developed model contains a substantiated transport modelling basis. In the continuation of this research, the focus is on the mode choice. Nonetheless, the other phases in the 4 step model are included as well to ensure a complete transport modelling structure in the SD model. Trip generation provides the input of trips and is combined with trip distribution. The route assignment is subsequently simplified because detailed route assignments can be problematic in a system dynamics environment (Shepherd, 2014). Besides, detailed route assignment is not of high interest in a macroscopic view. Therefore there is no dedicated route network and there is only one assignment option.

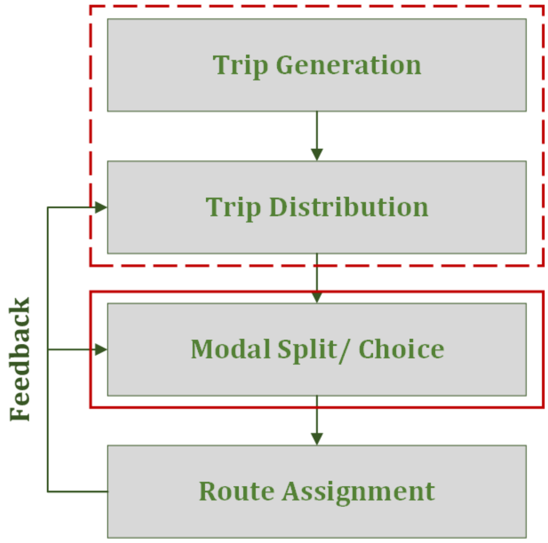



**Figure 3.1:** Point of interest in the 4-step model

## 3.5. Exploratory Modelling Analysis

For analysing the model outcomes and exploring the influences of uncertainty, Exploratory Modelling and Analysis (EMA) is used. Bankes (1993) introduced the concept of EMA in 1993. With the use of computational support, it is possible to perform a high number of experiments and analyse the uncertainties of a model (Kwakkel, 2017). The use of a high number of experiments (N >1000) in combination with the possibility to vary the range of input parameters enables the exploration of the model outcomes in a base ensemble instead of a single base scenario. Within EMA it is possible to perform scenario discovery. With the use of a scenario discovery algorithm, computer-assisted scenario development is possible (Bryant and Lempert, 2010). Computational scenario discovery extends traditional scenario design where at first a storyline is developed and afterwards simulation takes place.

The SD model is heavily dependent on COVID-related input, which is often based on estimations and best guesses from the literature. Therefore, the use of exploratory modelling and analysis allows analysing of model outcomes under different conditions, providing a stronger perspective on the future mobility impacts. The combination of EMA and the SD model is seen as valid as the goal is to observe the impacts on bandwidths to establish insight into the behaviour over time. Furthermore, the use of EMA in system dynamics is often used and validated (Kwakkel and Pruyt, 2015), therefore providing a strong analysis method useful for the SD model. The EMA workbench is an open-source tool implemented in Python that enables the implementation and analysis of the SD model (Kwakkel, 2017). With the EMA workbench experiments and the subsequent visualisation of outcomes can be performed.

## 3.6. Chapter conclusion

This chapter started with an introduction to exploratory modelling and the use of system dynamics in transport research. The second sub-question *How can the mobility impact of COVID-19 be quantified and explained?* can be answered based on the findings in this chapter.

To conclude, system dynamics is found to be a suitable method for this research due to a high level of uncertainty, the complexity of the mobility system and the presence of feedback and delays in this system. Therefore, a system dynamics model will be developed, focusing on the mode choice component. With a quantified SD model, it is possible to explore the behaviour of impacts over time to study the direction and the degree of mobility impacts due to COVID.

With the combination of transport modelling and exploratory modelling, an uncommon combination of methods is mixed. Therefore, it is essential to consider previous SD modelling work during the development phase. Earlier SD models can provide guidance in the development of a logical model structure. Nonetheless, the model-building process starts from scratch due to the absence of a previously validated model. Moreover, the design of the SD model will follow the structure of the 4-step transportation model to establish a robust foundation for the model and make the model applicable to cases other than COVID.

# 4

# COVID-19 mobility model

This chapter presents the developed System Dynamics model. The model is structured by answering sub-question 3: *How can the uncertainties originating from the pandemic be implemented and modelled?* The first section (Section 4.1) provides the conceptual design and a high-level overview of the model. After which Section 4.2 elaborates on the description of the sub-models and the application of the model by defining the model components and input. Thereafter, the experimental setup and the input parameters are discussed in Section 4.3. Finally, Section 4.4 expands on the model usability in practice.

## 4.1. Conceptual model

The conceptual model description presents an overview of the model structure by means of a Sub System Diagram. Furthermore, the mode choice and its inclusion in the system dynamics model are outlined.

### 4.1.1. Model overview

The System Dynamics model captures changes in travel behaviour as a result of COVID. The behaviour within the system is made insightful, and the model outcomes result in mobility impacts under the fluctuation of input uncertainties. The model structure is primarily based on the 4-step transport model by Ortúzar and Willumsen (1990) for the robust transport modelling basis and the inclusion of mode choice. In addition, supported by SD model work from Pfaffenbichler et al. (2008) regarding the implementation of trips in an (urban) mobility model.

In short, the objective and the main components can be described as follows: In the model, the trip generation originates from a base year and is influenced by population growth. The focus is on the dynamic mode choice. By developing a choice model hypothetical observations of travellers can be observed. Thereafter, the influences of COVID change the traveller's choice with a delay during the pandemic. Which subsequently might or might not have an impact on mobility in a post-COVID era. With the use of travel data, the model is implemented, validated and applied to the Netherlands. By adding a feedback loop between the number of car trips and the attractiveness of the car through a congestion component, the model is further extended into a dynamic model. The Sub System Diagram (SSD) in Figure 4.1 illustrates the structure of the SD model.

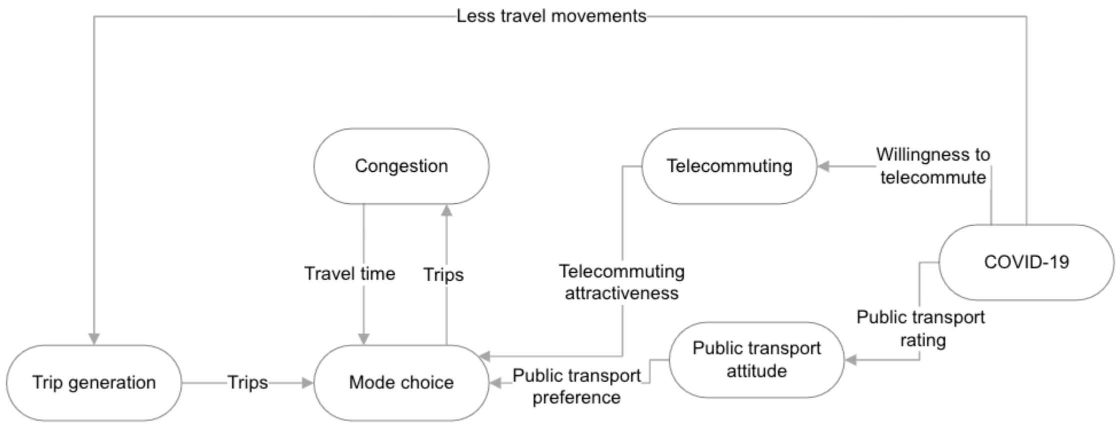



**Figure 4.1:** Sub System Diagram

The SD model structure can be summarised in the Sub System Diagram (SSD) in Figure 4.1. The mode choice component operates as the main model component. The main impact of COVID can be seen in the appreciation of public transport, remote working and trip generation. The remainder of this chapter will discuss each submodel in more detail.

**Key Performance Indicators**
The goal of the model can be structured by the use of Key Performance Indicators (KPIs). By defining the measurable outcomes the purpose of the model becomes more transparent. Table 4.1 below presents the KPIs in this research. Important is to keep the macroscopic exploratory approach in hindsight, meaning that the goal is not to observe specific precise outcomes or predict explicit values. Therefore, the model outcomes consist of bandwidths of the KPIs under the influence of uncertainties.

| | |
|---|---|
| Modal split (trip based) | Road intensity |
| Number of trips (Yearly & Monthly) | Relative congestion levels |
| Number of remote workers | |
| Number of public transit riders | |

**Table 4.1:** Key Performance Indicators

### 4.1.2. Trip categorisation

The change in the attractiveness of modes can be observed based on different trip characteristics. By changing the input parameters, the result can be observed in the monthly number of trips per mode and per trip purpose, distance class and degree of urbanisation. The various elements within these categories that are taken into account are specified in Table 4.2. With the distinction in trip types, the modal split and number of trips can be observed for each of the 100 combinations of trip types. Therefore, observing the differences in, for example, a commuting short trip originating in an urban area and a long educational trip originating in a non-urban area.

With the use of travel data from the travel survey *Onderweg in Nederland* (ODiN) trips in the Netherlands are categorised (CBS, 2020). The trip purposes and the distance classes are combined categories from data available in the travel survey. The categorisation of distance classes is constructed around the average commuting distance in the Netherlands, which is 19 kilometres. For travellers with a high education background, the average commuting distance is even longer at 35 kilometres (Ritsema Van Eck et al., 2020). The average distance travelled for trips with social-recreational and shopping purposes is lower. Combined, this results in the categorisation of trip lengths into 4 distance classes (Table 4.2). The categorisation of trip purposes is based on the purposes with the highest potential of COVID impact (De Haas et al., 2020a). Besides the different trip purposes and distance classes, the model is extended with a geographical aspect. This addition results in outcomes specific to certain areas of the Netherlands, on top of the general outcomes for the entire country. With the use of ODiN data, it is possible to filter the data on arrival and departure municipalities (see Appendix D). By assigning the departure municipalities to an area type based on the degree of urbanisation, a geographical layer is added to the model. The current degree of urbanisation is divided into 5 classes and based on the surrounding address density (CBS, 2019b).

**Use of subscripts**

In the SD model the distinction between trip purpose, distance and area type is done by the vectorisation of variables, creating a copy of a set of variables or model structure. In SD the vectorisation of variables is modelled with the use of subscripts. These subscripts essentially create a copy of the model structure for each aspect, in this case; the trip purpose, distance class and area type (Table 4.2). As a result, the KPIs regarding the modal split and the number of monthly trips can be analysed in total or separately. However, this also poses a risk. Because the categorisation is done for all modes of transport, this leads to 500 different modal split and monthly trip KPIs. Therefore, only the relations that generate meaningful results are explored.

| **Trip purpose** | **Distance class** | Distance [km] | **Area type** (origin) | Address density [Addresses/ km^2] |
|---|---|---|---|---|
| Commuting | Short | <7.5 km | Extremely urbanised | >2500 |
| Educational | Middle short | 7.5 - 15 km | Strongly urbanised | 1500 - 2000 |
| Social recreational | Middle long | 15 - 40 km | Moderately urbanised | 1000 - 1500 |
| Shopping & Personal care | long | >40 km | Hardly urbanised | 500 - 1000 |
| Other motives | | | Not urbanised | <500 |

**Table 4.2:** Subscripted trip categories

### 4.1.3. Attractiveness of modes in conceptual form

The attractiveness of modes of transportation is the core of the model. From the literature it was identified as an area of interest, thereafter it was linked to transport modelling in the methodology chapter. The mode choice is calculated at every time step, which provides the outcomes to the modal split KPIs.

**Choice modelling**

To cope with the choice between alternatives, choice modelling is proposed. Discrete choice models are considered an important tool in the decision-making process of the traveller

(Train, 2003). Especially within the choice of mode of transportation. The main theory behind the use of choice models is the utility theory (McFadden, 1980). Choice models in the field of transportation are usually based on utility maximisation. The decision-maker chooses between alternatives, in which each alternative has a level of utility (Pel, 2018). The decision-maker chooses the alternative that has the highest utility. The utility maximisation theory originates from the economic theory, where Random Utility Maximisation (RUM) is an assumption within consumer behaviour theory (Hess et al., 2018). The alternative a decision-maker chooses can be determined with the use of a logit formulation for mode choice (Ortuzar and Willumsen, 2011). The probability $P$ of the decision-maker choosing alternative $i$ is calculated with Equation 4.1.

$$P_i = \frac{e^{V_i}}{\sum_{r=1}^{n} e^{V_r}} \tag{4.1}$$

*Where:*

$P_i$ = *Probability of choosing mode i;*
$V_i$ = *Utility of mode i;*
$V_r$ = *Utilities of all the modes r;*
$n$ = *Number of modes in consideration;*

The alternative specific utilities are calculated with Equation 4.2. This is the basic form of a utility function and consists of mode-specific attributes such as travel time and travel cost. The calculation can be extended with additional mode-specific attributes such as waiting time, comfort or COVID-dependent variables, which enter the equation direct or through the travel time or travel cost.

$$V_i = TT_i \cdot \beta TT_i + TC_i \cdot \beta TC_i + ASC_i \tag{4.2}$$

*Where:*

$V_i$ = *Utility of mode i;*
$TT_i$ = *Travel time of mode i;*
$\beta TT_i$ = *Sensitivity parameter of travel time of mode i*
$TC_i$ = *Travel cost of mode i;*
$\beta TC_i$ = *Sensitivity parameter of travel cost of mode i*
$ASC_i$ = *Alternative Specific Constant of mode i*

**Modal split**
The utilities are influenced by exogenous variables which determine the attractiveness of the mode. The variables or utility attributes are the input of the utility functions. Because each mode is in essence a competitor, increased utility for mode X results in a decrease in attractiveness for one or multiple of the other alternatives. By changing the attributes, the distribution of modes is calculated and this leads to a modal split value. Utilities for the alternative car are additionally changed endogenously by modelling congestion through a feedback mechanism.

In line with the theory from choice modelling, the mode choice on a conceptual level is illustrated in Figure 4.2. The attractiveness of the alternatives consists at first of travel times and travel costs. The conceptual models for the separate alternatives are presented in Appendix B.

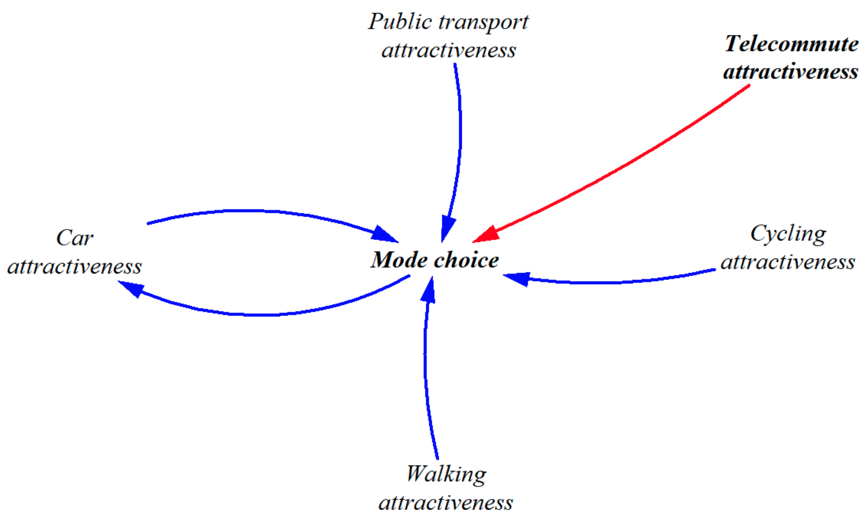



**Figure 4.2:** Conceptual model of mode choice

**Modes of transportation**
There are numerous different modes of transportation, hence, a selection of the relevant alternatives is made. The choice has been made to include five main modes of transport, being: ***car***, ***public transport***, ***bike***, ***walking*** and ***tele-activity***. With these main modes, significant changes resulting from COVID can be observed, because the predictions from the literature pointed in the direction of the distribution between public and private modes of transport (Gkiotsalitis and Cats, 2020). Furthermore, the potentially changing role of active modes, such as cycling and walking, is stated by Van der Drift et al. (2021).

**Tele-activities**
Tele-activities have a substantial influence on the future system as indicated in the literature. Therefore, tele-activities have been taken into account as an additional alternative in the mode choice. This results in a decision-maker choosing a tele-activity trip, which in fact is a choice to not travel. Instead, the choice is made to work or study from home for commuting or educational trip purpose. Within tele-activities, the focus is on remote working and remote studying. Other tele-activities are not taken into account and are outside the scope of this research. Considering that working from home and studying from home are the two main tele-activities expected to have a permanent effect (Hamersma et al., 2021).

The addition of tele-activities as a competitive alternative to the other modes of transport has resulted in tele-activity being transformed into a dynamic component. The benefit of modelling tele-activities in this way is that a utility can be observed corresponding to choosing a tele trip. Hence, the attractiveness of tele-activities can be observed under changing input uncertainties throughout the entire run time of the model. In the continuation of this thesis, tele-activities are referred to as telecommuting and include both educational trip purposes and work-related trip purposes. Nonetheless, in the model, remote working and remote studying feature their own parameters.

### 4.1.4. Model boundaries

The developed SD model has a robust verified basis by which the impacts of COVID and other mobility disruptions can be seen in the modal split and number of trips. However, the model has some simplifications due to the exploratory nature of the model; this is inevitable and does not impact the goal of the model. The constructed model meets all of the requirements set and is, through calibration and verification, later tested for practical use.

Future expansion of the model can build on some of the current simplifications. First, with the use of distance classes, a simplification is implemented in the model. By categorising all trips into scaled distance classes, the trips within one distance class are generalised and have an average trip length. The simplification of distance classes is due to the otherwise, extensive size of the model for both subscripts and output variables. As a result, interchanges between distance class is not yet possible. Second, the 5 modes of transport in the model can be extended with additional alternatives. Currently, the 5 modes included are considered to be most relevant to the outcomes. Furthermore, due to data availability, the number of alternatives is constrained. In addition, the inclusion of shared mobility alternatives (bikes, scooters and mopeds) could be beneficial to observe their increase or decrease as a result of the pandemic. Third, besides the choice to not make a trip for educational and work-related purposes, tele-activities for other trip purposes could be included. For instance, the rise of e-commerce and online grocery delivery companies during the pandemic has impacted shopping trips, the lasting effects could be studied with this model. The choice to include only remote educational and remote work activities is due to their higher predicted impact and societal relevance.

## 4.2. Model description

This section elaborates on the description of the model components and the application of the model to the situation in the Netherlands. The sub-models and sub-components: trip generation, mode choice, congestion, public transport, telecommuting and COVID are discussed.

### 4.2.1. Trip generation

The 4-step transport model (Ortúzar and Willumsen, 1990) is, to a certain extent, used as a guiding principle. The first and second step *trip generation* and *trip distribution* are simplified and considered as a constant base year input. The trip generation is however dependent on population growth.

With the use of CBS survey data from the *Onderweg in Nederland* (ODiN) survey in 2019 a pre-pandemic base year is constructed (CBS, 2020). The base year travel data function as the constant trip generation input of the model. The trips are distinguished by the defined trip categories (trip purpose, distance class and area type). With the use of statistical software SPSS, the data is cleaned and prepared for use. Appendix D elaborates on the process of data collection and cleaning.

To simulate travel demand, the number of trips in one year are generalised to the population and used as the main input. In survey data, a distinction is made between households and individuals. In this research, the focus is on the trips of an individual (CBS, 2020). The consideration to work with individual travel behaviour is due to the fact that this method is more appropriate for evaluating changes in travel behaviour. Although individual travel data is used, travel behaviour is not studied on an individual level. Travel behaviour is analysed at the population level on account of the macroscopic scope of this research.

Besides population growth, the trip generation is influenced by a decrease in trips during the pandemic, as shown in Figure 4.1. The decay of trips is subtracted from the number of trips during the active period of COVID-19 for trip purposes with no option for tele-activities. In the decay of trips, a distinction is made between the decay rate during the first wave and later waves. Due to the difference in the decrease of trips between the initial first wave and the COVID waves near the 'end' of the pandemic (MuConsult, 2021).

The ODiN data set does not incorporate a form of remote working. To cope with the initial number of telecommuting trips the initial degree of telecommuting before the pandemic is calculated. The degree of remote working before COVID was averaged at 3.5 hours per week (Jongen et al., 2021; Hamersma et al., 2021). This translates to an initial telecommute percentage of $\approx$ 11% for an average workweek of 32 hours (CBS, 2022c). There is no information about the hours of home education in the Netherlands before COVID. Therefore, studying from home for higher education is assumed to be similar or slightly higher compared to remote working. The other forms of education are estimated to have a considerably lower degree of remote activities. On average, this results in a slightly lower rate of home educational activities. The calculations of initial tele-activity trips per trip type can be found in Appendix D.

### 4.2.2. Construction of the mode choice

To include the mode choice as a dynamic component in the SD model, a choice model is constructed where a hypothetical decision-maker makes a choice between the 5 alternatives (Car, PT, Bike, Walk and Tele). The attractiveness of a mode of transport is translated to utility functions. Subsequently, the choice behaviour of travellers is calculated with choice models. The underlying mathematical formulation is based on a logit function for mode choice (Train, 2003).

The main formulation and the attributes to calculate the attractiveness of an alternative are illustrated in Equation 4.2. The calculation of the utilities is based on the mode-specific travel time and travel cost, including sensitivity parameters ($\beta$) and Alternative Specific Constants (ASC). The exogenous input variables are often an indirect part of the travel time or travel cost function or direct input in the utility function. Figure 4.3 illustrates the main attributes.

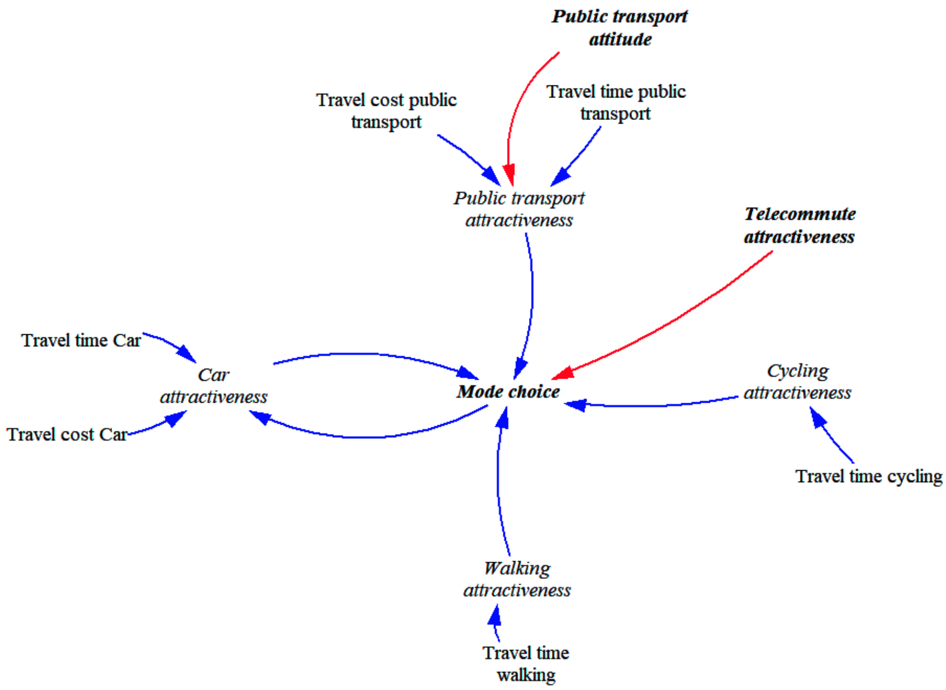



**Figure 4.3:** Mode choice component

**Travel time and travel cost**
Each mode of transport has a corresponding initial *travel time* that depends on the distance class and area type. For public transport the travel time is divided into in-vehicle time, waiting time and access and egress time. Travel times are calculated in excel, thereafter, the initial travel times are included in the SD model. Appendix C describes the calculation of travel time and presents the input values for the SD model. The travel times have an initial value and change exogenous over time. Car travel times additionally change endogenous through the congestion submodel.

The *travel cost* are calculated likewise, consisting of variable and fixed travel costs. Travel costs are present solely for the alternatives; car and public transport, for simplicity reason the cost of owning and driving a bicycle have been reduced to zero in the mode choice. Contrary to the travel time, the travel cost changes exogenous due to input parameters. The variable car cost is influenced by the fuel price, other variable car costs and distribution of the vehicle fleet (EV/ICE) over time. These parameters have base input values, however, they can be regarded as uncertainty inputs, because the input is based on estimations. Appendix C describes the calculations of travel cost and presents the initial values and their change in time.

**Sensitivity parameters**
Sensitivity parameters in the constructed choice model for the SD model are based on parameters in estimated choice models of existing traffic models (Octavius and LMS). The implementation and calculation of the parameters can be found in Appendix C.

Travellers (decision-makers) are sensitive to attributes that determine the utility of a mode of transportation. When travellers are more sensitive to a certain attribute (e.g. travel time), that attribute should have a higher added value in the total utility (Chorus, 2020). Price sensitivity and travel time valuation are derived from elasticity's (Bakker, 2018; MuConsult, 2015). If for example, the sensitivity for travel time is relative low, a change in travel time will not quickly lead to different choice behaviour.

The sensitivities are translated in weighted ($\beta$) parameters for the corresponding attributes. These weights are estimated. The estimated parameters are relative to another alternative. This results in sensitivity parameters for modes of transport in regard to the fixed mode. In other words, weight is relative to the other mode of transport, because it is the difference in utility that matters (Chorus, 2020).

**Elasticity's change due to COVID-19**

It is important to question whether the elasticity of the period without COVID would present accurate elasticities and weighted parameters for the period after the pandemic. Due to the fact that elasticity and subsequently beta parameters based on new behaviour are not available, changing travel perceptions of travellers are dealt with in a different way.

There have been some studies towards changing travel time valuation due to COVID commissioned by, for example, the *Kennisinstituut voor Mobiliteitsbeleid* (Thoen and Kouwenhoven, 2021). However, the authors mentioned the exploratory nature of this new value of travel time and elasticities. In addition, the use of these values in the model calculation is discouraged and could lead to biased results (Faber, 2021). In further research, when new travel time valuation is in a further verified stage, new parameters could be added to the choice model and implemented in the SD model alongside the existing elasticities and parameters.

In the SD model there is specific attention to the negative/positive attitude towards public transport. By changing the level of trust and comfort travellers experience in public transport, the sensitivities of travellers change.

**Alternative Specific Constant**

The utility function consists of observed factors, travel time and travel cost. In addition, there are also unobserved factors, such as specific travel preferences. These factors are unobserved and are captured in a constant (Chorus, 2020). The travel preferences consist of everything not captured in the attributes in the utility function, such as the need to change trains and car ownership. The Alternative Specific Constant (ASC) captures specific travel preferences of travellers for a certain mode of transport under various circumstances (Train, 2003). For example, the use of the bicycle for long trips for trip purpose commuting has a negative preference by the majority of travellers. These travel preferences are captured in the ASC. It is shown that a relatively large negative ASC results in a lower utility and thus attractiveness. ASCs are estimated at the same time as the weight coefficients (beta). For the SD model, the ASCs are similar to the weight coefficients obtained from existing estimated traffic models.

### 4.2.3. Congestion feedback

The congestion model component provides the mode choice with its dynamic component. The mode choice introduced the presence of a feedback mechanism between car attractiveness and mode choice. Through the use of a simplified capacity and intensity constraint, the degree of congestion on the road can be determined. By comparing the congestion level with the initial congestion level, the dynamic change of congestion can be established. Thereafter, increasing or decreasing congestion influences the car travel time and thus the utility function. The Congestion feedback is seen as a simplified form of route assignment, the last step from the 4-step model. With the use of the congestion feedback mechanism car traffic is assigned to the general main road network as a whole, in which the capacity and intensity values are mirrored from the actual values in the Netherlands in the base year of 2019 (Rijkswaterstaat, 2019). The simplified form of assignment meets the current requirements in the macroscopic approach.

### 4.2.4. Telecommuting

The use of telecommuting as an added component in SD mobility models is not completely new. In an extension of *The Scenario Explorer* model in 2001 Malone et al. added telecommuting as an exogenous scenario input variables. The authors were interested to see what the possible effect on travel demand would be. In particular, the connection between telecommuting and trip generation was emphasised. In the model, telecommuting affected only the number of trips that would be made. Telecommuting was not modelled as a dynamic component of the model itself. It was rather difficult to observe the effect of telecommuting due to a lack of information about remote working and studying at that time (Haghani et al., 2003). Haghani et al. (2003) mentioned the upcoming phenomenon of telecommuting in the late 1980s and the implementation of telecommuting in their SD model for land use/transportation system performance modelling in 2003. Similar to the implementation of Malone et al., the effect of telecommuting was determined by subtracting the fraction of the workforce that worked remotely from the trip generation. The model developed in this research differentiates itself from the earlier models through the addition of tele-activities in the mode choice.

Besides including tele-activities as a new alternative, the degree of telecommuting is also modelled dynamically. Telecommuting is defined by the decay rates of remote working incentives during and after the pandemic and the expected number of hours people will work remotely in a post-pandemic era. The pre-pandemic degree of telecommuting is overall around 11 % of the worked hours. The pre-pandemic level is divided into educational and commuting and divided per distance class and area type in the model (Hamersma et al., 2021, p.119/ p.122).

The expected future degree of telecommuting is according to a survey study (MPN) of KiM around 1-3 days a week (Hamersma et al., 2021). This is endorsed by Jongen et al. (2021), who on behalf of the Centraal Planbureau (CPB) expect a doubling of the number of remote working hours. The expected days or hours that will be worked from home are uncertain and currently based on rough estimations from the above-mentioned survey study. In addition, the maximum number of people that can work from home has to be considered, as around 60% of the population in the Netherlands have jobs with no remote working possibilities (CROW, 2022c).

#### 4.2.5. Public transport attitude

Overall, the popularity of public transportation has decreased since the start of the pandemic (Tirachini and Cats, 2020). There are several different determinants for travel satisfaction within public transport. Ingvardson (2017) suggests a strong link between travel satisfaction and the role of attitude and social norms. The negative attitude of travellers towards the use of the train or bus/metro/tram has increased. The positive or negative attitude influences the mode attractiveness. The rate at which travellers gain back a more positive attitude towards public transport is based on the *Rate of gaining back a positive attitude*. With this rate the attitude levels are determined. A lower rate of gaining back trust implies a negative attitude is longer present. The quantification of this value is accomplished with the use of change in the valuation of PT during the different stages of the pandemic (De Haas and Faber, 2022). This is supplemented with results from the *OV-Klantenbarometer* which monitors the general satisfaction of PT travellers (CROW, 2022b). Based on the result of De Haas and Faber (2022) and CROW (2022b), assumptions for input ranges of the rate travellers gain back a positive attitude after COVID can be explored and defined. The recovery of a positive attitude is slightly adjusted with an adoption curve (Rogers et al., 2008) due to the high degree of uncertainty. Such an adoption curve provides guidance towards the percentage of travellers early returning or late returning. The negative attitude is modelled throughout the entire pandemic and there is no distinction between the various stage of COVID.

#### 4.2.6. COVID

The COVID submodel exists as a representation of the COVID waves during the pandemic. This is initially constrained between March 2020 and the last (5th) COVID wave around march 2022 (RIVM, 2022). COVID waves each have a duration and an interval between the waves and are modelled in a sequence of 5 waves. The different waves feature different decay rates in the number of trips, as the first wave for example showed a higher decrease in people activity than the later waves (Van der Drift et al., 2021; De Haas et al., 2020b). The distinction between trip purposes enables the representation of changed activity patterns specific per trip purpose. The decay in the number of trips is higher for social recreational travel than for (grocery) shopping for instance (De Haas et al., 2020a). The decrease in trips during the COVID waves impacts trip generation for all trip purposes except commuting and education, due to their implementation through the addition of the tele-activity alternative.

### 4.3. Uncertainty input & Experimental setup

Once the model is specified, the experimental setup can be described. Each of the subcomponents described in this chapter includes exogenous variables that are uncertain to some extent. A higher degree of uncertainty contributes to a high degree of unpredictability for what the future beholds. By discovering the uncertainties and explaining their ranges and influences in the system, uncertainty can be coped with. This eventually leads to an improved understanding of the model outcomes. The general and COVID uncertainties currently included in the model are presented in Table 4.4 & Table 4.3.

By changing input parameters the mobility impacts under different conditions are shown. It is, however, important to not change input variables that change the initial utility. To prevent misalignment between initial values and model calculated values, the choice model is calibrated on the input data. By changing values after the first time step, this problem is coped with. Not all of the model uncertainties are taken into account in the experimental phase of this research. The uncertainties included in the experiments are stated at the beginning of the results.

| Telecommuting | Public transport attitude | COVID |
|---|---|---|
| Expected telecommute hours after COVID | Rate of gaining positive attitude | Decay rate of trips first wave |
| Percentage of the labour force able to work from home | | Decay rates of trips in 2nd, ... , N waves |
| Decay remote working incentive during the pandemic | | Last COVID wave |
| Natural decline rate of remote working | | Delay time COVID measures |

**Table 4.3:** COVID uncertainties

| Variable Car Cost | Public transport | Other |
|---|---|---|
| Development variable fuel cost | Recovery time of public transport supply | Estimated population growth |
| Increase of electricity/fuel cost for EV | Development variable cost in PT | |
| Development distribution ICE/EV | | |
| Development of other variable car costs | | |

**Table 4.4:** General uncertainties

**Experimental setup**
For modelling with an SD approach, a time horizon should be determined to establish the run period. The starting point is the year 2019 as a pre-COVID period and the final time is set to 2040. Based on the response time of travel behaviour, approximately 20 years is an adequate run time to observe near-future and distant-future model outcomes. The SD model is developed with the system dynamics software package of Vensim (version: Vensim® 9.3.0 x64), which provides a user-friendly graphical modelling interface (Ventana Systems, 2022). For the analysis of the model outcomes, as well as performing a high number of experiments, the EMA workbench (version: 2.1) is used. The EMA workbench is implemented in Python and features an integrated connector for the models in the Vensim package to be implemented in the workbench (Kwakkel, 2017).

## 4.4. Calibration and Validation

### 4.4.1. Calibration

The construction of a choice model and the use of a logit model in the SD model results in a combination of survey travel data (ODiN) and calculated attributes. Because the choice model does not thoroughly match the initial travel data from ODiN, there is a slight mismatch between the model input en model calculated output. This misalignment arises from the fact that travel times and travel costs are determined separately based on average trip length per distance class. In order to fix the misalignment, the utility functions are slightly altered.

By re-estimating the Alternative Specific Constant (ASC) the utility functions are updated to match the initial model input. Because the model is specified for different modes and different trip types, there are 500 ASC values in total. These values need to be re-estimated to correct the misalignment. The re-estimation step causes the SD model to be calibrated on validated input data. In the calibration, one of the modes is fixed in order to estimate the other 4 modes relative to the fixed mode.

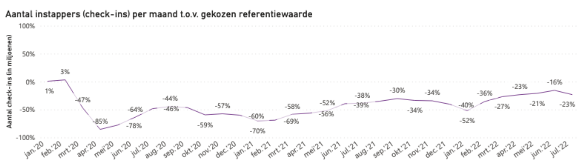
The calibration of the ASC is done with the use of an optimisation script in Python. The initial model-calculated utilities (n=500) are exported from the SD model in Vensim. The initial trips per alternative divided per trip category obtained from the data set are appointed as targets. Finally, the combined initial trips for the 5 alternatives are summed (n=100). By running the optimisation script, the SD model-based utilities are compared with the trip initials resulting in the utility difference. Subsequently, new ASC values can be obtained by which the SD model implemented ASCs can be increased or decreased.

The order of estimating the ASC is not in line with the accurate transport modelling and discrete choice modelling order of estimating constants. The weighted coefficients (beta) and the ASC are normally estimated at the same time. Nonetheless, this step was necessary. By adding a 'new' mode such as telecommuting, there is no predefined ASC value which can be used. Therefore the ASC of telecommuting has to be estimated manually. Hensher (1981) emphasises the importance of incorporating an ASC for new modes in logit models. Often ASC values are left out in such cases. This impacts the usually sensitive mode share, resulting in incorrect outcomes of a model. Due to the high number of ASC in the model, estimating ASC for telecommuting by hand is impossible. Therefore, estimating the ASC values of telecommuting is performed simultaneously with the calibration of the ASC values of the other alternatives. Moreover, the method of adjusting constants afterwards can be accounted for within the SD modelling cycle, in which, the model testing and validation part require feedback between model use and testing.

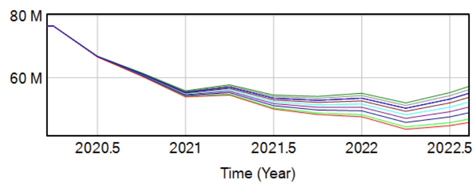
### 4.4.2. Validation

In the validation, it is checked if the developed model represents the actual system adequately. By comparing the model or by running tests, it is possible to build additional confidence in the model. In this case, the similarity with COVID behaviour in the real world. The pandemic started around March 2020, which means the behaviour of the real world can, to a certain extent, be matched to the model-produced behaviour.

Because exploratory modelling is used, the goal is not to mimic the actual past trend of COVID. Nonetheless, validating if the model somewhat represents the correct direction is useful. A comparative analysis with observed data is performed. Survey data from *Nederlands Verplaatsingspanel* (NVP) (Goudappel, 2022) and *Mobiliteitspanel Nederland* (MPN) (De Haas et al., 2020b) on the number of trips made between March 2020 and June 2022 is used to compare model-calculated number of trips in the same time period.




**(a)** Public transport check-ins between March 2020 and June 2022 (Translink, 2022)




**(b)** Public transport trips between March 2020 and June 2022

**Figure 4.4:** Public transport behaviour comparison

With data of Translink (CBS, 2022a) the PT check-ins are monitored and can be compared to model computed behaviour. There is a small misalignment between the model's computed number of trips and the PT check-in data. Further analysis showed that during COVID times, for commuting and educational trip purposes, the mode of telecommuting removed too much PT share in comparison to the other alternatives, based on observed levels during 2020-2022. At first sight, this is not really a severe problem due to the fact that the behaviour is more important and not the actual values. Nonetheless, a COVID penalty variable is added to the utility functions of the competitive modes to assign a small penalty during the active COVID period. By adding this penalty, the number of trips and the modal split represent a more accurate situation.

## 4.5. Chapter conclusion

To conclude the system dynamics model chapter sub-question 3 can be answered:
*How can the uncertainties originating from the pandemic be implemented and modelled?*

Modelling the uncertainties from COVID has resulted in a developed SD model where the main effects of the pandemic are modelled through mode attractiveness. Utility functions are used to determine the difference in utility of each alternative and subsequently choice models to determine the attractiveness of modes. With the inclusion of a tele-activity alternative, the model differs from existing models. Modelling the choice to not travel and substituting a trip with telecommuting shows the attractiveness of remote working over the forthcoming years.

With the distinction of trip types in trip purpose (i), distance class (ii) and area type (iii), the results can be analysed on multiple levels. First, the nationwide total mobility impacts can be assessed. Second, more detailed results on all combinations of trips can be explored. This provides insight into the difference between, for example, a traveller making a long trip from an urban area and a short trip from a non-urban area and the subsequent incentive to substitute that trip with remote working.

Through validation and calibration, the model is adjusted for use in practice. The inclusion of a new alternative in the choice model requires the estimation and calibration of the Alternative Specific Constant for telecommuting. It is shown that the model can be used to simulate behaviour based on input uncertainties. By altering input parameters, the model outcomes are consistent with the expected model behaviour.

# 5

# Results

This chapter presents the results of this research obtained through exploratory modelling analysis. Subsequently, the outcomes of the analysis can answer sub-question 4: *What are the quantified mobility impacts of COVID-19?* With the construction of a base ensemble, the most likely future situations can be established (Section 5.1). Subsequently, the outcomes can be endorsed, supported and made more robust by exploring the input uncertainties that affect the mobility impacts under different conditions. With the use of scenario discovery and increased uncertainty scenarios, more extreme situations are explored in Section 5.2. This results in the answer to sub-question 5: *What is the role of uncertainty in the future impact of COVID-19 on mobility?* Finally, this chapter concludes with an interpretation of the final results in Section 5.3.

The results are structured by a two-part story-line: What is the situation we are likely to see as a result of the pandemic and what happens outside the range of this prediction? The consequences of both will subsequently be elaborated on in the discussion. Section 5.1 presents the outcomes for the situation that is most likely. Based on literature and stated choice research the ranges for input parameters/uncertainties are defined. Due to the complexity and uncertainty in the system, it is beneficial to explore more extreme situations. Section 5.2, therefore introduces the outcomes in the event that alternative scenarios become reality. To prepare for the future and support the problem owner in their plan of action, the input parameters of high magnitude are explored. Once the significant uncertainties are identified the decision to intervene in the system and design specific policy options is enabled. Section 5.2 also introduces scenario discovery as a tool to identify these parameters of interest. Presenting the options to intervene, if necessary, and support decision-makers in their plan of action.

This research developed a model which is suitable to explore the future of mobility under changes in the mobility system. In this research, the model is used to explore the mobility impacts of COVID. The COVID-19 pandemic is therefore used as a case study. The model is designed in such a way that it is suitable to explore the impacts of other disruptions in mobility, with the addition of sub-components.

## 5.1. COVID-19 base ensemble

A COVID-19 base situation is constructed where the input uncertainties related to COVID are specified according to the literature. With the use 0f multiple computational experiments (n=1000), the input parameters are varied. With the Key Performance Indicators, the mobility impacts can be observed. The model experiments performed varies each of the input parameters within their range using a Latin Hypercube sampling (Kwakkel, 2017). This statistical sampling method generates a near-random sample of the input parameters. The experiments can be used to explore the range of possible outcomes (Bankes et al., 2013). As not one case is highlighted as a base COVID scenario the base situation is regarded as a base ensemble. In exploratory modelling, the use of a base ensemble, multiple runs under a base input bandwidth, is more suitable than a single base scenario used in traditional modelling (Auping, 2018). Therefore the outcomes are observed with a base ensemble. This is consistent with the exploratory nature of SD, which implies that the goal is not to make estimations about the specific results at a period in time. However, SD is very suitable for exploring future scenarios where the outcomes are observed on a range or bandwidth. Not all the KPIs in the modal are explored, a selection has been made that is beneficial in achieving the goal of this research.

The input uncertainties used in the experiments to construct the base ensemble are selected from the 16 uncertainties in the model (Section 4.3) and are presented in Table 5.1. The uncertainties are focussed on the COVID uncertainties and supplemented with general uncertainties when required. For the base ensemble, this means the variable travel cost and the development of the adoption rate of electric vehicles, due to its powerful impact on travel cost. These parameters are already modelled with an exogenous growth prognosis. Nonetheless, they are subject to unpredictability, therefore included as uncertainties in the mobility system.

The situation without COVID-19 is modelled alongside to determine the change between the situation with and without COVID. To answer the main research question the approximate delta between both situations need to be defined. In the following of this chapter, the scenario without COVID is regarded as the initial trend-line or the no COVID ensemble; and consists of the general prognosis of the mobility developments. In other words, the outcomes of the model if COVID has no influence on the system.

The model input parameters, unrelated to the pandemic, that change over time are implemented primarily based on estimations from *WLO scenarios* and additional prognoses from *Centraal Planbureau* and *Centraal Bureau voor de Statistiek* (Snellen et al., 2015; Van Meerkerk et al., 2021). The parameters are amongst others, population growth and mode-specific travel cost development. As specified in the model description, the prognoses when obsolete are updated. For example, the prognoses of variable car costs have been updated until 2022 (Appendix F). The parameters can be regarded as uncertainties from 2022 onwards, the input uncertainties follow the predicted prognosis. Nonetheless, the prognosis line is changed from a single scenario to an ensemble with the use of an upper and lower range for the parameters applicable as defined in Table 5.1.

| Uncertainty | Range | Unit |
|---|---|---|
| The natural decline rate of remote working | 0.05 ; 0.15 | Dimensionless |
| Expected telecommuting | 0.15 ; 0.25 | Percentage of worked hours |
| Rate of gaining back a positive attitude towards public transport | 0.12 ; 0.3 | Dimensionless |
| Development variable fuel cost | -0.05 ; 0.075 | Euro / km |
| Development variable travel cost in PT | -0.025 ; 0.025 | Euro / km |
| Development distribution ICE/EV | 0.05 ; 0.2 | Dimensionless |

**Table 5.1:** Base ensemble uncertainties

### 5.1.1. Total trips and modal split

The main impact is observed through the number of trips and the modal split. The attractiveness of modes in a post-pandemic era is expressed in both their share and presence. As the trip-based modal split is used in the model these KPIs are closely related. With the use of primary plots supplemented with other figures, the results are visualised. Of the five alternatives taken into account in this research, telecommuting is of particular importance. The inclusion of tele-activities (i.e. option to not travel) as ’new’ mode of transportation, enables the direct observation of working from home over the years. An important remark is that the telecommuting description consists of both not travelling for commuting and educational trip purposes.

**Telecommuting**

After the last active COVID period (5th COVID wave) in the Netherlands, the number of telecommuting trips starts to drop. The number of telecommuting trips does not reduce to pre-pandemic levels (Figure 5.1), indicating the first sign of a higher future number of telecommuters than before the pandemic. This comes as no surprise, based on the existing literature about future tele-activities. As stated in the literature the future extent of telecommuting is uncertain (Reiffer et al., 2022). In the predictions originating from survey data from the Netherlands regarding remote working incentive, the future number of remote working days were estimated at 1-3 days per week (Hamersma et al., 2021). Moreover, increases in remote working hours were predicted to approximately double according to Jongen et al. (2021). These rough estimations show the wide variety of future scenarios, and therefore the high degree of uncertainty. With the use of the above-mentioned estimations the ranges of the telecommuting input uncertainties; *expected number of telecommuters* and *the decline rate of remote working*, were set. In addition, the *rate of gaining back a positive attitude towards public transport* was also set as input uncertainty.

Figure 5.1 shows the future number of telecommute trips being made. Over the years this results in a wide range. The future telecommute trips per month increase with approximately 25% of trips per month near the end of the time horizon compared to initial pre-pandemic levels. Around 2017, roughly five years after the ’end’ of the pandemic the number of telecommuters are even higher. In addition, the range of outcomes is also larger, indicating more uncertainty in the near future compared to the distant future.

Besides the COVID base ensemble, Figure 5.1 illustrates the situation if COVID never happened. As observed the COVID line is not a single scenario but also an ensemble of high and low. Due to the inclusion of telecommuting in the mode choice, the attractiveness of telecommuting is influenced when other attributes (i.e. travel time, travel cost) change. The initial number or telecommuting trips before COVID are validated through the use of long-term travel surveys (Hamersma et al., 2021). It is shown that if the mobility disruption due to COVID had not taken place the expected increase of people working or studying from home would increase by approximately 13%.

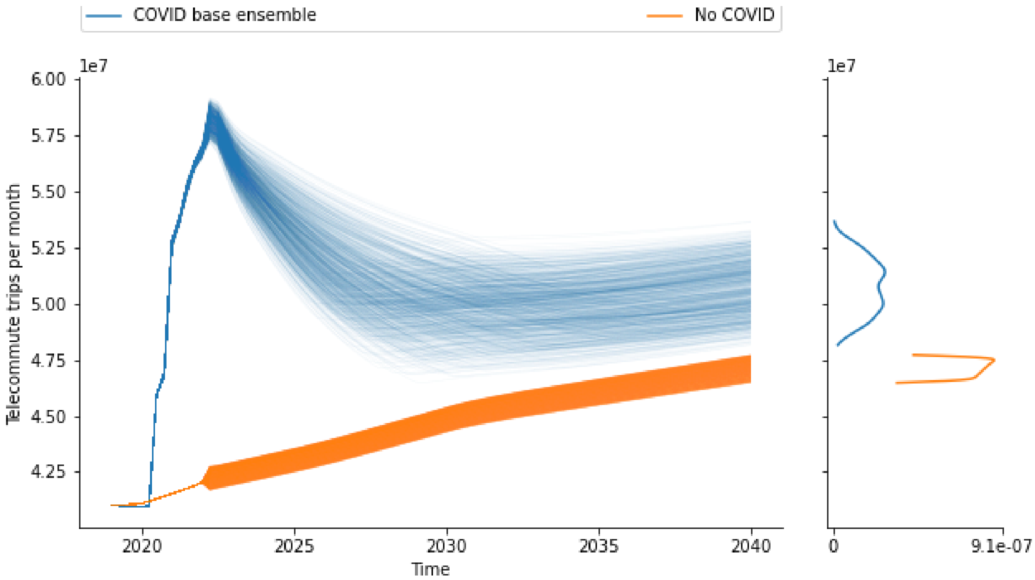



**Figure 5.1:** Total monthly telecommuting trips

**Decrease of traditional modes**
The increase in telecommuting trips inherently leads to a decrease in trips in other modes of transport. Figure 5.2 presents the monthly public transport trips, illustrating that public transport lost a significant amount of travellers. Moreover, it is assumed that travellers will start to come back around mid-2022, even though it is difficult to determine. The gradient of the number of trips influences the recovery of PT. The outcomes that reach the original no COVID situation show a relatively fast recovery compared to the outcomes at the bottom illustrating situations where the result of COVID has a more severe impact.

In an optimistic scenario, public transport passenger numbers are expected to reach the original expected pre-COVID trend lines between 2030 and 2040. However, in a pessimistic scenario, passenger numbers recover more slowly, causing passenger numbers to not recover to the original expectations within the time of the simulation. Nonetheless, the density curve on the right illustrates that a full recovery of PT is plausible by 2040. It shows that most of the outcomes are located above the initial trend line, supporting the statement of a full recovery. Essential to keep in mind is the fact that the attitude towards PT during and after COVID is less straightforward than, for example, working from home attitude, as mentioned in the model description. Therefore, the model outcomes for PT trips and, subsequently, the recovery depends on a more significant degree of uncertainty. To cope whit this Section 5.2 explores the more extreme future scenarios.

The question arises if the decay of PT is almost in full relation to the increase of telecommuting. With the comparison of the PT trips and telecommute trips, it becomes clear that not only telecommuting extracts travellers from public transport. Figure 5.1 & Figure 5.2 suggest that there are additional factors that contribute to the degree to which public transport will recover. Public transport lost a maximum of more than 30 million in absolute trips. It is noticeable that the number of remote working trips increased with no more than 18 million trips.

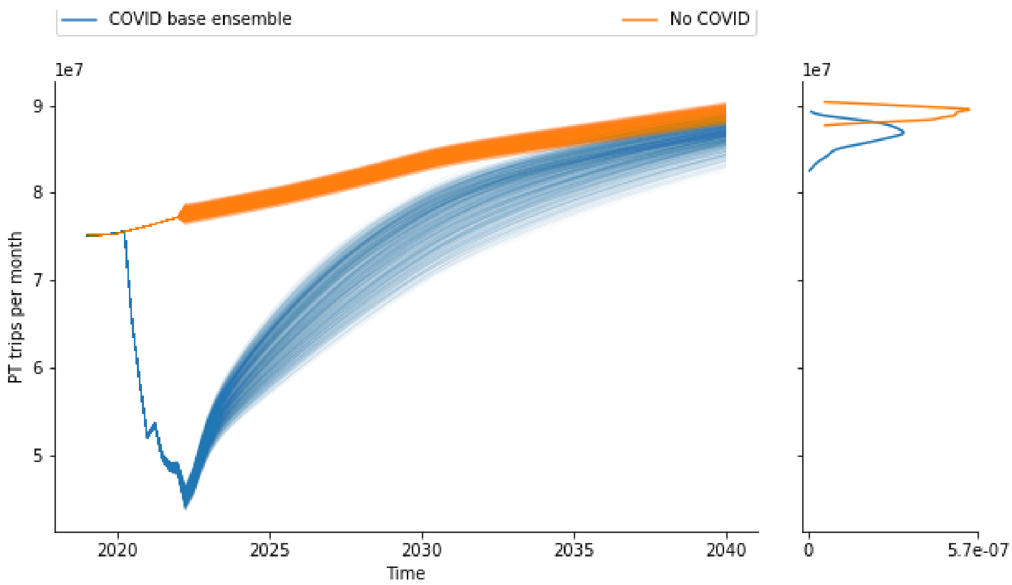



**Figure 5.2:** Total monthly public transport trips

**Driving, cycling and walking**
Besides the alternatives of remote working and public transport, the attractiveness of the remaining modes; the car, bicycle and walking are likewise subject to change. To compare the attractiveness of all modes of transport, the modal split is studied more closely. The modal split in the developed SD model is modelled as a trip-based modal split. The initial share of modes of transportation in 2019 is shown in Figure 5.3, this is the total modal split in the Netherlands at the start of the run period. The new alternative telecommuting is added to the modal split based on pre-COVID working from home travel behaviour (Hamersma et al., 2021; Jongen et al., 2021). The share of telecommuting trips is around 3,13 % of all trips, the inclusion of telecommuting resulted in the modal split values for the traditional modes as presented in Figure 5.3.

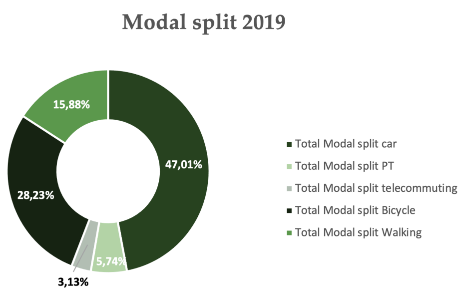



**Figure 5.3:** Modal split 2019

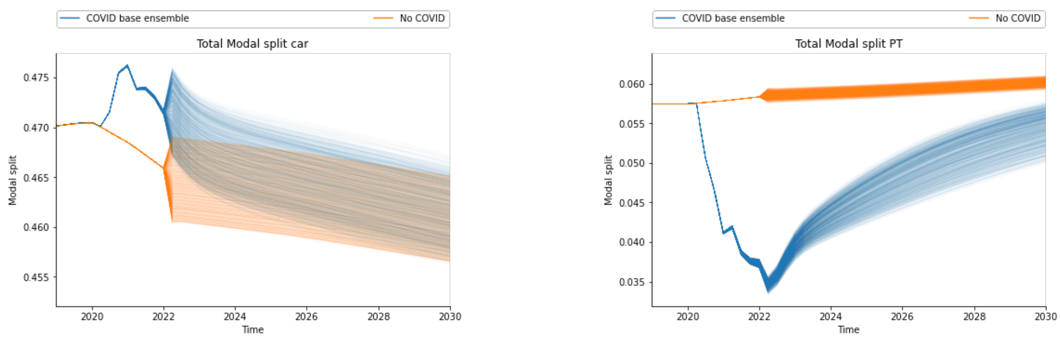
The modal split between **2019 and 2030** is for respectively car, PT, bicycle, walking and telecommuting shown in Figure 5.4a, Figure 5.4b, Figure 5.5a, Figure 5.5b and Figure 5.6. The modal split value is presented until 2030 to explore the development of mode share over the next ten years.

*Car*
The attractiveness of the car decreases after the pandemic. Even though the absolute number of car trips keeps rising (see Appendix E), the share of car decreases for two reasons. First of all, the attributes of the car change in a negative direction under the current circumstances. As a result, the utility of the car decreases compared to the utilities of other alternatives. Second, the level of car traffic on the road increase or decreases the attractiveness of driving. When the congestion level rises, the car becomes less attractive through the feedback mechanism in car traffic. Subsequently pushing travellers to other alternatives as a result of increased travel times.

The COVID base ensemble in Figure 5.4a clearly shows that near 2030, the initial no COVID trendlines are reached. The attractiveness of driving decreases with a high gradient for about 1 - 1.5 years, until they slowly decrease towards the original prognosis. Around the 'end' of COVID (mid-2022), the mode share of the car is about 0.75 percentage points higher than if COVID would never have occurred.

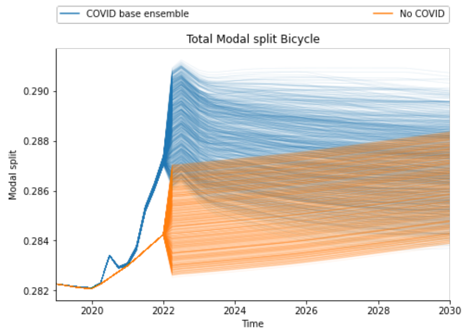
*Active modes*
Furthermore, both active modes; cycling and walking acquire an increased share in the modal split in the near future after COVID. Hence, increased attractiveness of the active modes. Figure 5.5a & Figure 5.5b illustrated that the increase in mode share initiated during the pandemic and continued in the year after.

Primarily the share of cycling increased compared to the no-COVID scenario. At the end of the pandemic, cycling increased by 0.3 percentage points compared to only 0.05 for walking. In the period after the pandemic, cycling attractiveness is clearly at a higher point. Nevertheless, the attractiveness of walking remains more stable than cycling. Derived from the trip-specific results, cycling was seen as an alternative for several short and middle short trips, whereas walking was not a feasible alternative for these trips.

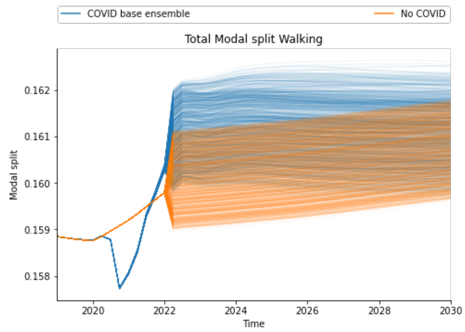



**(a)** Modal split car **(b)** Modal split public transport

**Figure 5.4:** Modal split **2019 - 2030**




**(a)** Modal split bicycle




**(b)** Modal split walking

**Figure 5.5:** Modal split **2019 - 2030**

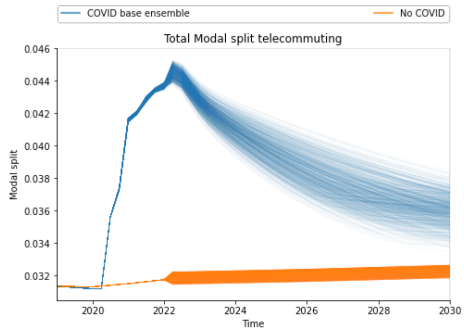



**Figure 5.6:** Modal split telecommuting **2019- 2030**

### 5.1.2. Trip categorical results

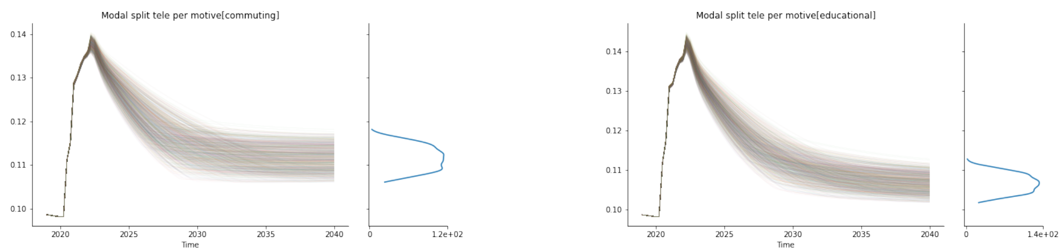
Focusing on more detailed outcomes shows several interesting findings. The developed model enables the exploration of the model outcomes on detailed levels. In fact, the developed model allows for exploring the mobility impacts of COVID in detail on every combination of trip characteristics. With the use of the previously mentioned vectorisation of variables, the SD model includes besides the total number of trips also data and parameters of trips divided per type. Therefore, the results can be observed for each of the 5 trip purposes, 4 distance classes and 5 area types. Furthermore, the combination of each trip type can be explored, resulting in more than 100 unique combinations of trip output for each of the 5 alternatives. In view of the most beneficial outcomes, the main focus has been on trips and modal split on a low level of detail to comprehend the overall situation in the Netherlands. As the main focus of the overall problem owner; the government focuses on the nationwide problem and approach (Francke and Bakker, 2022).

Nevertheless, the exploration of results with a higher detail level are equally important to be able to support policymakers in the approach to intervene if necessary. This section, therefore, highlights several of the interesting results. The comparison between trips for commuting, educational and recreational trip purposes and the effect of congestion on the road for different trip lengths are discussed in more detail.

**Comparison between trip purpose**

In this research, there are a total of 5 trip purposes, as explained in the model description. Exploring the difference in modal split and the number of trips for various trip purposes presents an extensive view of the mutual differences. Therefore, the trip purposes; commuting, educational and social recreational are highlighted in this section. The figures illustrate the modal split of the 5 alternatives specified for one trip purpose.

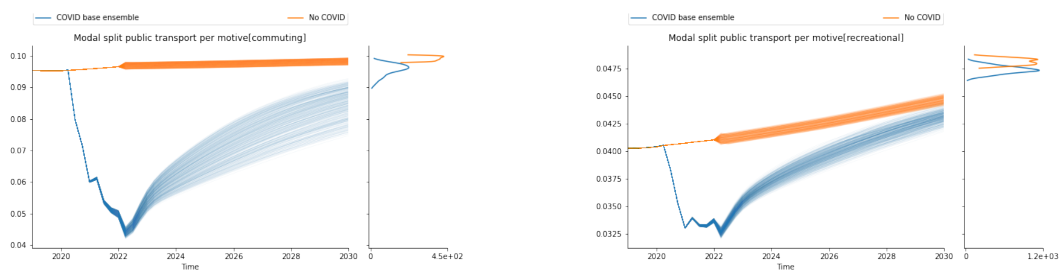
Telecommuting is used as a collective term for both working and studying from home in this thesis. In the model, working and studying from home have separate parameters. There are differences in the behaviour of travellers who do not make a trip for commuting trip purposes and educational purposes. Figure 5.7 presents the course of the future attractiveness to work and study remote. In the future, remote working attractiveness will stabilise, whereas remote studying attractiveness slightly decreases.




**(a)** Modal split telecommuting [Commuting] **(b)** Modal split telecommuting [Educational]

**Figure 5.7:** Modal split telecommuting [commuting and educational]

The differences between recreational and commuter travel are of interest for, among others the planning of public transport. Figure 5.8 shows the differences in the mode share of PT for commuting and recreational trips between **2019 and 2030**. It is shown that the recovery for both trip purposes is similar in the near future, towards the distant future the recreational trips are seen to match the no COVID prognosis slightly earlier. Furthermore, the modal split of recreational PT travel reaches the 2019 pre-COVID level much faster. Therefore, recreational PT travel recovery tends to be faster compared to commuter travel. Nevertheless, the faster recovery is also explained by the fact that the no-COVID prognosis saw a higher modal split for recreational travel relative to commuting. This causes the faster recovery of recreational travel to be put in perspective.

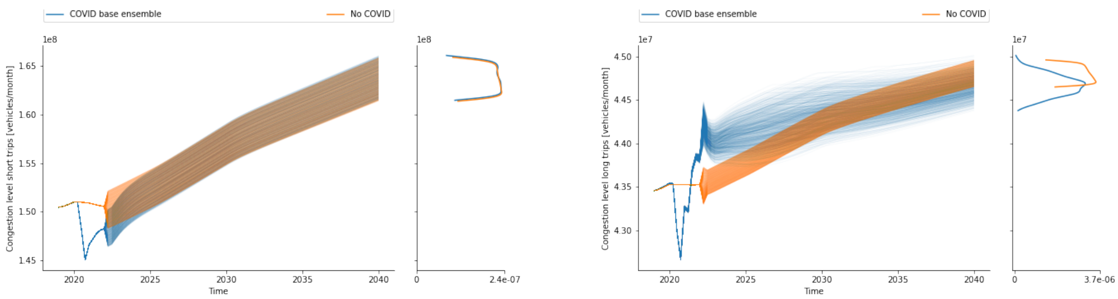



**(a)** Modal split public transport [Commuting] **(b)** Modal split public transport [Recreational]

**Figure 5.8:** Modal split public transport [commuting and recreational]

**Road intensity and congestion level (distance class)**

Road intensity is expressed with the variables of congestion level in vehicles per month. The road intensity for trips up to 7.5 km (short trips) is seen to equal the no-COVID situation within a few years after the end of the pandemic (Figure 5.9a). In contrast, the longer car trips above 40 km see a persistent effect in the near future and are likely to be above the initial no-COVID prognosis until 2027 (Figure 5.9b). This means that the car has become more attractive for long trips during and after the pandemic. Considering the general low attractiveness of PT for short trips and higher attractiveness for long trips confirms that the car gained travellers at the expense of long PT trips. In the future, it becomes evident that the use of the car for longer trips will remain for at least 3-5 years. Therefore the longer trips experience a considerably longer impact from COVID. The fact that long car trips are more uncertain can probably be explained due to the fact that longer trips are more attractive to substitute with telecommute trips. This effect was already noticed in pre-pandemic telecommute behaviour (Hamersma et al., 2021).




**(a)** Congestion level for short trips (<7.5 km) [vehicle/month] **(b)** Congestion level for long trips (>40km) [vehicle/month]

**Figure 5.9:** Road intensity differences

### 5.1.3. Conclusion COVID base ensemble

With the initial results Sub-question 4: *What are the quantified mobility impacts of COVID-19?* can partly be answered. The main impacts can be summarised in a slow recovery of PT, which will inevitably continue in the coming years. Nevertheless, without any interventions, a full recovery until the prognosis without COVID is not likely until the distant future (≈ 2040). Furthermore, telecommuting remains in de modal split with a considerable share post-COVID. However, the extent of the impact in the distant future is probably not to the same degree as predicted in the literature. Furthermore, cycling increased in attractiveness for short trips at the expense of the car, while the car gained attractiveness over the long distance, at the expense of public transport. Differences within trip distance and area type showed the high attractiveness for longer trips (in non-urban areas) to be substituted with remote working.

## 5.2. Scenario exploration

Following the previous results, this section explores the situation outside the base ensemble. In other words, what are the outcomes if future travel behaviour and activity behaviour are not within the expected ranges. This addresses sub-question 5: *What is the role of uncertainty in the future impact of COVID-19 on mobility?* First of all, a scenario with increased uncertainty is implemented, where the results are compared with the base ensemble. Thereafter, with the use of four extreme scenarios, the impact on the modal split is further explored. Finally, with the method of scenario discovery, analyses are performed in which the input parameters are studied to a greater extent.

### 5.2.1. Increased uncertainty

The ranges within the COVID uncertainties are broadened/extended. By means of this, the future mobility impacts are presented under a wider variable range by which alternative situations are explored. Table 5.2 presents the input parameters that are varied and to which extent. On top of the uncertainties in the base ensemble, additional uncertainties are taken into account. The ranges for the decay rate of trips during COVID are included as uncertainty input due to their influence on after-pandemic travel behaviour. The decreasing number of trips during COVID will have a minor continuous effect in the near future, especially in the recovery in the years after the pandemic. Moreover, the use of panel data is not always sufficient to establish an actual decrease in trips during COVID or present a limited view.

| **Uncertainty** | **Range** | **Unit** |
|---|---|---|
| The natural decline rate of remote working | 0.05 - 0.15 | Dimensionless |
| Expected telecommuting | 0.12 - 0.35 | Percentage of worked hours |
| Percentage of labour force able to work from home | 0.4 - 0.45 | Percentage of working population |
| Rate of gaining back a positive attitude towards public transport | 0.1 - 0.6 | Dimensionless |
| Recovery time of Public transport supply | 0.25 - 1.5 | Years |
| Development variable fuel cost | -0.05 ; 0.1 | Euro / km |
| Decay rate of trips in 2nd, ... ,N COVID wave for recreational trip purposes | 0.05 - 0.1 | Dimensionless |
| Decay rate of trips in 2nd, ... ,N COVID wave for shopping trip purposes | 0.05 - 0.07 | Dimensionless |
| Decay rate of trips in 2nd, ... ,N COVID wave for other trip purposes | 0.05 - 0.09 | Dimensionless |
| Development distribution ICE/EV | -0.02 ; 0.05 | Dimensionless |
| Development variable travel cost in PT | -0.025 ; 0.025 | Euro / km |

**Table 5.2:** Uncertainty input

In Figure 5.10 the recovery of public transport elapses with a different incline rate under an increased range of uncertainty. Opportunities for a faster recovery of PT have increased. The main reason for this is the wider range of gaining back a positive attitude in public transport modes. Around 2025 the number of trips deviates only approximately 7 % from the number of trips in 2019. Therefore, this scenario demonstrates the possibility of a faster recovery of PT. Nevertheless, after 2025 it is shown that the gradient of inclination is flattening and most of the outcomes almost equal the no-COVID scenario. On the other hand, telecommuting is also subject to a wider range, which could have a potential reducing effect. Figure 5.11 shows for the telecommuting trips, an increase in the range of model outcomes is witnessed compared to the base ensemble. Primarily the upper bound of telecommuters increased. The effect is due to both a wider range of expected telecommuters in the future in combination with increased variable car costs in 2022.

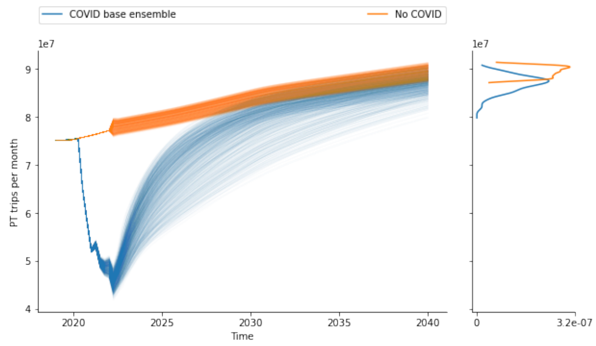



**Figure 5.10:** The number of public transport trips under increased uncertainty between **2019-2040**

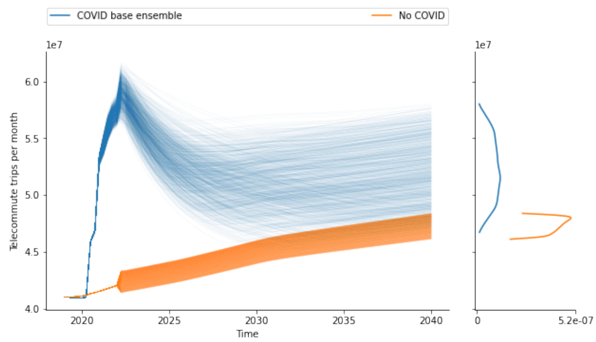



**Figure 5.11:** The number of telecommuting trips under increased uncertainty between **2019-2040**

### 5.2.2. Scenario design for extreme situations

As shown in the first part of the scenario exploration, the outcomes differ considerably under changing input circumstances. With the use of the wider input ranges (Table 5.2) four scenarios are constructed to observe the results in the near future as the model behaviour towards the end of the time horizon (2040) is adequately described in the analysis so far.

The design of "extreme" scenarios presents a future look into the mode attractiveness for approximately five years after the pandemic. Establishing a norm for the end of the pandemic is rather difficult. The end of the final COVID wave in the Netherlands is selected. This timeline is supported by the general predictions about the duration of the pandemic (Murray, 2022). The scenarios specified below, therefore, contain a time period until mid-2027. Beforehand a storyline is built for four possible scenarios in the near future in the Netherlands.

The attractiveness between **2019 and mid-2027** is presented with a stack area plot. Due to the relatively large share of the alternatives, car and bicycle, only the area of interest has been featured in the analysis. Figure 5.12 illustrates that the mode share of alternatives is focused in the range of [0.5 - 0.7]. Furthermore, alternative walking has been removed from the modal split in this analysis. Walking was found to have a limited effect on modal share change, mostly because it is less able to substitute for PT, car and telecommuting. The modal split is adjusted accordingly to visualise only the four selected alternatives.

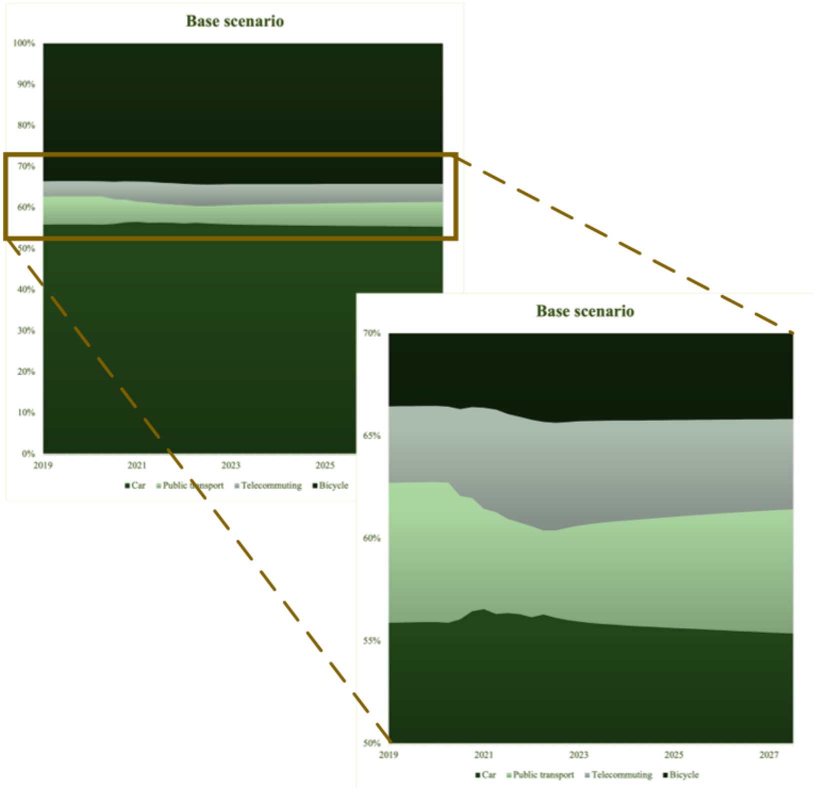



**Figure 5.12:** Base scenario focus point

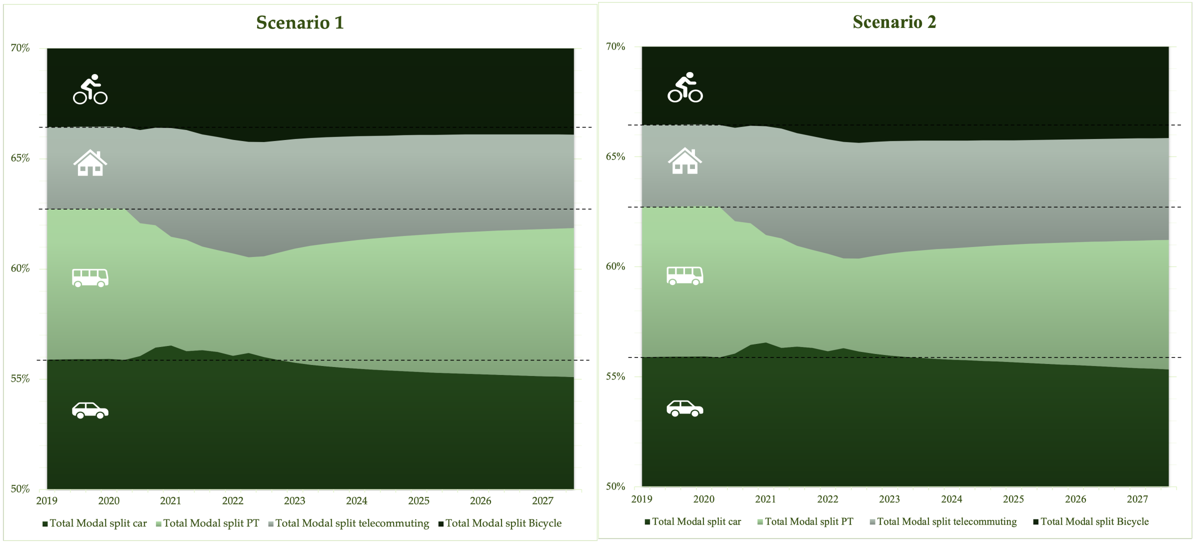
The four scenarios specified below are based on more extreme situations than expected. Nonetheless, they are not unlikely to occur. Because complexity and uncertainty are intertwined with the outcomes of the experiments, the possibility for these scenarios to become a reality is imaginable.

**Scenario 1: Public transport attractiveness increases combined with positive economic development.**
In this scenario, public transport experienced a positive post-COVID recovery phase with a fast rebuild of the image of PT. The public image of PT services increased after the pandemic leading to travellers rediscovering the benefits of PT. With a positive appearance, the number of PT trips recovers relative fast, leading to many travellers choosing the train or bus/tram/metro to travel to their desired location. Alongside the positive image of PT, this scenario features an average level of future working from home, where a positive economic perspective has increased job opportunities. Nonetheless, due to PT's positive image, many travellers also choose to combine online and onsite work, resulting in a moderate degree of future telecommuters.

**Scenario 2: Promoted remote working scenario**
In this scenario working from home is perceived as a positive change. Employers actively support the possibility of working remote, and employees use this effectively. This results in remote work being perceived as a positive development. Both by travellers and governmental parties, as it solves a lot of pre-COVID congestion issues. However, this development results in travellers not returning to other alternatives.

**Scenario 3: Increase of travel cost as a result of challenging economic times for consumers**
Due to challenging economic times, travel costs have increased across all alternatives. The rise of travel costs for multiple modes, specifically the car, results in less attraction for the more expensive modes.

**Scenario 4: Public transport attractiveness remains low**
In this scenario, the image of PT is contrary to scenario 1, perceived as negative. With less demand and scaling down operations, PT operators struggle to provide the level of service desired by travellers. With less supply and the effects of the pandemic that did not favour PT, it is hard to rebuild the (positive) image PT had before the pandemic.



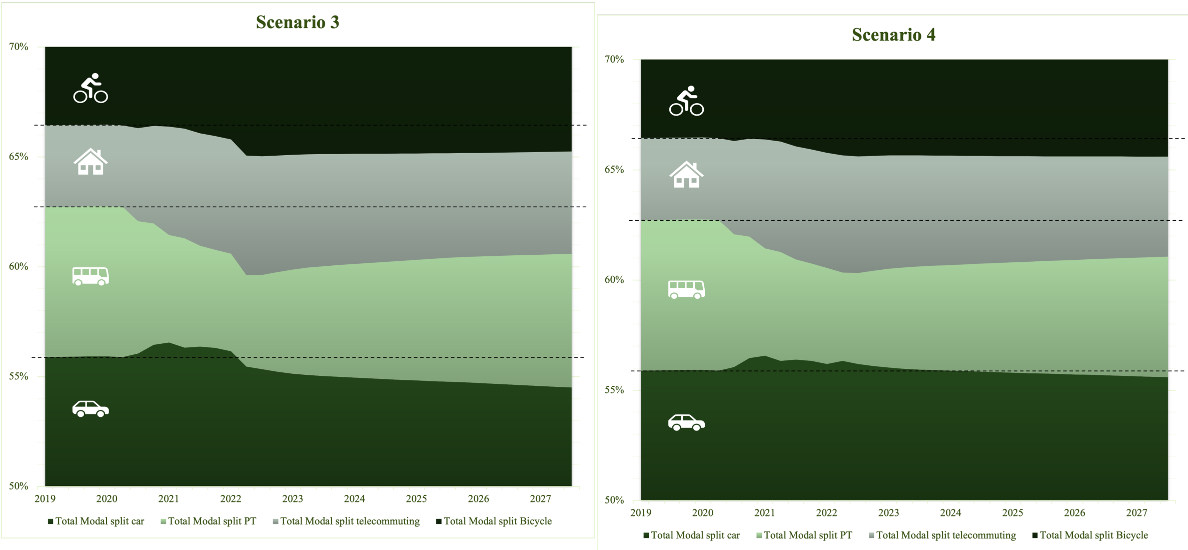

**(a)** Scenario 1: PT attractiveness increases combined with positive economic development

**(b)** Scenario 2: Promoted remote working scenario

**Figure 5.13:** Scenario 1 & 2

**Scenario design results**
The four designed scenarios show the changing modal split between 2019 and mid-2027. There are differences in our future modal split values in each of the "extreme" scenarios. Small changes in modal split can lead to relatively significant changes in the use of particular alternatives. An important side note is that the scale of Figure 5.13 & Figure 5.14 is compressed and therefore shows the modal split zoomed in on a small part of the actual modal split as indicated in Figure 5.12. Furthermore, the interest is in identifying the near future post-COVID situation, hence the focus on the results from **2022-2027**.

As shown in scenario 1 (Figure 5.13a), the modal split of PT almost fully recovered by 2027, indicating that the setback of PT as a result of COVID has disappeared. Compared to the other scenarios, this is not the case. In scenario 3, the decrease in PT is limited due to the considerable drop in car attractiveness.




**(a)** Scenario 3: Increase of travel cost as a result of challenging economic times for consumers

**(b)** Scenario 4: Public transport attractiveness remains low

**Figure 5.14:** Scenario 3 & 4

In addition, scenario 2 (Figure 5.13b) shows that telecommuting has gained a significant share in the modal split, primarily gained at the expense of public transport. The increase in the share of telecommuting comes as no surprise. However, this increase initiates a conflict between the two alternatives as Figure 5.13b illustrates that the effect is almost solely at the expense of PT attractiveness.

Cycling encounters an increase in attractiveness in almost all scenarios except the first. In scenario 3, the increase is most distinguishable. The increase in cycling attractiveness shows that an increase in travel costs rapidly sees a transition in more travellers opting for active modes (Figure 5.14a). Besides active modes, working from home also encounters an increase due to travel cost growth in scenario 3.

Finally, it becomes evident that the negative PT perspective of travellers has a severe impact on the attractiveness of public transport. Scenario 4 (Figure 5.14b) shows the remaining low level of attractiveness for public transport in the years after COVID. Based on a more in-depth analysis of the scenario outcomes for different trip purposes as shown in Appendix E, primarily commuting PT travel encounters a decrease in the modal split. Whereas recreational PT travel in scenario 4 lost near 2027 less of its attractiveness compared to commuting travel. The additional stack graphs also illustrated that when PT reputation is positive (i.e. scenario 1), the modal split for recreational travel reaches pre-pandemic levels faster than commuting travel.

Nevertheless, it has to be mentioned that the no-COVID prognosis of recreational PT attractiveness is estimated to increase relatively more than the commuting PT attractiveness prognosis. Therefore, putting the faster recovery of recreational PT into perspective. This is in line with the trip-specific results (Section 5.1.2) where the same effect was uncovered.

### 5.2.3. Scenario discovery

The four designed scenarios revealed and visualised the impact of uncertainty. To gain more insight into the underlying uncertainties, the application of scenario discovery methodology is useful. With the use of a scenario discovery algorithm, computer-assisted scenario development is possible by selecting desired and undesired runs from the ensemble (Bryant and Lempert, 2010). The scenario discovery is contrary to traditional scenario design not based on storylines. As illustrated in Section 5.2.2 the design of scenarios can identify extremes, nonetheless, the number of scenarios is limited.

With the use of the patient rule induction method (PRIM) algorithm, scenarios can be discovered in the EMA workbench (Kwakkel, 2017). The use of PRIM is suitable for observing the role of uncertainties under desired and non-desired outcomes of the KPIs. With PRIM influential input variables can be discovered within the desired threshold level of a KPI. The cases of the modal outcomes are therefore divided into desired and non-desired values. The PRIM algorithm finds the most influential uncertainties with the use of scenarios. The experiments are performed with the same input ranges as presented in Table 5.2. The number of experiments is increased to 5000 as the cases are selected based on threshold level, with the use of 5000 experiments the algorithm has enough experiments to eliminate the cases not used.

The PRIM algorithm is a so-called bump hunting algorithm and was originally developed by Friedman and Fisher (1999) as a form of data mining technique. The algorithm is used for discovering regions of interest in high-dimensional data. In the case of scenario discovery, PRIM is useful as it presents the user with the option to assess the quality of the scenario, based on coverage, density and interpretability (Bryant and Lempert, 2010). A scenario can be selected based on its high combination of coverage and density. A selected scenario with a high coverage indicates that it can explain a high share of the outcomes. Subsequently, with a high density, the confidence and certainty of a predicted scenario is shown. Therefore a high combination of coverage and density improves the significance of the scenarios.

Derived from the initial results, the modal split of public transport and road intensity are appointed as the KPIs of interest. Because the input uncertainties for the future mobility impacts are based on sometimes rough estimations, the scenario discovery with PRIM contributes to the explanation of the result. The results are observed in the timeframe until **2040**, similar to the increased uncertainty scenario.

**Public transport modal split**

The modal split for PT, in 2019 is 5,74% (0.0574), adjusted for the implementation of telecommuting (Figure 5.4b). The favourable outcome for PT is a modal split at least above 0.06, this value is derived from the no COVID prognosis to establish a full recovery. Hence, the threshold for desired outcomes is set at this level. The application of the PRIM algorithm and the subsequent results indicate how to attract more travellers to public transport.

For the modal split of PT to reach the desired 0.06 in 2040 the outcomes are illustrated in Figure 5.15. Where an increase of at least 0.01 euro/km of variable car cost on top of the current situation (mid-2022) is necessary. In addition, the rate of gaining back trust should be above 0.23 and the percentage of telecommuting hours of total work hours cannot exceed the 27% boundary. The results indicated that the extent to which travellers' attitude requires change is within the middle of the range. However, compared to the base ensemble and associated input ranges Table 5.1 it is evident that 0.23 is near the upper bound, therefore entails a notable minimum degree of improvement in PT attitude. Furthermore, the extent to which travellers telecommute in the future is still able to reach a relatively high level (27%). Indicating that besides telecommuters, public transport travellers with other trip purposes are of impact, this substantiates the findings of the designed four scenarios.

The coverage in Figure 5.15 indicates that the chosen scenarios represent almost half of the cases in which the desired modal split applies. With the density, it is illustrated that this scenario can predict all the cases with that modal split value.

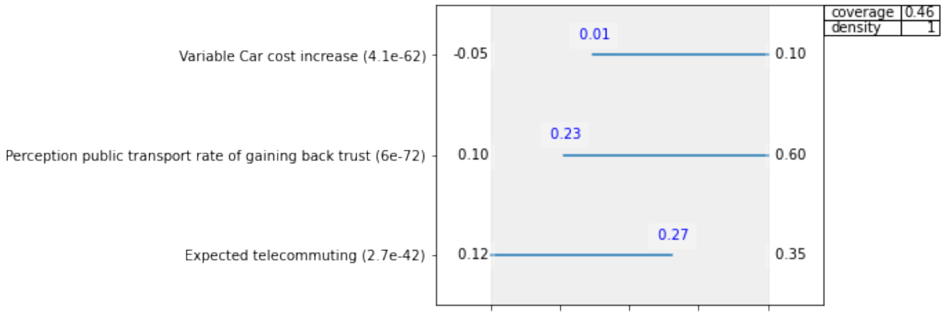



**Figure 5.15:** Scenario (box 23) for the modal split PT

**Degree of congestion**

Limitation of the degree of congestion, thus the intensities on the road, is a second model outcome that is useful as a benchmark. The initial 2019 value for congestion level is 1.110.000 kilometre-minutes per month. The initial trend line is interrupted by setting the threshold of desired outcomes to below 1.160.000 km-min per month. Hence, a more desired outcome applies.

Figure 5.16 illustrates the variables that cause the desired decrease in the degree of congestion compared to 2019. The variable cost should increase more than 0.05 euro/km, whereas the rate of gaining back a positive attitude in PT only requires to be around 0.15. On the other hand, the expected telecommuting requires at least above 22%. The results confirm the relationship between car travel and remote working. Whereas, the degree of remote working requires almost a quarter of our working hours to achieve the desired decrease in congestion in the future. Hence, the positive impact remote working has on the road intensity on the main road network. Figure 5.16 indicates that the chosen scenario represents 48% of the cases. The density indicates that the selected scenario can predict all the cases.

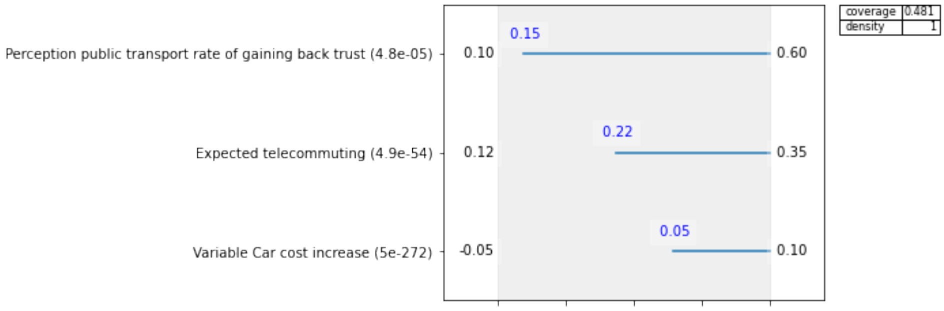



**Figure 5.16:** Scenario (box 33) for the congestion level

### 5.2.4. Conclusion scenario exploration

To conclude, the results of the scenario exploration contribute to a broader understanding of our travel behaviour in a post-COVID era. With the outcomes, sub-question 5 can be answered: *What is the role of uncertainty in the future impact of COVID-19 on mobility?*

First of all, the input parameters are generally based on literature and prior research, which is associated with a high degree of uncertainty. Therefore, broadening the ranges of input variables shows the magnitude of impacts on top of the base ensemble outcomes that are considered to be likely.

Second, the designed storylines allowed the exploration of more extreme scenarios in which input parameters follow low and high directions. In some scenarios, the conflict between public transport and telecommuting became even more noticeable. Both alternatives compete for the same travellers, resulting in a considerable decrease in travellers in a scenario of a long-lasting dissatisfactory image of public transport. On top of that, it is argued that the rise of social-recreational travellers should be put in perspective regarding the no COVID prognosis. Social-recreational travel is expected to reach the pre-pandemic level faster than commuting travel. However, the time it takes to equal the prognosis of travellers without the disruption of COVID is similar to commuting travel.

Third, following the recovery of public transport, the use of the Patient Rule Induction Method (PRIM) algorithm in scenario discovery emphasized the role of a positive attitude towards PT services to reach the desired level of PT attractiveness. Compared to the base scenario ensemble, PT attitude increase is located near the upper boundary of the range, meaning travellers' attitude to PT services has to improve significantly to reassure the return to the original trend prognosis of passenger numbers. In addition, the scenario discovery revealed that telecommuting has a substantial role in the future of road intensity. If the population that can work from home would work slightly less than a quarter of their working hours from home, the level of congestion can be reduced to the desired situation.

Finally, the role of uncertainty is considered substantial, as demonstrated in the extreme scenario design and scenario discovery. It is conceivable that the future is more comparable to one of the more extreme scenarios than the initial COVID-19 base ensemble. Therefore, resulting in a different time or magnitude of the impacts. With the exploration of the extremes and the uncertainties, it becomes possible to make a more powerful statement about the impact.

## 5.3. Final results

The chapter is divided into two main analyses. In the first part, the base COVID ensemble was explored, resulting in likely outcomes regarding the situation in the near and distant future in mobility (behaviour). The second part explored various scenarios, uncertainties and alternative situations. Both analyses provide strong validated outcomes that can support policymakers in deciding what to accomplish.

The base ensemble illustrated that it will take a long time for public transport to reach a full recovery. The speed of recovery is mainly due to the future valuation of PT and the degree of remote working. In addition, part of the valuation of PT is not only captured by the positive/negative attitude from the traveller, but also by the fact that some modes of transport experienced a permanent increase as a result of the previous measures in place. As illustrated in the results, the attractiveness order rearranges, resulting in travellers preferring a certain alternative mode of transport after the pandemic. This substantiates the contribution to the future slow recovery of PT. Furthermore, there is a relationship between telecommuters and PT, where the number of future PT travellers is in addition dependable on the number of telecommuters. Nonetheless, it was shown that a return of onsite work does not equal the return of public transport use to the full extent. Since the attractiveness of the car for long trips turned out to be a rediscovery for many travellers, PT encounter a remaining loss of these travellers in the coming years. Besides the frequently argued relationship between telecommuters and PT travellers, telecommuting and car travellers feature a connection. If the remote working hours doubled compared to pre-COVID remote working hours, the increase in congestion on the road stays within desired limits.

For public transport there is also a clearly visible difference in the recovery between the expected scenario (COVID base ensemble) and the scenario exploration. It is evident that the attitude toward PT should improve significantly to reach desired levels. The designed scenarios show that in the near future ($\approx$ 2027), attractiveness could be back at the old level in a positive PT attitude scenario. With the attractiveness of public transport back, the share of PT is back within five years after the pandemic. As a result, the modal split for car, bike and telecommuting reduces. Nonetheless, the other scenarios show a more pessimistic recovery of PT attractiveness. Supported by the PRIM analysis, the value for gain in a positive attitude towards PT should appear within the upper half of the uncertainty range to cause a modal split of the desired threshold value. In relation to the COVID base ensemble, this indicates almost the maximum level of positive attitude increase. Therefore, it can be concluded that public transport reaching its old level of attractiveness within a few years is unlikely to happen without any intervention.

# 6 Discussion

This thesis explored the future mobility impacts of the COVID pandemic with an exploratory modelling approach. This chapter presents the discussion. First, the results are interpreted and the interesting findings are highlighted and related to the literature. Second, the implications of these results are identified and an action perspective can be proposed. Subsequently, policy recommendations and their implementation in the system are discussed. Third, the limitations of this research and the developed model are mentioned. Finally, the recommendations for future model development and future research are discussed.

## 6.1. Discussing the results

This section provides an interpretation of the results, as well as the results in relation to the literature and other research. Furthermore, the new contribution these results provide and their role in scientific work is mentioned. Due to the development and use of a system dynamic model, the novel model implementations are highlighted as well.

### 6.1.1. Interpretation of the results

The interpretation of the results is discussed for public transportation and telecommuting. The relation between telecommuting and PT and the combined effects are additionally addressed.

**PUBLIC TRANSPORT**

From the results, it has become evident that without interventions the number of travellers is not likely to reach the original passenger numbers anytime soon. The negative perspective travellers have towards PT has a significant impact on the results. The effect is estimated to be present for multiple years after the pandemic.

The impact of future negative attitude is contradictory to recent research of De Haas and Faber (2022), where the authors estimate negative attitude to have little impact in the future. As De Haas and Faber (2022) acknowledge the fact that the negative attitude is present, the extent could be underestimated, as argued by the results of this thesis. The fact that the negative PT attitude remains is, according to this thesis, also due to the lasting increase in positive attitudes for other modes. Furthermore, there is a lack of research towards the future of negative attitudes. The current literature focusses primarily on the attitude change during the pandemic (De Haas et al., 2020b; Ton et al., 2021). According to Ton et al. (2021), it is also challenging to measure changes in attitude due to a lack of data on pre-pandemic attitude.

In regard to estimations drafted in the literature, it is seen that a lot was still unknown for the estimation of how long PT would endure the consequences of COVID. In recent research by Francke and Bakker (2022) on behalf of the *Ministry of Infrastructure and Watermanagement*, updated predictions of PT ridership numbers are presented for the near future (2022-2026). According to this new prediction of Francke and Bakker (2022), the basic estimate shows that in 2023 the level of 2019 can be reached again. It is however important that the quality of PT services remains at a certain standard. In the alternative scenarios, it would take an additional 4-5 years for PT to reach its pre-pandemic level of passenger numbers. These alternative scenarios are designed in order to map the situation under negative circumstances evolving from the conflict in Ukraine, and PT services that do not provide the same level of service as they did before the pandemic (Francke and Bakker, 2022).

In relation to the result of this thesis, the outcomes contradict the length of the public transport recovery in Francke and Bakker (2022). According to the authors, in a positive scenario, the pre-pandemic level of PT attractiveness is reached around 2026. However, in a more negative scenario, it takes significantly longer to equal pre-COVID numbers. In comparison to the study of Francke and Bakker (2022), the results of this thesis show a more hesitant road to recovery. Nonetheless, the statement of Francke and Bakker (2022) regarding the essential role of travellers' trust in public transport in alternative scenarios is endorsed by this thesis. The fact that there are some differences in outcomes demonstrates the existence of uncertainty in the overall determination of future mobility impacts. In the implications (see Section 6.2), the future situation with regard to public transport is elaborated on, as well as the potential recommendation for the course of action from the perspective of the problem owner.

**TELECOMMUTING**

The results and analysis of telecommuting are discussed and compared to the literature. Three interesting findings regarding telecommuting are highlighted in this section. First, the fact that a conflict arises between public transport and telecommuting. Second, the differences between remote studying relative to remote working. And finally the relationship between telecommuting and the situation on the road.

**Comparison with other research**

The mobility impacts of telecommuting in this thesis provide a more detailed look at working from home and telecommuting behaviour over time. Therefore, this supplements other telecommuting research in which primarily estimated results are presented at a certain moment in time (Hamersma et al., 2021; Mouratidis and Peters, 2022). It was found by Ton et al. (2022) through the use of longitudinal data and Latent class cluster analysis that teleworkers can be separated into several groups. Each with their own preferences towards working from home. This thesis also contributes to the categorisation of telecommuters, however, not on the basis of assigned latent classes, but through the use of trip types. Based on the results of this thesis, it becomes possible to separate telecommuters based on their trip type. With the possibility to gain insight into the differences between, for example, a traveller making a long trip from an urban area and a short trip from a nonurban area and the subsequent incentive to substitute that trip with remote working.

**Conflict between public transport and telecommuting**

As shown in the analysis of the results there is a connection between tele-activities and the use of public transport. Zooming in on the commuter and to a limited extent educational travel, it is illustrated that public transport and telecommuting are competitors and seek the same type of traveller. This has consequences for the future, as naturally, remote working keeps travellers out of PT. When both are stimulated through the use of either policy or behavioural change, a conflict might arise. To prevent opposing interventions, potential measures need to be aligned. It is not possible to design policy for one, without taking the other into account. Interventions in the system should therefore primarily be aimed at improving the distribution of travellers throughout the day. Instead of only stimulating people to work several days from home to limit congestion and crowdedness, it is beneficial to focus on improving the spread of travellers. The methodology of system dynamics is particularly suitable for implementing policy interventions and determining the impact on the system. It is therefore recommended to analyse the policy interventions in future research.

**Differences between remote studying and remote working**

Following the results, it was witnessed that between working from home and studying from home differences occur. The differences were mainly visible in the future extent of tele-activities. The first explanation is the fact that the lasting effects of remote studying are primarily focused on higher education institutions. Due to the practical limitation of other forms of education to be suitable for hybrid or full remote working. Therefore, post-COVID, a lot of remote educational activities were switched back to onsite completely. This is partially the explanation for why remote studying is present to a lesser extent than remote working in the future.

Second, students generally have a lower ability to study remote than remote workers. In pre-COVID times, Valenta et al. (2001) already emphasizes the factor of the ability to study from home and identifies its significant contribution to students' attitude towards tele-activities. The results of this thesis showed that remote studying is still present, primarily, in the near future. Current numbers of on-campus students verify the research results and confirm that the number of students attending onsite education is less than before COVID (Last and Dopmeijer, 2022). Students discovered studying from home and avoided the trip to campus more often than if COVID would not have occurred.

The travel choice and mode choice of students are based on multiple factors according to Versteijlen et al. (2021). The change of 'habit' in choice behaviour is identified as an effect that explains the slow return of people to onsite activities (Thomas et al., 2021). The factor of habit is currently not implemented in the model, but it would be a useful addition to the model.

**Congestion and remote working**

Telecommuting is not only responsible for a decrease in PT travel. The results showed that remote working, and to a limited extent, remote studying also contributes to the decrease in car traffic. It is shown that telecommuting will be used as an alternative mode of transport in circumstances or scenarios where travel costs rise or congestion levels are high. In a pre-pandemic time, Van der Loop et al. (2019) described the combination of working from home and congestion. The authors argued that between 2000 and 2016 travellers already made the choice to work from home or travel to work after peak hours to avoid congestion. They argued that if flexible or remote working would have not been present during that time there would have been an increase of 2.6% in car kilometres. Related to the model outcomes of this thesis; the scenarios with an increased degree of telecommuting caused the level of congestion to drop. Due to the increased attractiveness of the car, on the other hand, the decrease in congestion is suppressed. In addition, scenario discovery demonstrated that the future extent of telecommuting contributed if congestion is intended to be kept under a preferred maximum.

### 6.1.2. Relation to prior scientific work

**Modelling technique**

This thesis implements/models a new alternative in the mode choice component of the simultaneously designed SD model. Within earlier SD mobility models the use of working from home had not been implemented in this way. Until now, telecommuting was included as a percentage of trips not being made for simplicity reasons (Haghani et al., 2003; Malone et al., 2001). Therefore, telecommuting was a static component which only affected the input of a model. With the transformation of telecommuting into a dynamic component, the attractiveness can be monitored when utility attributes change, similar to the traditional modes of transport. Due to tele-activities becoming embedded in people's daily life, modelling telecommuting as an alternative in the mode choice outside of exploratory modelling is a relevant element to study in travel behaviour research in general.

By means of modelling with an SD approach instead of the traditional traffic and transport modelling technique, the behaviour of the system can be analysed. Moreover, the exploration of future travel and behaviour is analysed in a different way compared to traditional transport modelling. This shows the strength of exploratory modelling and enables the application of vision and validate as mentioned in the theoretical framework (Section 1.2). With relative small adjustments in the input variables, it was feasible to explore multiple scenarios and potential future situations. Therefore, the designed model provides a tool to model endless potential future scenarios by changing the various input uncertainties in combination with the presence of extensive trip types. In this thesis, the analysis of scenarios has been limited to the scenarios of interest to answer the main research question.

**Results**

Over the course of this research, the literature regarding future mobility impacts of COVID expanded significantly. The outcomes and subsequent analysis in this thesis contributed to the existing research by providing new insights, as well as verification and additional interpretation of estimates from other studies. Therefore, providing a complete view of the course of travel behaviour over time (i.e. dynamic) in addition to estimated values (i.e. static) from the literature.

In addition, the strength of this thesis lies in the coherence of the effects in particular. The inclusion of multiple mobility impacts of the pandemic at the same time enables the exploration of a coherent future situation. Therefore, the results are seen as cohesive: effect A influences the attractiveness of alternative X positive, while effect B for example leads to dampening results. Furthermore, it is proven that the role of uncertainty has a large impact, as predicted by Papakatsikas et al. (2021) & Chatterjee et al. (2021). In the framework of uncertainty in transport systems (Marchau et al., 2010) as introduced in the theoretical framework, the disruption as a result of COVID complies with the requirements to be categorised as an external force of influence.

## 6.2. Implications and policy recommendations

Similar to the interpretation of the results, the implications are discussed separately. When applicable the relationship between telecommuting and public transport is noted.

### 6.2.1. Implications for public transport

The future situation of public transport as outlined in the results causes several implications which are generally considered undesired. Providing accessible public transport is essential to prevent transportation inequality (Gutiérrez et al., 2021). In the Netherlands, providing access to public transport is the responsibility of the government. The main implications are regarding transport poverty and sustainable mobility. The policy recommendation focus on pricing and supply to potentially attract new travellers.

**Transport poverty**

A decrease in public transport use could jeopardise the current public transport supply. The reduced frequencies and less dense networks could subsequently lead to social inequality and transport poverty (dutch: vervoersarmoede). Transport poverty arises when travellers have limited options to modes of transport (Snellen et al., 2021; Ranchordás, 2020). Scaling down public transport as a result of fewer users enables transport poverty to increase, especially in non-urban areas where PT already demands more perseverance from the user with long access/egress and waiting times. On top of that, public transport in the Netherlands is planned to be scaled down in 2023 due to primarily staff shortage. The scaling down of PT is contrary to the ambition of both operators and the government, as presented in their outlines of the future vision for 2040 (Ministerie van Infrastructuur en Waterstaat, 2019). This raises the question if current developments increase the effect of a negative attitude towards PT, and potentially stimulate once again the aversion to PT.

**Sustainable mobility**

Second, the objective of promoting sustainable transport over the past years and forcing a positive modal shift by promoting PT over the car has to cope with an enormous setback. Because the primary objective is currently getting travellers back in PT in general, the focus on promoting sustainable mobility disappeared. Therefore leading to an undesired situation, especially within the mobility transition (Griffiths et al., 2021). A sustainable mobility transition conflicts with the current and future events in mobility as drafted by the results from this thesis.

This thesis showed the increase in attractiveness of relative unsustainable modes of transport such as the car on some occasions, which implies that the general transition to sustainable mobility will be affected in a negative way. In other words, an undesired situation arises. To cope with the undesired situation from the perspective of the problem owner, solutions can be designed. With the use of additional analysis of (trip-specific) results, future research can establish where in the system specific interventions are required. In this case, SD can support policymaking by determining the area of interest for interventions.

**Pricing**
Because the recovery of PT occurs slowly, the use of certain **policy interventions** could be proposed. Inherently, a decrease in ticket prices will lead to an increase in travellers. Primarily an increase in recreational travellers due to their higher price elasticity compared to educational and commuting travellers.

In Germany, the government decided to implement a temporary 9 euros per month ticket for the duration of three months (Cantner et al., 2022). Researchers seized this opportunity to observe the impact of a price modification on mode choice in a post-COVID era. With the use of travel surveys, Loder et al. (2022) found that the price reduction led to increased demand (approximately 15%) and positive signals of travellers choosing public transport over the car. The temporary cheaper tickets led to a positive impact on the image of PT, which is likewise favourable for the situation in the Netherlands, as shown in the results. However, Pladson (2022) argued whether the image of PT actually increased due to the policy intervention. As travellers point out that the level of service decreased rapidly Pladson (2022).

The experiment in Germany provides an ideal example for policymakers in the Netherlands. As presented in the results, a scenario where a positive attitude increases rapidly causes PT to be back at its previous level within 5 years after the pandemic. It is beneficial to explore the potential of similar policy interventions in the Netherlands. Although to prevent similar negative outcomes as the experiment in Germany, such measures should not be implemented when operators are not able to handle the extreme increases in demand as seen in Germany.

**Supply**
Besides ticket prices, the supply of PT could be used as an intervention option. The pandemic has resulted in a lower supply of PT in the near future as a result of the current and future loss of demand. Increased supply of public transport services, therefore, higher frequencies have a positive impact on the use of PT. Nonetheless, scenario discovery shows that altering the length of the recovery of PT supply has little effect on the recovery of PT. Hence, the effect of such an intervention is questioned.

**New travellers**
According to Van den Toorn (2022) and Van Vliet (2022) the pandemic has resulted in a permanent loss of certain travellers in public transport that do not return. This raises the question if the focus should be shifted towards finding 'new' PT travellers for which PT previously was not an attractive mode of transport. Besides the abovementioned measure of pricing, it is complicated to attract new travellers. Durand et al. (2021) address the complications in attracting new or infrequent travellers, among which digital difficulties and sometimes inaccessibility play a role. Therefore, stimulation measures directly aimed at irregular train travellers could potentially increase their attractiveness. However, a positive PT image is essential.

### 6.2.2. Implication of telecommuting

As shown in the results, telecommuting reduces the amount of traffic on the main road network and public transport network. It is debatable if the effect of more telecommuting is always desired. From a financial perspective, Borggreven (2020) argues that social welfare increases in general, due to more remote working. On the other hand, Last and Dopmeijer (2022) argue that working and studying from home also causes various negative effects.

Therefore, stimulating remote working as a policy measure is questionable. Nonetheless, the focus of this thesis is limited to telecommuting implications in mobility. Aside from congestion, implications are additionally present in other aspects of mobility.

Telecommuting can be seen as a sustainable mode of transport, as more working from home generally means less pollution due to a trip not being made (White et al., 2010). This effect applies of course mainly to car trips that are being substituted. Beyond the mode of transport, it is debatable if working from home is in fact the more sustainable option.

Furthermore, White et al. (2010) argues that the distance travelled and general traffic volume does not decrease in line with the increase in the amount of remote worked hours. This is in line with the expectation defined in the literature where the decrease in travel time and travel distance is questioned as a result of, among others, the concept of a constant travel time budget (Mouratidis and Peters, 2022). As a result, the pollution avoided by not making a trip could be replaced by another trip. When this results in a commuting PT trip being replaced by a recreational car trip, the opposite objective is achieved. Due to the trip generation not being influenced by the change in telecommuting, the rise of replacement trips as a result of more remote working cannot be studied and is therefore outside the scope.

**Situation on the road**
Because the car has become a more attractive mode of transport in the near future, the implementation of policy interventions to redirect travellers from the car towards other modes could be desired. The stimulation of remote working is often mentioned as a policy instrument to reduce traffic on the main road network (Olde Kalter, 2022). The results of this thesis endorse the positive effect remote working has on road congestion.

## 6.3. Limitations of the research

The research and the developed system dynamics model in this thesis are limited in some ways. Hence, features some simplifications and aspects that are outside the scope. The main limitations are highlighted below.

**Transport modelling limitations**
With the use of system thinking and the construction of a model to represent a system, model limitations are inevitable. Within the developed SD model, the scope is aimed at the mode choice part, resulting in other factors of the transport modelling cycle being simplified in a few ways. In the methodology, it was proposed to use the 4-step model (Ortúzar and Willumsen, 1990) as a guiding principle and apply focus on the mode choice. In hindsight, the choice to focus on the mode choice caused some simplification in the constructed model.

First, the absence of dynamic trip generation results in the model outcomes not being able to influence the number of total trips. Second, the simplification of the assignment step causes the outcomes to be only visible at a nationwide level and the five geographical specified area types. The inclusion of a detailed zonal network could extend the route assignment part. The route assignment is closely related to the network of nodes and links used (see Section 6.3). There was no need for an underlying synthetic network to be able to answer the research question. Moreover, Shepherd (2014) also illustrated that SD modelling is not the best application for detailed route assignment. For the purpose of overcomplexity, the mentioned limitation and simplification are implemented. In a new version of the model, most of the simplifications and some of the limitations can be added.

**General demand and supply issues in the Netherlands**
It is beyond the scope of this research to address the general mobility problems surrounding transport demand and supply in the Netherlands. The fact that in the future the mobility system in the Netherlands encounters overload on several networks by reaching maximum capacities is a general problem wider than the implications addressed in this research (Bakker and Moorman, 2021). Although, the current model could be applied to the broader transport demand issue and provide insight, on a macroscopic level, into potential bottlenecks for future demand and supply of transport.

**Attractiveness of the telecommuting alternative**
Modelling telecommuting as an alternative in an SD model integrated choice model requires a utility function for telecommuting. The utility of telecommuting is included in a simplified form. In fact, there are multiple more attributes that influence the decision to work from home or travel to work or an educational institution. More and more is known about the motivation to work from home since the pandemic (Reiffer et al., 2022). Future research regarding motivation to work from home could benefit the way the attractiveness of telecommuting is measured. This limitation is currently accepted, as the utilities of traditional alternatives such as public transport, bike and car likewise consist of simplifications in this model. It causes the Alternative Specific Constant of telecommuting to capture the unobserved factors with the use of the calibration step. Besides the willingness and the ability to work from home, the choice is influenced by, among others, the factors: communication with peers and colleagues, household type, single mode and multimode commuters and several other factors (Reiffer et al., 2022; Thomas et al., 2021).

**Geographical limitation**
A modelling trade-off occurs in the way the geographical element could be modelled. A synthetic network can be modelled in SD with the use of vectorisation of variables. Where either the *zones* (nodes) or the *origin-destination relations* (links) can be modelled. Recent SD transport models with the inclusion of a geographical element saw differences in modelling considerations. Puylaert et al. (2018) used the OD types between five specified area types as the geographical element. The model study of Puylaert et al. (2018) was able to exclusively explore a few of the OD types. The recommendation was made to extend the model with the vectorisation of variables, which allows copying a set of variables and thus exploring significant more combinations. The study of Legêne et al. (2020), used a different approach, by modelling a large number of zones (n=860).

In this thesis, a mix of both methods is used. As the use of modelling geographical elements with a relatively low level of detail is favoured over modelling municipalities in detail. Modelling zones on the level of the municipality in combination with the already defined trip types, results in even more KPIs than currently in the model, potentially causing enormous runtimes and an overfit of the model. Moreover, the main interest lies in a distinction in the area type detail level instead of the municipality level. Therefore the geographical elements in this thesis consist of five area types that are modelled with the use of vectorisation of area-type variables, as suggested by Puylaert et al. (2018)

## 6.4. Recommendations for future research

The recommendations for future research are divided into practical model use, model extensions and general future research. Whereas the model recommendations are largely derived from the current simplification in the model, the recommendation for future research focuses on the underexplored elements and future applications.

### Model relevance

The model developed in this research is suitable for analysing the changes and impacts in mobility related to COVID. Furthermore, the developed SD model can be used more widely. The transport modelling basis of the SD model is suitable for future use and can answer questions regarding the impact of other trends, innovations or disruptions in transportation. With the developed SD model, the possibility of simulating designed scenarios in a fast and exploratory way is achieved. Therefore, the model is a useful exploration tool that is beneficial long after the end of the pandemic. As noted in the limitations, the model could, on a macroscopic level, explore several future scenarios regarding broader issues in transportation. Combined with the emergence of changing approaches regarding the demand for transport, the developed model is helpful for the Ministry of Infrastructure and Water management. In addition to the relevance of mobility disruptions of COVID for the Ministery of I & W, the general question of what is desired in future mobility is relevant from the broader perspective of society.

### Model additions

In the limitations, several additions were identified as potentially beneficial for the strength of this model. First of all, the current model structure only features a feedback mechanism for road traffic. The alternatives are therefore only influenced by the feedback originating from the mode choice and differences in utility. The implementation of a feedback mechanism for the other modes is of significant added value. The crowdedness especially in public transport is of interest. With the use of an occupancy rate in trains, this feedback loop can be constructed. For cycling, the feedback loop is less relevant as capacity saturation of the cycling network is not an issue that affects the mode choice highly. Nonetheless, more cyclists on the network could impact travel times (Yuan et al., 2019).

Second, in a future expansion of the model, location attractiveness can be added. As it is assumed that the effect of tele-activities has an effect on accessibility and subsequently location attractiveness (Mouratidis and Peters, 2022). The research of Bons (2021) identified the attributes affecting housing preference due to COVID. The author also took the role of telecommuting into account. Moreover, changed telecommute behaviour is specifically identified to stimulate potential relocations, with the use of extensive panel data over the course of the entire duration of COVID, according to the study of Reiffer et al. (2022). With the use of updated housing preferences and the already include area types, the future attractiveness of relocation can be modelled.

### Future (model) research

First of all, the policy recommendations made in this thesis can be implemented and simulated in the model. Currently, the simulation of policy measures is outside the scope of this research. Nonetheless, it is beneficial to study the effects of such interventions. The combination of measures, in particular, is of interest as the potential conflict between stimulating public transport and remote working was identified as a point of attention. The system dynamics methodology is suitable for policy testing, as policies' robustness and impact on model behaviour can be explored. In addition, the trip types in the SD model enable the exploration of where specific policies should be applied.

Second, further research is proposed with the developed model itself, by creating more possible scenarios to simulate future situations. The extensive number of trip types results in potential model outcomes for 500 KPI's. In this thesis, only the relations of interest have been studied. In the unexplored combinations of trip types, there are undoubtedly more interesting results to answer follow-up research questions.

Third, originating from the limitations, the model can be applied to a more specific area than the classified area types in the Netherlands as a whole. Because area types are used, these area types can be adjusted according to, for example, a province in the Netherlands. By changing the input data from the entire country to a province and altering the location-specific variables in the choice model, the results for a specific area in the Netherlands can be made explicit.

Third, future research into the attributes defining the attractiveness of remote working benefits the accurate determination of telecommuting utility. The utility part of telecommuting can be extended with additional attributes. As mentioned in the limitations, the attractiveness of telecommuting is determined based on a limited set of parameters. The goal of this thesis is aimed towards exploratory modelling of the mobility impacts of COVID. The optimization and estimation of choice models are therefore outside the scope of this research, as the objective of this thesis is not aimed at the in-depth exploration of utility functions, their attributes and parameters. However, the utility calculation of especially telecommuting can be improved, as the literature around the incentives for working from home is quickly expanding (Thomas et al., 2021). Most pre-pandemic telecommute research is based on conceptual factors only and lacks the implementation in choice models (Mokhtarian and Salomon, 1994). In addition, the pandemic changed travellers' telecommuting behaviour, making the current literature outdated.

**Relevenace for commissioner**

With this thesis, research towards developing new mobility models is enhanced. The focus in mobility models is shifting towards novel ways of exploring the future of mobility. Therefore, traditional microscopic transport models are not always the preferred and desired choice. The commissioner, Goudappel, is a mobility consultancy supporting and advising their clients with expertise in the mobility and transportation sector. Goudappel is interested in the development of new mobility models for two main reasons. First, Goudappel develops and manages multiple transport models of their own and applies those for mobility-related issues of their clients. From this point of view, Goudappel itself has a high interest in developments in the market of transport models.

Second, the topics in mobility issues more often ask for a new approach, where the need to gain insight into the behaviour of outcomes over time is relevant. Such as the mobility disruptions of COVID. With the use of system dynamics in mobility models, this angle is being explored more, contributing to the development and the use of SD models in mobility issues. The innovative use of SD models is explored and, to a certain extent, adopted by Goudappel.

**Recommendation for commissioner**

For future use of system dynamics, it is essential to demonstrate the possibilities of SD and the deficiencies of SD in mobility models to its users. It should be emphasised that the goal is not to replace other mobility models but to supplement them. The focus should be on demonstrating the added value of exploring mobility with SD models to future users, such as transport planners and policymakers.

In regard to the model, to increase the validation of the SD model, it is beneficial to estimate its own sensitivity parameters for utility attributes in the choice model. The current combination exists of adopting the majority of parameters from an estimated choice model in Octavius combined with recalculated LMS parameters. This combination works rather well. However, updating the choice models enables more validated model outcomes.

# 7 Conclusion

In this chapter, the conclusion is presented that can be drawn throughout this thesis. With the use of the sub-questions, the main research question is answered: *What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?*.

The main direction of future mobility impacts of COVID is primarily established through the use of earlier qualitative research and survey data. The knowledge gap that has presented itself in the literature is the difficulty of estimating the duration and extent of change due to a high degree of uncertainty in a complex system. To enhance the future results of COVID and gain a better understanding of the uncertainties affecting future mobility an, exploratory modelling approach is used.

Developing a System Dynamics model enabled exploration of the relationship between the attractiveness of modes as a result of COVID. The observations found in the analysis of the literature are implemented in the construction of the SD model. Because travel behaviour and attitudes of travellers change, the use of behavioural changes are included in the development of the model. Sensitivities of travellers are not yet able to be translated into accurately weighted coefficients, therefore the use of positive and negative attitudes towards an alternative are used to model behavioural changes. With the combination of transport modelling and exploratory modelling, an uncommon combination of methods is mixed.

The approach chosen in this thesis differentiates itself from other transport modelling approaches. With the developed model it is attempted to find a novel way of exploring the future of transport. To prove the use and validity of this new method, the case study of the mobility disruptions as a result of the COVID pandemic has been applied. This has resulted in the endorsement of system dynamics modelling as a feasible method to explore the impact of disruptions or trends in mobility. The system dynamics approach to modelling transport is not a substitute for current traffic and transport models. On the contrary, it is a supplemented method and tool used for preliminary explorations as a step ahead of larger transport models. In addition, it provides a method to base policy measures on and assess the influence of those policy measures in the system. By means of this, the model differentiates itself from traditional transport models by being able to be used for the concept of vision and validate. Additionally, the demand for transport nowadays is more and more focused on transitions in mobility instead of providing what is necessary based on extrapolating the current growth. The demand for vision and thus the desired situation points in the direction of a problem owner, who would benefit from the use of this modelling approach and subsequently the developed model. The use of the model in the future is therefore practical for the Ministry of I & W. For whom not only the mobility disruptions of COVID are of relevance but the general question of what is desired in future mobility from the wider perspective of society.

Modelling the mode choice of travellers was found to be the suitable approach to observe the COVID impacts of interest. First of all, remote working and therefore not travelling was uncovered in the literature, as well as, the effect of the attractiveness of public transport modes. To capture the impact of both these potential effects, the mode choice was extended with an additional alternative. By including the choice not to travel in the mode choice, the SD model differentiates itself from previous studies incorporating tele-activities in system dynamics models. The inclusion of tele-activities as a new mode of transport also generated complications. A novel alternative requires an associated utility function with attributes and constants. In order to resemble the attractiveness of telecommuting in an accurate way, the Alternative Specific Constant is estimated and calibrated based on validated pre-pandemic telecommute travel behaviour, to capture the unobserved attributes of telecommuting.

The constructed model enables the visualisation of nationwide results as well as more specific results based on trip type. Consequently, more than 500 different combinations can be explored. It was discovered that the general attitude of travellers regarding public transport has encountered a setback, which is considered a non-desired situation. The goal over the past years has been to establish a positive mode shift from private to public modes. Travellers' shifting from public transport to remote working is witnessed a lot in the future, yet presents no issue for a negative mode shift. The permanent increase of remote working does however induce a slow recovery of public transport. The slow recovery is additionally caused by travellers rediscovering other modes such as the bike and the car of which the latter poses a risk of a negative mode shift. The exploration of possibilities to intervene in the system and steer travel behaviour in the desired direction resulted in conflict between stimulating public transport and working from home. It has been demonstrated that coordination of policy measures is of high importance to prevent counter-effects between both alternatives.

To conclude, this thesis has identified the noteworthy future impacts of the COVID pandemic. With the use of a system dynamic model, the development of the impacts over the years is established in the near and distant future, as well as potential post-pandemic scenarios that the mobility sector could encounter in the upcoming years. At last, it is shown that a novel method for exploring future disruptions and uncertainty in mobility is accomplished.

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# A

# Scientific paper

Appendix A presents the scientific paper on the next page.

# Is Telecommuting Our New Mode of Transportation? A System Dynamic Approach Into The Mobility Impacts Of COVID-19

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ABSTRACT

The COVID-19 pandemic has changed travel behaviour and mobility in the Netherlands. It is questioned if the mobility system is subject to change in the near and distant future. To supplement current research into COVID-19 mobility impacts, this study aims to observe the development of mobility impacts over time with a quantitative approach. Current traditional transport models have difficulties implementing uncertainties such as the mobility disruptions of COVID-19. These models lack the exploratory nature to cope with quickly arising events and changes. Using system dynamics, a model is developed to observe the mobility impacts of disruption and trends in transportation. The developed model and alternative transport modelling approach are tested and validated by applying the case of the COVID-19 mobility disruptions in the Netherlands. With the inclusion of a tele-activity alternative in the mode choice component of our SD model. The option not to travel is specified and modelled as a contender to the traditional modes of transport using choice models. Applying the model to the COVID-19 situation provided insight into new relations and understandings of the development of the mobility impacts over time in the near and distant future. It was found that the future attractiveness of modes of transport changes as a result. Travellers' preference for private modes of transport will remain high in the forthcoming years, causing public transportation to recover slowly. With the outcomes of this study, it can be concluded that the system dynamics modelling approach is beneficial and has accomplished the construction of a model more widely applicable than the case study of COVID.

## 1. Introduction

In December 2019, the COVID-19 outbreak started a pandemic with far-reaching consequences (Zhu, Zhang, Wang, Li, Yang, Song, Zhao, Huang, Shi, Lu, Niu, Zhan, Ma, Wang, Xu, Wu, Gao and Tan, 2020). Within a few months, the pandemic had caused implications worldwide. With a focus on the limitation of people's activity, the disruption of the transportation system as a result of COVID-19 was tremendous (De Haas, Faber and Hamersma, 2020). During the ongoing pandemic research, it soon became evident that the changes in travellers' behaviour could affect the transportation system well into the future (Van Wee and Witlox, 2021). The question of how and to what extent mobility will change causes uncertainty in the already uncertain domain of transport and mobility planning (Chatterjee, Burrieza Galán, Lyons and Isaksson, 2021).

*Research gap*

Half a year since the pandemic is considered to be controlled in Europe (Murray, 2022), the effects are still visible in the transport system. Where everyday life is considered recovered, travel behaviour has not fully returned to the pre-pandemic situations. Supported by literature and real-time travel data, the effects of remote working (Hamersma, Krabbenborg and Faber, 2021) and a change in mode choice (Ton, De Bruyn, Van Hagen, Duives and Van Oort, 2021) are present for an unknown extent and unknown period. To cope with increased uncertainty in the mobility system and study the extent to which the system is subject to change, this paper proposes an exploratory modelling approach. Therefore, we propose the following research question; *What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?*

Traditional transport models lack the exploratory nature to cope with quickly arising events and changes. Qualitative research lacks the ability to quantify the mobility impacts and perform scenario explorations to analyse system behaviour. Therefore, the unusual/uncommon choice is made to use exploratory modelling (Shepherd, 2014), which is particularly suitable for observing the behaviour of complex systems with a high degree of uncertainty. In this paper, a system dynamics approach is proposed to observe the future mobility impacts of COVID-19. With this method, it is moreover attempted to provide a model which is not only applicable to the mobility disruptions as a result of COVID, but also to the wider disruptions and trends in mobility in general.

*Literature*

Since the start of the pandemic, numerous studies have been initiated and published. This paper attempts to contribute to the broader aspect of research on COVID and associated mobility disruptions in the Netherlands. Before starting the modelling process, a preliminary exploration is performed to establish the aspects of travel behaviour

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in specific that are potentially subject to change. To scope the research, we used the currently available research to establish several points of interest in the mobility system in the Netherlands that might encounter substantial change. Based on the available qualitative and quantitative research, we were able to identify that especially the mode choice was of interest.

The rise of remote working and the decrease in public transport (PT) use can be seen as the two current COVID-19 developments that are expected to impact the mobility system in the future.

COVID-19 instigated the transition to work from home. The forced nature of this transition caused employees and employers to adapt to a fully online or partially online work environment (Van Wee and Witlox, 2021). As of today, the hybrid working mode, a combination of online and onsite working, has made its appearance in a post-pandemic era (Hamersma et al., 2021; Ton, Arendsen, de Bruyn, Severens, van Hagen, van Oort and Duives, 2022). According to Thomas, Charlton, Lewis and Nandavar (2021), these developments have impacted our commuting behaviour and formed new habits. Reiffer, Magdolen, Ecke and Vortisch (2022) addresses likewise the increased uncertainty that originates from changes in our telework and commuter behaviour. Travellers are more likely to substitute a commuting trip with working from home and thus not travel.

Furthermore, COVID-19 influenced travellers' mode choices directly, as travel preferences changed, and public modes of transportation were avoided during the pandemic (Gkiotsalitis and Cats, 2020; Shelat, Cats and van Cranenburgh, 2022). With post-pandemic travel data, it has become apparent that not all travellers return to PT (Ton et al., 2021).

## 2. Methodology

### 2.1. (Mobility) System Dynamics

The methodology of System Dynamics (SD) makes use of both qualitative and quantitative modelling approaches. SD uses causal relations between elements of the system, quantifying the relations of a system enables the exploration of the behaviour of a system over time (Pruyt, 2013). Hence, an SD model consists of a set of integral equations that are numerically solved. The equations represent behaviour such as accumulation, feedback and delays. With a stock-flow structure, these elements are modelled, and subsequent dynamic behaviour occurs when flows accumulate into stocks (Abbas and Bell, 1994). The concept of feedback is essential in this as it adds dynamic facets and prevents elements based only on linear behaviour (Auping, 2021). Examples of feedback in our model structure are found in the modal split, the number of (car) trips, the impact of COVID on trips, telecommuting behaviour and appreciation of public transportation.

SD is not an out-of-the-box option for the exploration of the future of mobility. As this paper showed the lack of exploratory nature in traditional transport models, we deviate from the normal route of providing decision-makers and transport planners model-based estimations. Using SD, we can provide a more complete prospect, displaying the dynamics of mobility impacts and the outcomes of changing uncertainties. There is an absence of prior SD research in this specific area which we can use as a basis for our model. Nonetheless, in the field of (urban) mobility, there are some examples of applications of SD as an exploratory transport modelling method.

Pfaffenbichler, Emberger and Shepherd (2010) developed an urban mobility SD model, which has been used in more than 15 cities and metropolitan areas to support future transport planning processes. Legêne, Auping, Homem de Almeida Correia and Van Arem (2020) used spatial system dynamics to evaluate the introduction and adoption of automated vehicles in urban areas. In the Netherlands, the first application was the development of the *ScnerioVerkenner* by Heyma, Korver and Verroen (1999), by which the first step towards a scenario planning tool was made. Nevertheless, the practical use of the ScenarioVerkenner is hardly seen nowadays. First, due to its development in the 1990s, meaning the model is currently outdated. Second, the fact that it was often used as a method to predict future demand and supply for infrastructure planning (Smits, van Maanen and Borgman, 1995). However, the methodology of system dynamics is more useful for observing model behaviour over time, and to a lesser extent, for the specific predictions of the future.

### 2.2. Transport modelling

To provide the developed model with a robust basis, the 4-step model, as presented in Figure 1, is used as a guideline for the structure of the model. The 4 steps consist of (i) trip generation, (ii) trip distribution, (iii) mode choice and (iv) route assignment (Ortúzar and Willumsen, 1990). As previous studies suggest potential effects within the mode attractiveness, the focus is aimed at the mode choice. Implementing a choice model in the system dynamics model enables the exploration of change in travellers' choices and thus travel behaviour after the pandemic. Nonetheless, the other phases in the 4 step model are included as well to ensure a complete transport modelling structure in the SD model. Trip generation is combined with trip distribution and is influenced by population growth to provide the input of trips. The assignment is subsequently simplified because detailed route assignments can be problematic in a system dynamics environment (Shepherd, 2014).

### 2.3. Exploratory modelling and analysis

For analysing the model outcomes and exploring the influences of uncertainty, Exploratory Modelling and Analysis (EMA) is used. Bankes (1993) introduced the concept of EMA in 1993. With the use of computational support, it is possible to perform a high number of experiments and analyse the uncertainties of a model (Kwakkel, 2017). The use of a high number of experiments (N >1000) in combination with the possibility to vary the range of input parameters

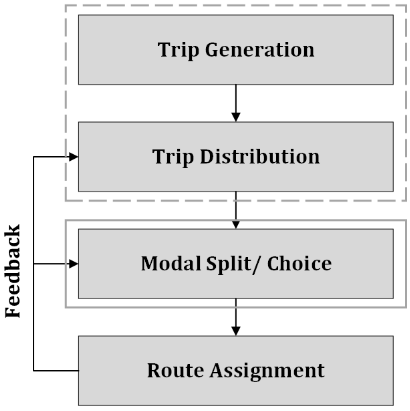


**Figure 1:** Point of interest in the 4-step model

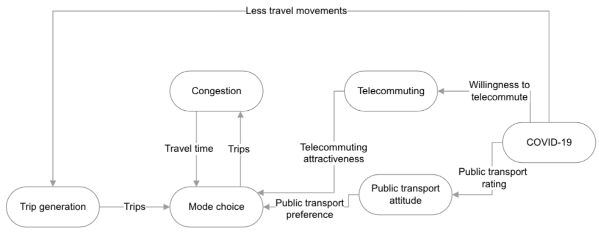


**Figure 2:** Overview of the system and sub-components

enables the exploration of the model outcomes in a base ensemble instead of a single base scenario. Within EMA it is possible to perform scenario discovery. With the use of a scenario discovery algorithm, computer-assisted scenario development is possible (Bryant and Lempert, 2010). Computational scenario discovery extends traditional scenario design where at first a storyline is developed and afterwards simulation takes place.

The SD model in this paper is heavily dependent on COVID-related input, which is often based on estimations and best guesses from the literature. Therefore, the use of EMA allows analysing of model outcomes under different conditions, providing a stronger perspective on the future mobility impacts. The combination of EMA and our model is seen as valid as our goal is to observe the impacts on bandwidths to establish insight into the behaviour over time. Furthermore, the use of EMA in System Dynamics is often used and validated (Kwakkel and Pruyt, 2015), therefore providing a strong analysis method useful for our model.

## 3. COVID-19 mobility model

We developed a model to observe the impacts of mobility disruptions as a result of the COVID-19 pandemic. To observe the mobility impacts of COVID, we study the behaviour of the impacts over time in the near and distant future and explore the uncertainties causing the impacts.

### 3.1. Conceptual overview

The structure of our model is based on the elements in the 4-step model, emphasising the mode choice component. Figure 2 illustrates the different submodels and components in the model. The two Key Performance Indicators (KPIs) we focus on in this paper are *modal split* and *number of trips*. Both originate from the mode choice sub-model and are considered most useful for the observation of the impacts of COVID. The KPIs are influenced by input parameters and uncertainties in each sub-model.

*The five modes of transport*

Because there are numerous modes of transportation, a selection of the relevant alternatives is made. We include 5 main modes of transport, being: *car*, *public transport*, *bike*, *walking* and *tele-activity*. Tele-activity is a new addition to the mode choice and can be seen as the option to not travel for commuting or educational purposes. Both are referred to as telecommuting from now on as a collective term. With these five modes, we can determine the most important changes in mode attractiveness due to COVID.

*Telecommuting*

To cope with the adoption of telecommuting as part of our mobility system, we propose a new method of modelling working from home. The emphasis on telecommuting results from the literature where the significance of telecommuting in our future commute and travel behaviour is mentioned several times (Ton et al., 2022; Reiffer et al., 2022).

In prior SD models, Haghani, Lee and Byun (2003) & Malone, Verroen, Korver and Heyma (2001) included telecommuting by subtracting part of the trips not being made from the initial trip generation. The possibilities of including the choice of not making a trip into the mode choice are studied in this paper, resulting in a preference to model telecommuting as a novel alternative in the mode choice. In relation to previous SD mobility models, our model enhances the dynamic element of telecommuting. Without considerable changes to the model structure because the alternative is modelled similar as traditional modes of transport.

Adding the alternative telecommuting to the modal split enables the option to explore the attributes influencing the choice to work on-site or remote. The choice to work from home depends on numerous variables, most of which were discovered during the COVID-19 pandemic. In the aftermath of the pandemic, we learn more about the variables that influence the traveller's decision (Reiffer et al., 2022). Therefore, the inclusion of telecommuting as an alternative in the mode choice causes an enhanced ability to explore the behaviour of working from home.

### 3.2. Choice modelling

To observe the (future) hypothetical mode choice of travellers, we implemented the use of discrete choice models in our system dynamics model. The inclusion of the choice model enables the change in attractiveness over time to be observed (Train, 2003). The alternative a decision-maker chooses can be determined with the use of a logit formulation (Ortuzar and Willumsen, 2011). The decision-maker chooses the alternative that has the highest utility (McFadden, 1980), because of the utility maximisation theory we adapt for our designed choice model. The probability $P$ of the decision-maker choosing alternative $i$ is calculated with Equation 1.

Each alternative has a corresponding utility function which consists of attributes, such as travel cost, travel time and comfort. The attributes differ per alternative. Where applicable the utility or attributes are influenced by COVID variables.

$$P_i = \frac{e^{V_i}}{\sum_{r=1}^{n} e^{V_r}} \tag{1}$$

*Where:*

*$P_i$ = Probability of choosing mode i;*
*$V_i$ = Utility of mode i;*
*$V_r$ = Utilities of all the modes r;*
*n = Number of modes in consideration;*

### 3.3. Validation of input data

In order to validate the choice model, we use travel data from the pre-COVID situation to construct a solid base year. The base year data is derived from travel data originating from survey data in the annual study, *Onderweg in Nederland* conducted by CBS (2020). The pre-pandemic base year is used as a starting point for the trip generation. Subsequently, the designed choice model is calibrated on the base year input data, resulting in a validated choice model for the SD model.

### 3.4. Distinction of trip types

Besides the nationwide impacts of COVID the more specific impacts, in certain areas, for different trip purposes and trip lengths, are of interest. The input data consist of base year trips on a detailed level. The trips are divided into trip types based on five trip purposes, five area types and four distance classes shown in Table 1. The trip types are modelled efficiently with the vectorisation of variables, essentially creating a copy of a variable and model structure.

Each trip type has separate attribute parameters and constants in their utility function. Subsequently, determining the mode attractiveness and the future number of trips for each combination (n=100) of trip types. This provides us with insight into the difference between, for example, a short commuting trip originating in an urban area and a long commuting trip originating in a nonurban area and the incentive to substitute that trip with a telecommute trip.

**Table 1**
Trip categories

| **Trip purpose** | **Distance class** | Distance [km] | **Area type** | Address density [Addresses/km^2] |
|---|---|---|---|---|
| Commuting | Short | <7.5 km | Very highly urban | >2500 |
| Educational | Middle short | 7.5 - 15 km | Highly urban | 1500 - 2000 |
| Social recreational | Middle long | 15 - 40 km | Moderately urban | 1000 - 1500 |
| Shopping & Personal care | long | >40 km | Little urban | 500 - 1000 |
| Other motives | | | Non-urban | <500 |

### 3.5. Experimental setup

The choice to model the input uncertainties under two sets of ranges results in the exploration of two sets of model ensemble outcomes. First, the COVID-19 base ensemble is constructed based on input ranges derived from the literature and travel behaviour (panel) data in the Netherlands. Second, due to the high magnitude of uncertainty regarding the input, the ranges are adapted and an additional ensemble is constructed for use in scenario exploration. With the exploration of both ensembles, we are able to observe the outcomes that are likely and on the other hand the more extreme/rare situations. With the results of both outcomes, this paper can relate to other mobility impact studies.

The SD model is designed with the system dynamics software package of Vensim (version: Vensim® 9.3.0), which provides a user-friendly graphical modelling interface (Ventana Systems, 2022). For the analysis of the model outcomes, and performing a high number of experiments, the EMA workbench (version: 2.1) is used. The EMA workbench is implemented in Python and features an integrated connector for the models in the Vensim package to be implemented in the workbench (Kwakkel, 2017).

The model experiments performed varies each of the input parameters within their range using a Latin Hypercube sampling (Kwakkel, 2017). This statistical sampling method generates a near-random sample of the input parameters. For the COVID-19 base ensemble, 1000 experiments are simulated, for the scenario exploration and wider ranges the experiments are increased to 5000, in order to perform scenario discovery.

## 4. Results

The attractiveness of modes of transport is expressed in their mode share over time. Based on the trip-based modal split, we study their increase or decrease in attractiveness post-COVID. The prognosis without the interference of COVID is additionally displayed, to observe the differences if the COVID pandemic never occurred. The results discussed in this paper are focussed on the near future, therefore, showcasing the model outcomes between 2019-2030. For the impacts over a longer period of time, the reader is referred to the complete study (Van Tol, 2022).

The initial modal split pre-COVID is shown in Table 2. The modal split is adjusted for the inclusion of a telecommuting alternative. Based on the studies from Hamersma et al. (2021) and Jongen, Verstraten and Zimpelman (2021) we were able to establish validated telecommuting input data.

**Table 2**
Modal split 2019

| | |
|---|---|
| Car | 47.01 % |
| Public transport | 5.74 % |
| Bicycle | 28.23 % |
| Walking | 15.88 % |
| Telecommuting | 3.13 % |

Figure 3 illustrates the modal split value of public transport in the near future. It can be established that in the presented time span the COVID-19 base ensemble (displayed in blue) is not able to equal the original prognosis (displayed in orange). Therefore, indicating that the future attractiveness of public transport appears not to recover by itself. Nevertheless, in an optimistic scenario, the 2019 pre-COVID level (5.74%) of attractiveness will be matched. As we observe a slightly higher density in model outcomes in the upper part of the ensemble in Figure 3, it is shown that the chances for recovery with such a gradient are higher.

First of all, one of the reasons is that telecommuting and PT are competitors, as illustrated in Figure 4. This is not surprising as commuters are a considerable share of public transport passengers. The decay of PT is not in full relation to the increase in telecommuting, indicating other factors impact the decrease of attractiveness as well. We witness that the mode share of telecommuting stabilises at various levels, contrary to the PT mode share, indicating different behaviour (Figure 3 & Figure 4). Furthermore, the absolute change in percentage points in the modal split value is different.

Secondly, the valuation of public transport in the years after COVID is still of considerable essence. Although telecommuting is responsible for a significant loss in the future number of public transport passengers, the increased attractiveness of other alternatives, car and bicycle remain (Figure 5 & Figure 6). Indicating travellers tend to use the (re)discovered alternatives to substitute PT. The bicycle is in the future mainly used as an alternative for short PT trips and the car is used for longer distances as an alternative for PT trips.

In order to determine the more in-depth causes of why public transport recovery proceeds slow, the various trip purposes were examined in more detail. It was found that PT travel with social-recreational purposes encounters, similar to commuter travel, a slow road to recovery. The attractiveness of social-recreational travel is expected to recover faster in the near future compared to commuting trip purposes. However, the original no-COVID trend was depicted to be higher, eventually showing similar progress of recovery for both commuting and social-recreational travel. This shows that, in addition to the lack of travellers who work from home, public transport also lacks the essential social-recreational travellers.

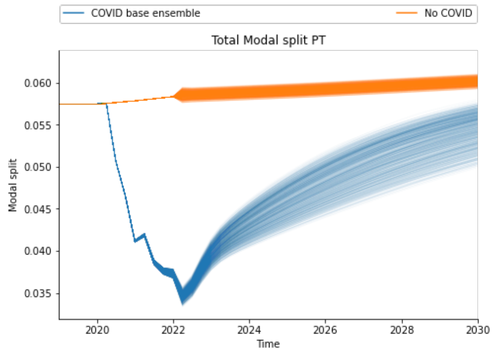


**Figure 3:** Public transport mode share

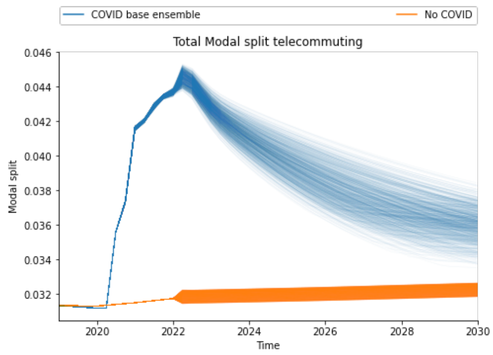


**Figure 4:** Telecommuting mode share

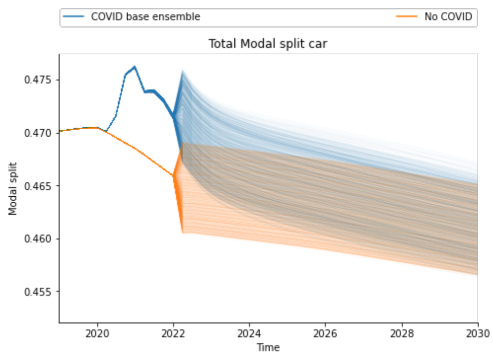


**Figure 5:** Car mode share

## 5. Conclusion & discussion

*Comparison with other research*

Our outcomes are in line with research from Francke and Bakker (2022) regarding the slow recovery. However, the authors predict a faster road to recovery than our results suggest. The effect of travellers' aversion towards the use of public modes did not improve as quickly as estimated by Francke and Bakker (2022). The attractiveness of other

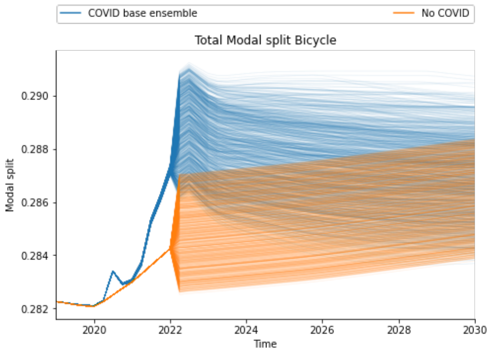


**Figure 6:** Bicycle mode share

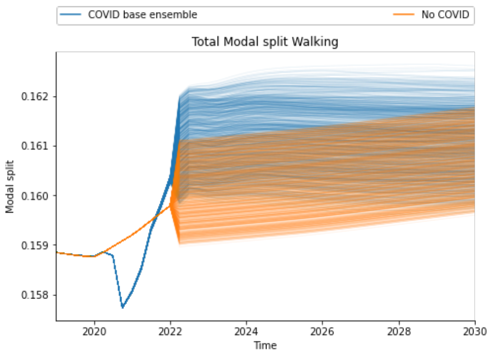


**Figure 7:** Walking mode share

alternatives, telecommuting, car and bicycle and the effect of negative attitudes remain influential factors.

The factor of telecommuting inevitable influences the loss of public transport travellers. This is in line with Hamersma et al. (2021), who suggested that mostly telecommuting is keeping travellers out of PT. In addition to Hamersma et al. (2021), we extend the results by showing the outcomes over time. We can conclude that the number of future travellers substituting their trip with working from home is slightly less than argued by Hamersma et al. (2021), for the underlying reason that we study the coherence of effects. Hence, we assume the shift in attractiveness to other modes has a minor dampening effect on telecommuting.

*Research question*

In this paper, we proposed the following research question: *What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?*

It can be concluded that our travel behaviour has changed as a result of the COVID-19 pandemic. The primary effect is the absence of travellers in public modes of transportation due to, first of all, our preference for working more on a remote basis and, secondly, travellers' increased preference to use the car or bicycle in the post-COVID era. This is substantiated by the remaining negative attitude towards public modes of transportation.

*Unexpected findings*

Public transport in the near future struggles to get back on top. Because we analysed the cohesive impacts, it was shown that besides the role of telecommuting, the attitude towards different modes of transport is still of considerable influence after the pandemic. In association with the negative PT attitude, the attractiveness of modes other than PT remains high in the post-COVID era. In contrast to other research, the role of travellers' attitudes in the future is undervalued (Francke and Bakker, 2022) or primarily focussed on travellers' attitudes during COVID (Ton et al., 2021).

Nonetheless, the effects of telecommuting are substantial for public transport. As shown in the analysis of the results, there is a strong connection between tele-activities and the use of public transport. Zooming in on the commuter and, to a limited extent, educational travel, it is illustrated that public transport and telecommuting are competitors and seek the same type of traveller. This has consequences for the future, as inherently, remote working keeps travellers out of PT. Therefore, the possible promotion of public transport in the future must be focused on attracting new travellers.

For telecommuting, it was already shown before the pandemic (Van der Loop, Willigers and Haaijer, 2019) that small amounts of telecommuting had a significant effect on congestion reduction. As a result, there is a high incentive to keep telecommuting at a certain minimum level. When telecommuting and PT are stimulated through either policy or behavioural change, conflict might arise. Potential measures need to be aligned to prevent opposing interventions. It is impossible to design a policy for one without considering the other.

*Model considerations*

It is found to be beneficial to explore telecommuting as a new alternative. Since the pandemic, remote working is embedded in our behaviour and has changed our concepts of commuting. The choice to avoid travelling has become easier for commuters and has impacted our mode and travel choice. With the inclusion of telecommuting in the mode choice, we could observe the dynamic progress of telecommuting over the years.

Furthermore, the developed SD model was found to be appropriate for the application to the case of COVID-19. Our approach and model were tested and validated by comparing our outcomes with mobility impacts found in the literature. Therefore, providing the possibility of applying the model to mobility disruptions wider than COVID. The objective of SD is different to traditional transport models, where SD models thrive outcomes with a different level of accuracy. It is, therefore, essential to notice that we do not desire to pinpoint a value from the presented plots to estimate the modal split or number of trips at a specific moment in time. Rather, we desire to observe the behaviour and the course of change of KPIs.

*Future research*

Finally, our model and research leave room for improvement and future research. Due to several simplifications in the current model, the future extensions focus on model additions to improve the model's explanatory power. Future research points primarily in the direction of quantifying the policy recommendations. The potential adjustment of travel behaviour with the use of measures or interventions is touched upon briefly in this paper. It would be beneficial to implement control measures or policy interventions in the SD model regarding the stimulation of PT, such as pricing, increased supply or positive image, to determine the subsequent effect on attractiveness.

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# B

# Conceptual models

This appendix provides additional conceptual models. These function as supplementary conceptual models to the main model structure. The conceptual models of car and public transport attractiveness are elaborated on, as well as the reasoning and conceptual model for the congestion feedback mechanism.

## B.1. Car & congestion mechanism

The attractiveness of driving was introduced by Sterman in his book *Business Dynamics*, where he dedicated a section to the dynamic behaviour of traffic congestion (Sterman, 2000a, p.182 ). The core principle of the feedback mechanism in traffic congestion is the effect of the number of trips on the attractiveness of the car as a mode of transport. Figure B.1 illustrates this feedback loop in aggregated form. This relation is simplified and exists of multiple factors in between.

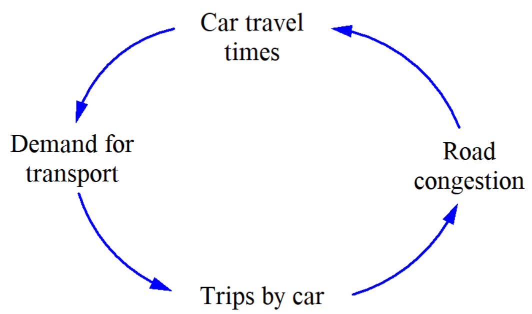



**Figure B.1:** Feedback mechanism private car (adapted from Malone et al. (2001))

The same feedback mechanism is found in the ScenarioVerkenner SD model (Malone et al., 2001) and the MARS SD model (Pfaffenbichler et al., 2010). The Feedback is an equilibrium where the relationship between intensity and capacity determines the congestion and travel times. The feedback originates from transport modelling and the circle of Wegener and is also seen in the 4-step model (McNally, 2007).

The concept of road traffic congestion can be extended by adding the variables in between, to the general feedback structure of Figure B.1. This results in the conceptual model in Figure B.2.

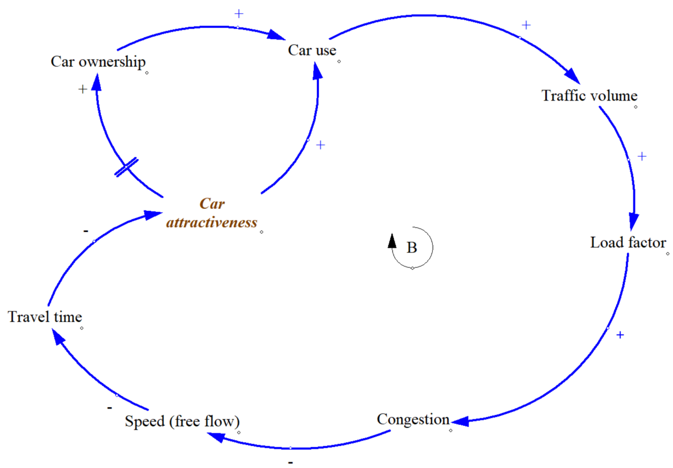



**Figure B.2:** Conceptual model of the attractiveness of driving

- Load factors increase –> congestion increases
- Congestion increases –> speed decreases
- Speed decreases –> travel times increase
- Travel time increases –> attractiveness of driving decreases
- Attractiveness of driving decreases –> car use decreases and with a delay car ownership decreases
- Car ownership decreases –> car use decrease
- Car use decreases –> traffic volume decreases
- Traffic volume decreases –> load factor decreases

A plus (+) symbol indicates a relationship in the same direction; a minus (-) symbol indicates a relationship in an opposite direction. Adding the polarities together results in a balancing feedback loop.

### Congestion

As presented in the conceptual models and the Sub System Diagram (Figure 4.1) car traffic is fed back to the system to incorporate the dynamic aspect of trips.

To include a working feedback cycle based on congestion in the Netherlands, the road situation in the Netherlands are imitated. With the use of a conversion factor, the road intensity of the Dutch main road network is simulated. By incorporating the travelled kilometres in the Netherlands in the base year (2019) and the congestion levels of the base year, the road capacity of the network is shaped (Rijkswaterstaat, 2019).

## B.2. Public transport

Subsequently, the attractiveness of public transport can be visualised in Figure B.3. The conceptual model is based on Causal Loop Diagrams from Suryani et al. (2021) and Tonini et al. (2021). Where Tonini et al. (2021) focuses on the mode choice, in specific the attractiveness of the two alternatives, public transport and private car transport (PC). With the use of satisfaction and dissatisfaction of PT and PC use, modelled as stocks, the change in the use of PT or PC can be observed. Due to the presence of more than 2 alternatives for the model in this research the reasoning of Tonini et al. (2021) does not apply. However, the concept of (dis)satisfaction of a mode of transport and therefore the effect on its use is useful for modelling potential (dis)satisfaction of an alternative as a result of COVID-19.

Similar to Tonini et al. (2021), Suryani et al. (2021) introduces a SD framework for urban mobility with a variable for *mobility performance*. Which is in essence mainly impacted by reliability for PT and congestion for PC (Suryani et al., 2020). The concept of accumulating all variables into one performance variable is, however, short-sighted. Nonetheless, the idea of introducing model components in SD to capture the performance or satisfaction of a mode of transport is confirmed in the literature.

**Attractiveness of PT**

The attractiveness of PT is partially derived from the SD work of Tonini et al. (2021) and Suryani et al. (2020). Together with elements that affect the attractiveness of public transport by Ingvardson (2017) the CLD in Figure B.3is designed.

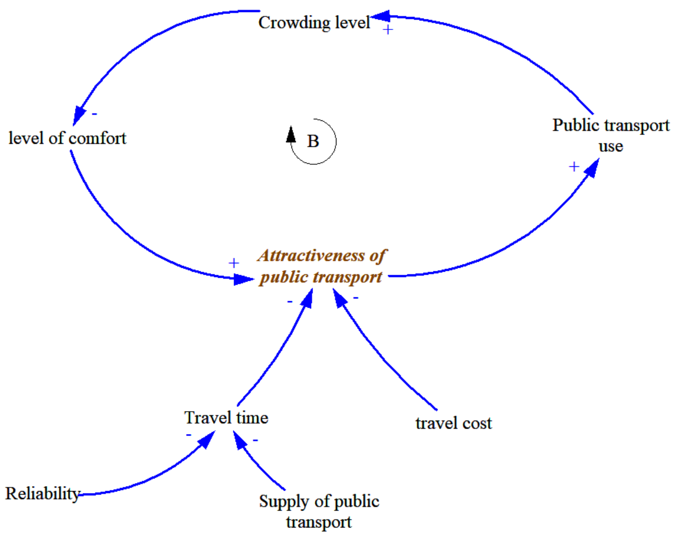


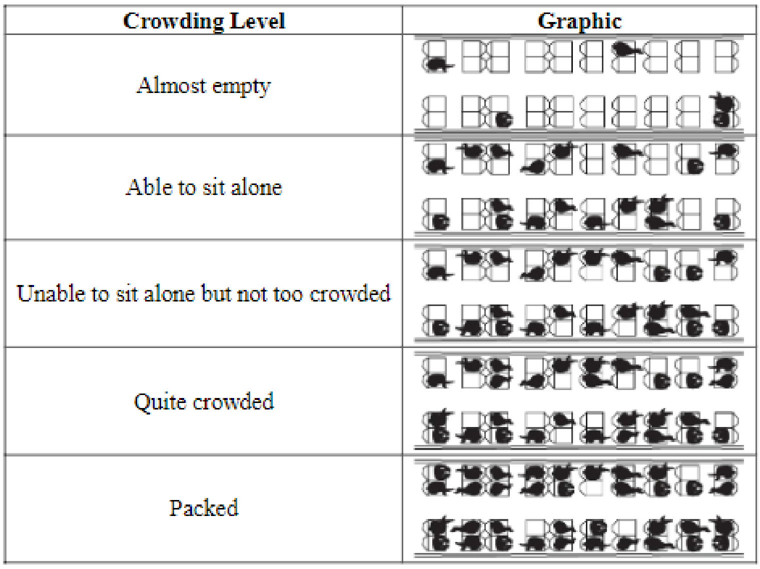

**Figure B.3:** Conceptual model of the attractiveness of public transport and feedback

- Reliability decreases –> travel times increases
- Public transport supply decreases –> travel times increases
- Travel times increase –> attractiveness of public transport decreases

- Public transport use increases –> crowding level increases
- Crowding level increases –> level of comfort decreases

- Level of comfort decreases –> attractiveness of public transport decreases
- Attractiveness of public transport decreases –> public transport use decreases

Crowding levels are equal to the occupancy rate in the conceptualisation of public transport. Figure B.4 illustrates the graphical representation of different levels of crowding.



| Crowding Level | Graphic |
|---|---|
| Almost empty | |
| Able to sit alone | |
| Unable to sit alone but not too crowded | |
| Quite crowded | |
| Packed | |

**Figure B.4:** Crowding levels (Shelat et al., 2022)

# C
# Model components

This appendix provides the input of the trip generation and the mode choice component. The input data for the attributes of the utility functions is calculated and presented.

## C.1. Trip generation formulation

The trip generation is mostly defined by the travel data from the ODiN data set. The travel date can be found in **??**. In addition to the trip input from ODiN, the trip generation is also influenced by population growth.

**Population growth**: The population is defined as all persons in the Netherlands above the age of 6. This is the same population taken into account in ODiN (CBS, 2020). *Population growth* and *initial population* are calculated based on CBS (2019a) numbers and added to the model from an external data file.

## C.2. Mode choice formulation

This section presents the utility functions for the alternatives. Furthermore, The attributes for travel time and travel cost are calculated.

**Distance classes/trip length:** With the use of distance classes a simplification is implemented in the model. By categorising all trips into scaled distance classes the trips within one distance class are generalised and have an average length. The average length is subsequently used in the calculation of utility attributes.

### C.2.1. Car utility

The utility of the car is calculated with Equation C.1.

$$V_{car} = TT_{car} \cdot \beta TT_{car} + TC_{car} \cdot \beta TC_{car} + ASC_{car} \tag{C.1}$$

*Where:*

$V_c$ = *Utility of the car;*
$TT_c$ = *Travel time of the car;*
$\beta TT_c$ = *Sensitivity parameter of travel time of the car*
$TC_c$ = *Travel cost of mode i;*
$\beta TC_c$ = *Sensitivity parameter of travel cost of the car*
$ASC_c$ = *Alternative Specific Constant of the car*

*Travel time car*
In Table C.1 the *Travel times* of the car are stated. With the average trip length and free-flow speed, the *travel time* is calculated. This is done through a standard average velocity-distance formula. The initial travel time is updated through the congestion feedback loop at every time step. The free flow speed is assumed to be lower for trips originating from urban areas, where drivers have to endure more traffic.

| **Urban degree** | **Distance class** | **Free flow speed [km/h]** | **Free flow travel time [hour]** |
|---|---|---|---|
| Sted 1: Extremely urbanised | 1: Short (<7.5 km) | 20 | 7.63 |
| | 2: Middle short (7.5-15 km) | 45 | 13.72 |
| | 3: Middle long (15-40 km) | 80 | 17.77 |
| | 4: Long (40> km) | 95 | 50.75 |
| Sted 2: Strongly urbanised | 1 | 20 | 7.63 |
| | 2 | 50 | 12.35 |
| | 3 | 80 | 17.77 |
| | 4 | 95 | 50.75 |
| Sted 3: Moderately urbanised | 1 | 30 | 5.09 |
| | 2 | 50 | 12.35 |
| | 3 | 80 | 17.77 |
| | 4 | 95 | 50.75 |
| Sted 4: Hardly urbanised | 1 | 30 | 5.09 |
| | 2 | 50 | 12.35 |
| | 3 | 80 | 17.77 |
| | 4 | 95 | 50.75 |
| Sted 5: Not urbanised | 1 | 30 | 5.09 |
| | 2 | 50 | 12.35 |
| | 3 | 80 | 17.77 |
| | 4 | 95 | 50.75 |

**Table C.1:** Initial travel time car

*Travel cost car*:
The travel cost in the utility function is calculated with the use of a natural logarithm, this is done for all the travel costs of the alternatives.

The *travel cost* consists of the *fixed car travel cost* and *variable car travel cost*. The variable car costs are determined by the *fuel cost per kilometre* and the *Remaining variable car cost per kilometre*. Both variables have a growth curve based on the estimations from the WLO scenarios (Van Meerkerk et al., 2021). The fuel cost are adapted on current prices (CBS, 2022b). For electrical vehicles, the electricity cost development is determined according to WLO predictions (Van Meerkerk et al., 2021). The development of other variable car costs also originates from WLO scenarios and consists of maintenance, and deprecation. The fixed car cost is calculated at 21.1 euro cent per km and is based on an estimation from NIBUD. The abovementioned variables car cost and their prognosis are sometimes altered due to insufficient or outdated prognosis. The process of updating the costs is illustrated in Appendix F.

*Distribution EV/ICE*
With the distribution between EV and ICE, a future prediction is made on the degree to which both will be present in the future fleet of vehicles. The distribution is an uncertainty input variable which can be changed. For the base situation the input is based on the current vehicle fleet in the Netherlands and the prediction in the future (Berings and Kop, 2021; Van Meerkerk et al., 2021).

### C.2.2. Public transport utility

COVID-related factors such as public transport supply and public transport valuation are modelled and incorporated in the utility function by multiplying them with the travel time and not as separate attributes of their own. The option to provide them with separate attributes caused incorrect outcomes. Therefore the COVID-related factors are multiplied in the utility function with the travel time to cope with this deficiency. This results in accurate changes in utility found through validation, by comparison with actual travel data. The factors are not displayed in the equation below.

$$V_{pt} = TT_{in-vehicle} \cdot \beta TT_{in-vehicle} + TT_{access/egress} \cdot \beta TT_{access/egress} \\ + TT_{waiting} \cdot \beta TT_{waiting} + TC_{pt} \cdot \beta TC_{pt} + ASC_{pt}$$

*Travel time public transport*
Travel time in PT can be divided into *in-vehicle time*, *access/egress time* and *waiting time*. The in-vehicle travel time is calculated similar to car travel time, with the commercial speed of rolling stock in public transport and the trip length (CROW, 2021b). The commercial or exploitation speed of PT is dependent on the distance class and the vehicle type. It is assumed that for short trips the Bus/Tram/Metro is used, for the middle short trips, metro or sprinter trains, for the middle long trips a combination of sprinter and intercity trains and for long trips intercity trains. The waiting time and access and egress time differ based on distance class and area type. All travel times; *in-vehicle time*, *access/egress time* and *waiting time* are weighted according to their weight parameters ($\beta$).

**In vehicle time**
The in-vehicle time is calculated based on commercial speed and the average trip length. The commercial speed of bus/tram/metro, sprinter and intercity trains vary substantially. Therefore the average operating speed differs between distance class and area type.

**Access and egress time and waiting time public transport**
Based on the values of CROW, the access and egress times and waiting times are estimated (CROW, 2022a). The average lost time due to access and egress depends on the distance and area type. In non-urban areas, the PT network is less dense than in urban areas. The most used mode of transport for access and egress are respectively walking and cycling. With the use of trip planner applications, the total trip length and travel times are checked.

| Urban Degree | Distance class | Commercial speed [km/h] | In -vehicle travel time [min] | Access/egress time [min] | Waiting time [min] |
|---|---|---|---|---|---|
| Sted 1: Extremely urbanised | 1 | 20 | 7.63 | 4 | 2 |
| | 2 | 46.25 | 13.35 | 5 | 2 |
| | 3 | 60 | 23.69 | 7.5 | 4 |
| | 4 | 77.5 | 62.21 | 10 | 7.5 |
| Sted 2: Strongly urbanised | 1 | 20 | 7.63 | 4 | 2 |
| | 2 | 46.25 | 13.35 | 7 | 3 |
| | 3 | 60 | 23.69 | 10 | 5 |
| | 4 | 77.5 | 62.21 | 15 | 8 |
| Sted 3: Moderately urbanised | 1 | 22 | 6.94 | 5 | 2 |
| | 2 | 46.25 | 13.35 | 8 | 3 |
| | 3 | 60 | 23.69 | 11 | 6 |
| | 4 | 77.5 | 62.21 | 15 | 10 |
| Sted 4: Hardly urbanised | 1 | 23.13 | 6.60 | 8 | 3 |
| | 2 | 46.25 | 13.35 | 10 | 4 |
| | 3 | 60 | 23.69 | 13 | 7 |
| | 4 | 77.5 | 62.21 | 20 | 11 |
| Sted 5: Not urbanised | 1 | 25 | 6.11 | 10 | 4 |
| | 2 | 46.25 | 13.35 | 12 | 5 |
| | 3 | 60 | 23.69 | 17 | 8 |
| | 4 | 77.5 | 62.21 | 25 | 12 |

**Table C.2:** Initial travel time PT

*Travel cost public transport*:

*Fixed travel cost PT* consists of a boarding fee which is the same for every operator and every PT mode (Vervoerregio Amsterdam, 2019). *Variable travel cost PT* is often calculated by PT operators in rate units instead of price per kilometre, the rate units also differ per operator. The average rate units are calculated and translated to kilometre price for variable travel costs (MRDH, 2020). The average kilometre price differs between BTM and train.

| | Variable travel cost [Euro/km] | Fixed travel cost [Euro] |
|---|---|---|
| Short | 0.15 | 0.98 |
| Middle short | 0.15 | 0.98 |
| Middle long | 0.2 | 0.98 |
| Long | 0.2 | 0.98 |

**Table C.3:** Travel cost public transport

### C.2.3. Bicycle utility

$$V_{bike} = TT_{bike} \cdot \beta TT_{bike} + ASC_{bike} \tag{C.2}$$

*Travel times bicycle*:

The average cycling speed is 15.8 km per hour according to the Fietsersbond. The cycling speeds in cities are additionally lower than outside urban areas.

| | Speed [km/h] | Travel time [Hour] | Travel time [Min] |
|---|---|---|---|
| Short | 14.6 | 0.17 | 10.45 |
| Middle short | 14.6 | 0.70 | 42.29 |
| Middle long | 15.8 | 1.50 | 89.97 |
| Long | 15.8 | 5.09 | 305.16 |

**Table C.4:** Travel time bicycle

### C.2.4. Walking utility

$$V_{walk} = TT_{walk} \cdot \beta TT_{walk} + ASC_{walk} \tag{C.3}$$

| | Speed [km/h] | Travel time [Hour] | Travel time [Min] |
|---|---|---|---|
| Short | 6 | 0.42 | 25.44 |
| Middleshort | 6 | 1.72 | 102.91 |
| Middlelong | 5 | 4.73 | 284.30 |
| Long | - | - | - |

**Table C.5:** Travel time walking

### C.2.5. Telecommuting utility

The inclusion of telecommuting as an alternative in the mode choice requires the inclusion of a utility function for this alternative. The sub-model of telecommuting gives substance to the degree of telecommuting through a stock-flow structure. The degree of telecommuting is subsequently translated to the willingness to telecommute which together with a parameter determines the utility of telecommuting. In other words the utility of not making a trip for commuting or educational activities. Due to the validation of the initial telecommuting trips by the literature, the model input for telecommuting trips is considered to be robust.

$$V_{tele} = Willingness\ to\ tele * parameter_{tele} + TT_{tele} \cdot \beta TT_{tele} + TC_{tele} \cdot \beta TC_{tele} + ASC_{tele} \tag{C.4}$$

The willingness to telecommute consists currently of a degree of telecommuting which is modelled through the use of stock flow structure in the SD model. The ability to telecommute is in the simplified form taken into account due to the unknown factors of the ability to telecommute. Similar to the degree of telecommuting, it is possible to implement the ability to work from home as an element consisting of fluctuating behaviour. Where factors such as the quality of the workplace and household situation are potential attributes. Furthermore, the discussion (Chapter 6) elaborated on the potential further attributes that influence the choice of tele.

### C.2.6. Beta parameters

The weighted coefficients are based on estimated parameters originating primarily from choice and traffic models.

#### Parameter estimation

The values obtained from the estimated choice models in Octavius are used as base values for the sensitivity parameters for travel time and travel cost. Due to the lack of accurate values for the mode of walking the parameters for walking are estimated with the use of travel cost and travel time elasticity derived from the Landelijk Model Systeem (LMS) (Rijkswaterstaat, 2021a; Willigers and De Bok, 2012). The elasticity in the LMS originates from the Groeimodel (Rijkswaterstaat, 2021b). This model presents elasticity and cross elasticity for travel time and travel cost valuation among the main mode of transport (Haaijer et al., 2012). With cross-elasticity values, the parameters for walking are estimated and implemented in the SD model. The elasticity for telecommuting is assumed and estimated by hand. It reflects the perception of people have towards telecommuting as presented in the KiM report regarding working from home estimates (Hamersma et al., 2021).

# D

# Data analysis process

This section provides an overview of data collection, cleaning and analysis of the travel data. Each component in the model heavily relies on data input. To accurately represent the situation of the Netherlands, ODIN 2019 is used as the main source for data input (CBS, 2020). With the use of CBS survey data from the ODiN survey in 2019 a base year is constructed. The dataset from 2019 is used as a base year for travel demand due to the presence of COVID-19 in 2020. It uses the number of trips for a trip generation input.

With the use of statistical software SPSS, the original ODiN 2019 dataset is cleaned, which results in useful cases. Thereafter, the data is weighted with the appropriate weight variables to generalise the number of trips from the sample to the population. In addition, SPSS is also used to re-code and define new categories and classifications of transport modes, trip purposes, distance classes and area types. To align the outcomes of the utility functions with the ODiN input data, the utility function has to be re-estimated or calibrated.

## D.1. Initial trips

Overview of the steps performed in SPSS. The dataset used is the stacked ODiN data 2018 & 2019.

1. Selecting the cases:
   - Year = 2019 (Only 2019 data used)
   - Verpl = 1 (Only new trips are used)
2. Weighting of the cases:
   (a) Multiply with weight factor (FactorV) to generalise the sample to the population.
   (b) With the use of custom tables re-code the alternatives, distance classes (n=15  n=4) and trip purpose (n=13  n=5)
   (c) With the use of custom tables scripts selects the cases which are required for the input.
3. Custom tables:
   (a) Divide per mode of transport

(b) Divide per trip purpose
(c) Divide per trip length (i.e. distance class)
(d) Divide per trip origin based on urban degree
   i. Categorise all municipalities in the Netherlands (n=355 as of 2019) in 5 area types based on address density.

## D.2. Initial Remote working trips

Hamersma et al. (2021) provides estimations of distributions of remote working trips before COVID to calculate the number of initial trips. Table D.1 shows the subsequent calculated trips per year. With the distribution of remote working trips in 2019 the trips are subsequently calculated for every distance class and area type combination (Table D.2).

| Distance class | Trip purpose | Base year trips |
|---|---|---|
| Short | Commuting | 35444381 |
| | Educational | 13796249 |
| Middleshort | Commuting | 70888762 |
| | Educational | 27592498 |
| Middlelong | Commuting | 106333143 |
| | Educational | 41388747 |
| Long | Commuting | 141777524 |
| | Educational | 55184996 |

**Table D.1:** Initial remote working trips (trips/year)

| Area type | Distribution |
|---|---|
| Extremely urbanised | 0.233 |
| Strongly urbanised | 0.212 |
| Moderately urbanised | 0.209 |
| Hardly urbanised | 0.182 |
| Not urbanised | 0.164 |

**Table D.2:** Distribution of initial remote working trips per area type

## D.3. Average trip length based on ODiN trips

For the calculation of travel times and travel costs, the average trip length of each distance class is used. The average trip length is derived from the ODiN data set with the use SPSS.

1. Compute new variable
   (a) New variable is the trip distance in km
   (b) Next new variable is *weighted distance* = factorV * distance trips in km
2. Summation of all new variables per distance class.
   (a) Performed in excel
   (b) Average trip length = SUM weighted distance/ SUM factorV

## D.4. Area types

The area types are defined by the degree of urbanization. The density of addresses categorises every municipality in the Netherlands into one of five area types. Figure D.1 illustrated on an aggregated level the distribution of municipalities and their corresponding area type.

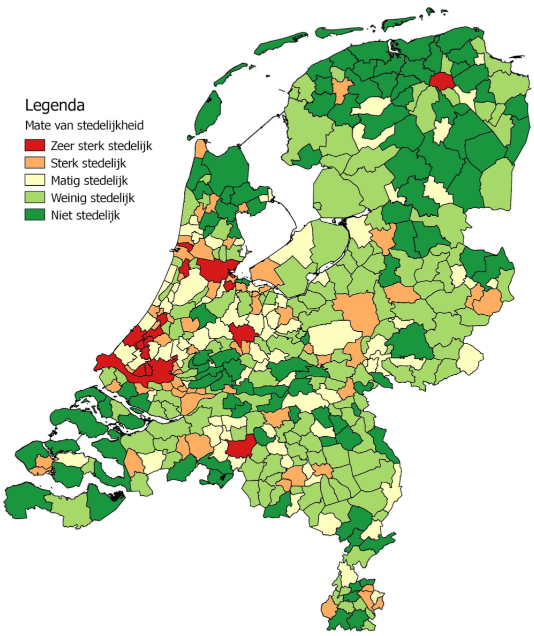



**Figure D.1:** Degree of urbanisation per municipality

# E

# Support plots EMA

## E.1. Total number of monthly trips

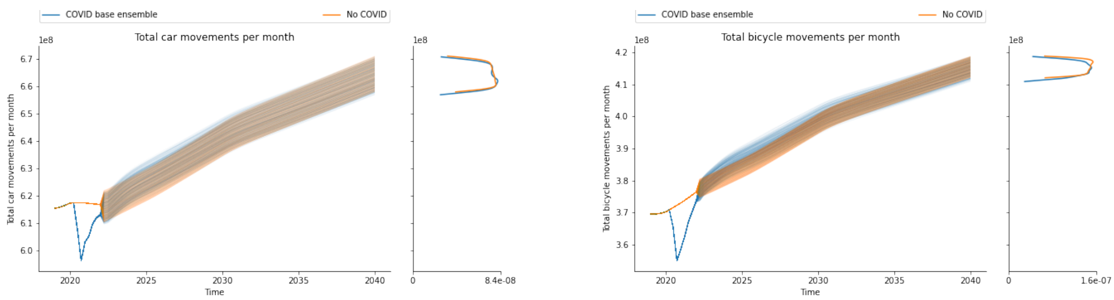



**Figure E.1:** Total trips for car and cycling

## E.2. Stack area plots

The following stack area charts are used for additional analysis between the various trip purposes in the four designed scenarios in Section 5.2.2. The trip purposes of scenarios 1: *increased public transport attractiveness* and scenario 4: *remainign low public transport attractiveness* are compared in Figure E.2, Figure E.3, Figure E.4, Figure E.5 & Figure E.6.

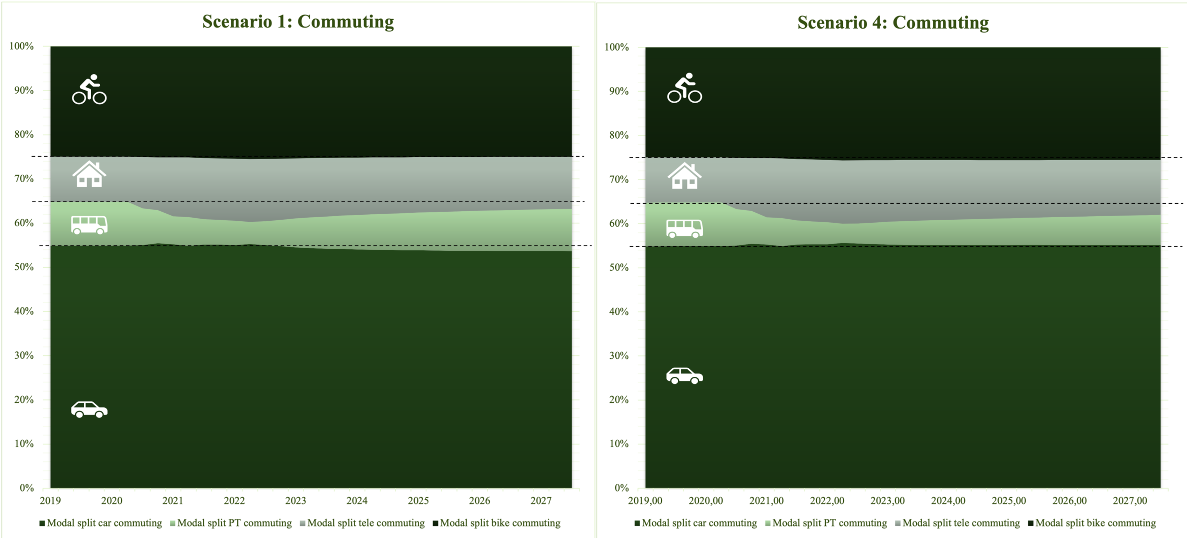



**Figure E.2:** Scenario 1 & 4 [commuting]

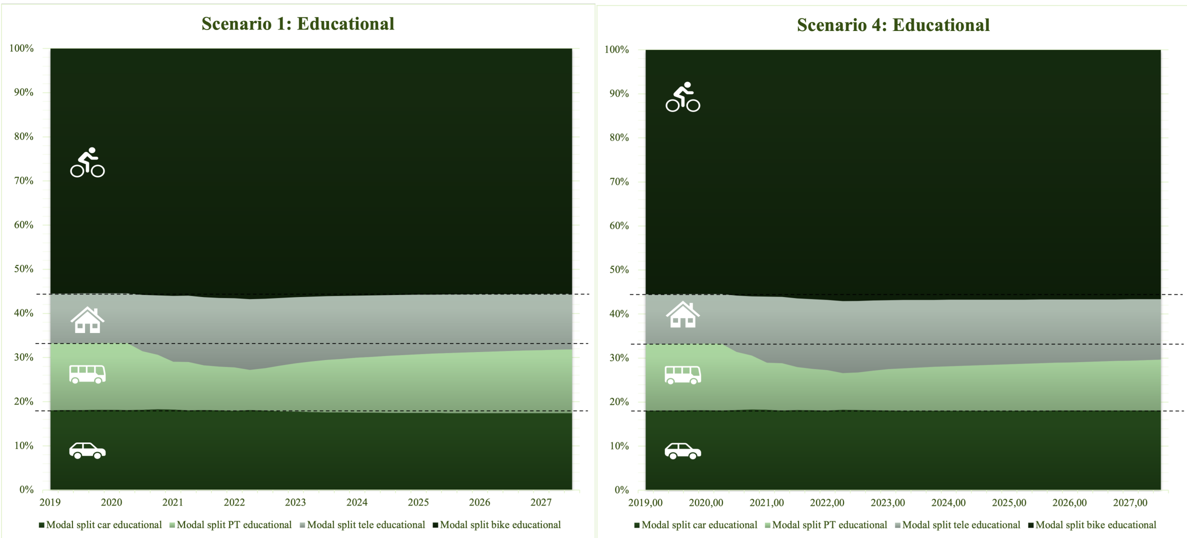



**Figure E.3:** Scenario 1 & 4 [educational]


**Figure E.4:** Scenario 1 & 4 [social recreational]

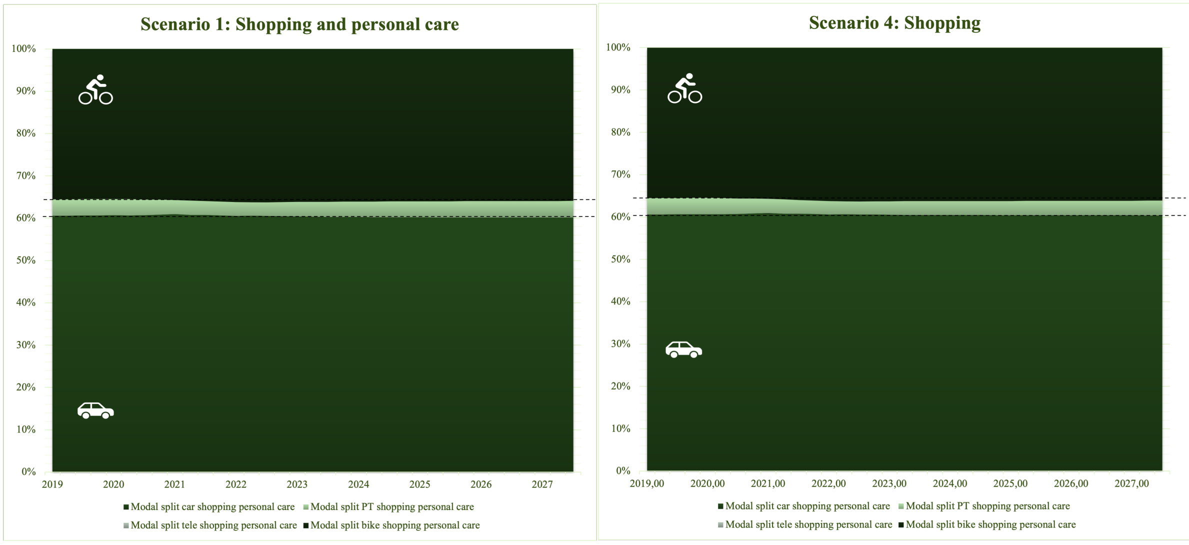



**Figure E.5:** Scenario 1 & 4 [shopping and personal care]

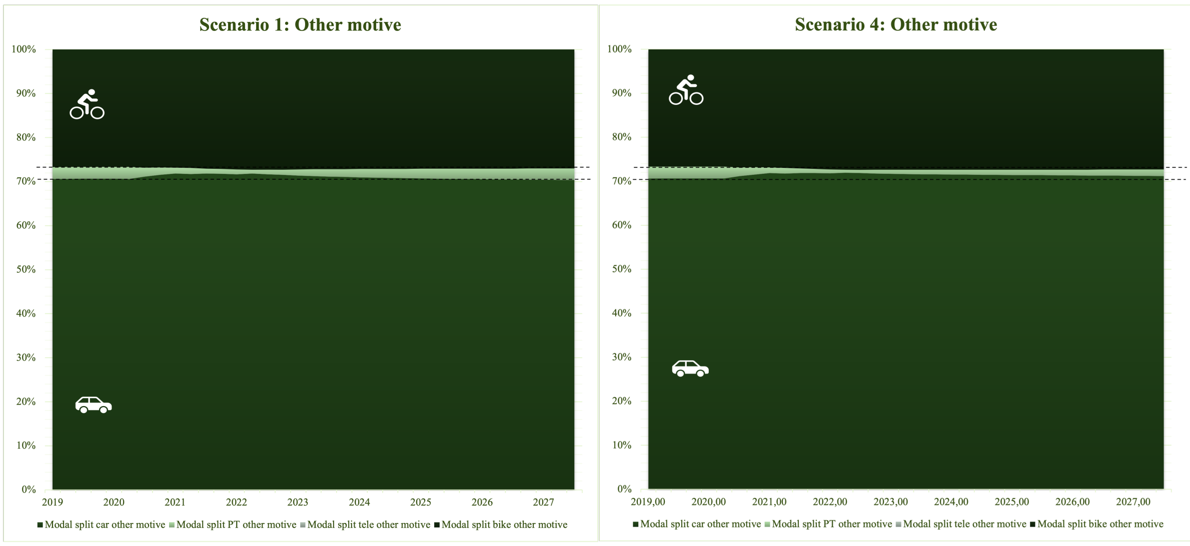



**Figure E.6:** Scenario 1 & 4 [other trip purpose]

## E.3. Modal split per trip purpose

From the additional analysis of different trip purposes, it was found that between the commuting trips and educational trips recovery periods elapse differently. Therefore, it can be assessed that the recreational PT trips in Figure E.8 recover in the distant future to a greater extent than for example commuter or educational trips. Nevertheless, the recreational trips feature a similar elapse in the near future, resulting in a recovery that will not be seen before 2026

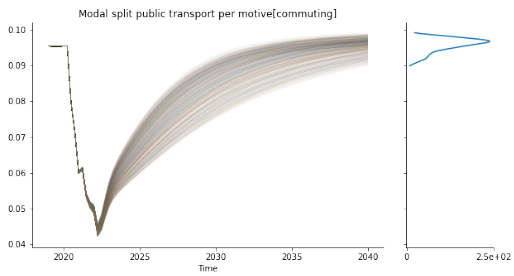



**Figure E.7:** Modal split public transport [commuting]

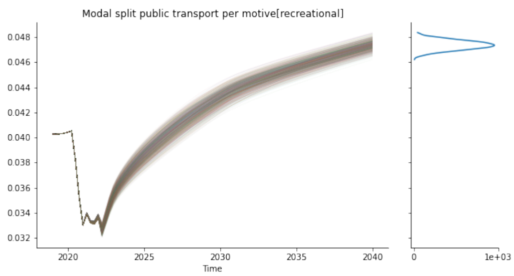



**Figure E.8:** Modal split public transport [social-recreational]

## E.4. Scenario discovery (PRIM)

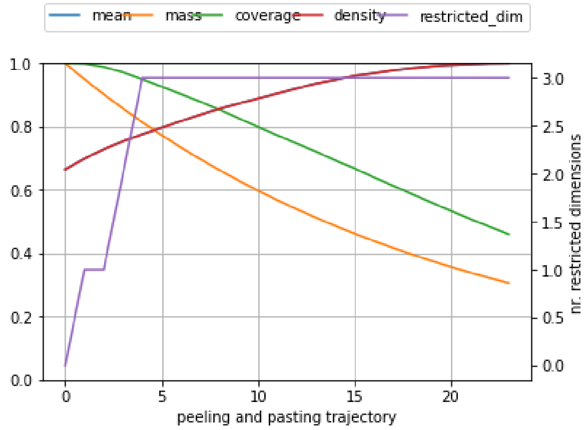



**Figure E.9:** Peeling and pasting trajectories modal split PT

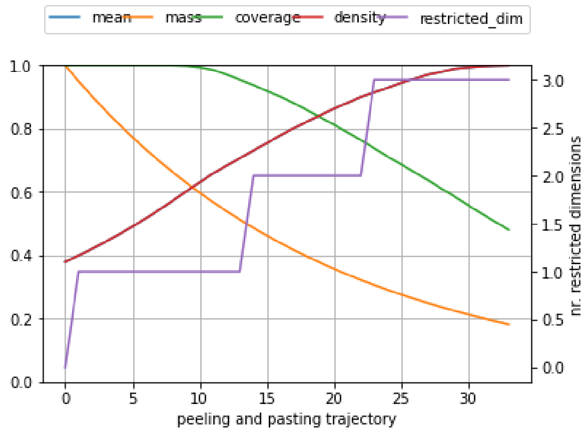



**Figure E.10:** Peeling and pasting trajectories congestion

# F

# Updated prognoses variable car cost

Due to the uncertainty of fuel prices and their future development, the prognoses from the literature are insufficient. The 2018 estimated prognosis is updated with current details. This results in a new prognosis for the development of variable car costs as of 2022. With the actualisation, the variable car cost in the model represents the current situation better. The variable car cost remains to be an input uncertainty. However, for the base scenario, the updated car cost are of impact. With the use of designed index variables, the estimation of fuel cost for fossil and electricity for respectively ICE and EV are calculated.

Disclaimer: The values are updated until the first of June 2022.

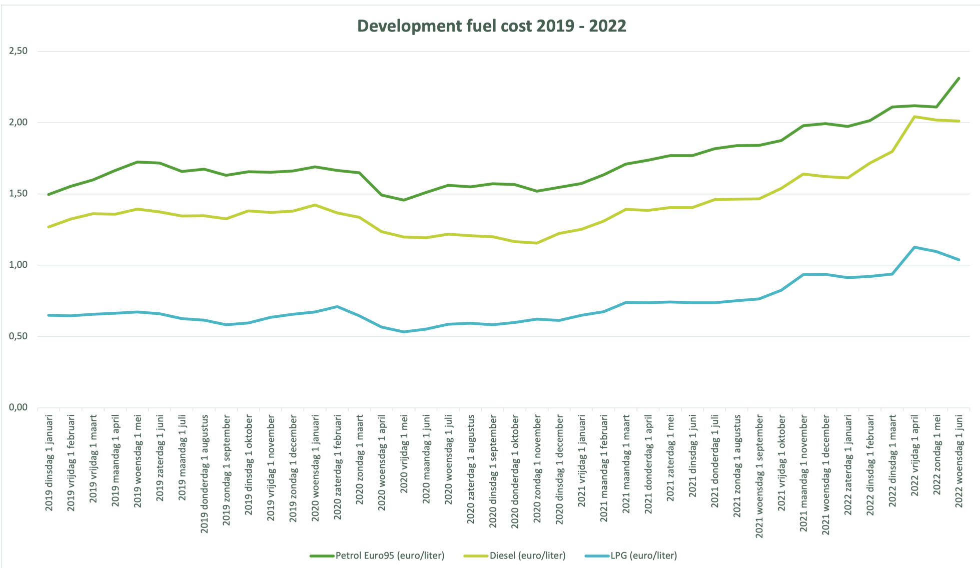



**Figure F.1:** Development fuel cost 2019 - June 2022

- Figure F.1 illustrates the development of the fuel prices between the start of the time horizon (1 January 2019) and the last update of the model (1 June 2022). The values originated from CBS (2022b) and are in euro per litre.

- Figure F.2 presents the prognosis of fuel cost which originates from 2018 (Snellen et al., 2015; Van Meerkerk et al., 2021). The prognosis from WLO is manually updated with the prices of 2022, as shown in Figure F.2.

- To include the changing fuel consumption of engines. The development of more sustainable ICE (and EV) throughout the current and future years is included in the calculation.

- Figure F.3 presents the updates prognoses from 2018 with the incorporation of updated fuel prices until first of June from Figure F.1. Due to the high degree of uncertainty about how much more the fuel prices will increase as of the first of June, the range of variables car cost can additionally be adjusted in the model through the use of an uncertainty input variable.

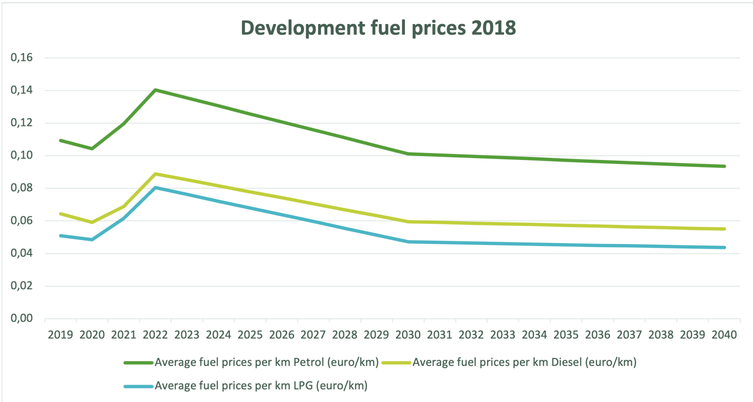



**Figure F.2:** Forecast development fuel prices 2018

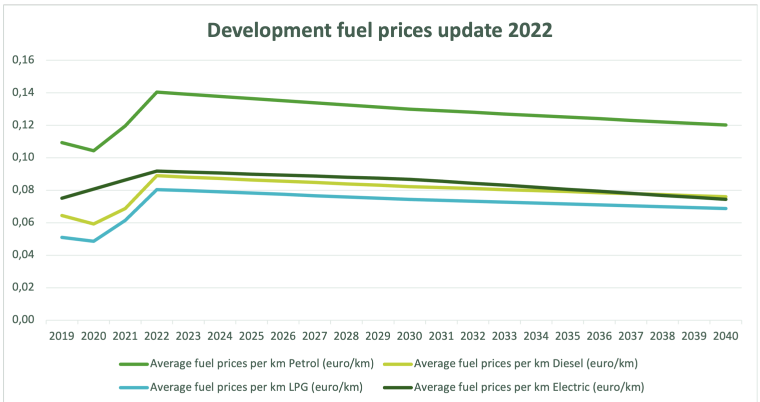



**Figure F.3:** Update development fuel prices 2022

# Is Telecommuting Our New Mode of Transportation? A System Dynamic Approach Into The Mobility Impacts Of COVID-19

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ABSTRACT

The COVID-19 pandemic has changed travel behaviour and mobility in the Netherlands. It is questioned if the mobility system is subject to change in the near and distant future. To supplement current research into COVID-19 mobility impacts, this study aims to observe the development of mobility impacts over time with a quantitative approach. Current traditional transport models have difficulties implementing uncertainties such as the mobility disruptions of COVID-19. These models lack the exploratory nature to cope with quickly arising events and changes. Using system dynamics, a model is developed to observe the mobility impacts of disruption and trends in transportation. The developed model and alternative transport modelling approach are tested and validated by applying the case of the COVID-19 mobility disruptions in the Netherlands. With the inclusion of a tele-activity alternative in the mode choice component of our SD model. The option not to travel is specified and modelled as a contender to the traditional modes of transport using choice models. Applying the model to the COVID-19 situation provided insight into new relations and understandings of the development of the mobility impacts over time in the near and distant future. It was found that the future attractiveness of modes of transport changes as a result. Travellers' preference for private modes of transport will remain high in the forthcoming years, causing public transportation to recover slowly. With the outcomes of this study, it can be concluded that the system dynamics modelling approach is beneficial and has accomplished the construction of a model more widely applicable than the case study of COVID.

## 1. Introduction

In December 2019, the COVID-19 outbreak started a pandemic with far-reaching consequences (Zhu, Zhang, Wang, Li, Yang, Song, Zhao, Huang, Shi, Lu, Niu, Zhan, Ma, Wang, Xu, Wu, Gao and Tan, 2020). Within a few months, the pandemic had caused implications worldwide. With a focus on the limitation of people's activity, the disruption of the transportation system as a result of COVID-19 was tremendous (De Haas, Faber and Hamersma, 2020). During the ongoing pandemic research, it soon became evident that the changes in travellers' behaviour could affect the transportation system well into the future (Van Wee and Witlox, 2021). The question of how and to what extent mobility will change causes uncertainty in the already uncertain domain of transport and mobility planning (Chatterjee, Burrieza Galán, Lyons and Isaksson, 2021).

*Research gap*

Half a year since the pandemic is considered to be controlled in Europe (Murray, 2022), the effects are still visible in the transport system. Where everyday life is considered recovered, travel behaviour has not fully returned to the pre-pandemic situations. Supported by literature and real-time travel data, the effects of remote working (Hamersma, Krabbenborg and Faber, 2021) and a change in mode choice (Ton, De Bruyn, Van Hagen, Duives and Van Oort, 2021) are present for an unknown extent and unknown period. To cope with increased uncertainty in the mobility system and study the extent to which the system is subject to change, this paper proposes an exploratory modelling approach. Therefore, we propose the following research question; *What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?*

Traditional transport models lack the exploratory nature to cope with quickly arising events and changes. Qualitative research lacks the ability to quantify the mobility impacts and perform scenario explorations to analyse system behaviour. Therefore, the unusual/uncommon choice is made to use exploratory modelling (Shepherd, 2014), which is particularly suitable for observing the behaviour of complex systems with a high degree of uncertainty. In this paper, a system dynamics approach is proposed to observe the future mobility impacts of COVID-19. With this method, it is moreover attempted to provide a model which is not only applicable to the mobility disruptions as a result of COVID, but also to the wider disruptions and trends in mobility in general.

*Literature*

Since the start of the pandemic, numerous studies have been initiated and published. This paper attempts to contribute to the broader aspect of research on COVID and associated mobility disruptions in the Netherlands. Before starting the modelling process, a preliminary exploration is performed to establish the aspects of travel behaviour in specific that are potentially subject to change. To scope the research, we used the currently available research to establish several points of interest in the mobility system in the Netherlands that might encounter substantial change. Based on the available qualitative and quantitative research, we were able to identify that especially the mode choice was of interest.

The rise of remote working and the decrease in public transport (PT) use can be seen as the two current COVID-19 developments that are expected to impact the mobility system in the future.

COVID-19 instigated the transition to work from home. The forced nature of this transition caused employees and employers to adapt to a fully online or partially online work environment (Van Wee and Witlox, 2021). As of today, the hybrid working mode, a combination of online and onsite working, has made its appearance in a post-pandemic era (Hamersma et al., 2021; Ton, Arendsen, de Bruyn, Severens, van Hagen, van Oort and Duives, 2022). According to Thomas, Charlton, Lewis and Nandavar (2021), these developments have impacted our commuting behaviour and formed new habits. Reiffer, Magdolen, Ecke and Vortisch (2022) addresses likewise the increased uncertainty that originates from changes in our telework and commuter behaviour. Travellers are more likely to substitute a commuting trip with working from home and thus not travel.

Furthermore, COVID-19 influenced travellers' mode choices directly, as travel preferences changed, and public modes of transportation were avoided during the pandemic (Gkiotsalitis and Cats, 2020; Shelat, Cats and van Cranenburgh, 2022). With post-pandemic travel data, it has become apparent that not all travellers return to PT (Ton et al., 2021).

## 2. Methodology

### 2.1. (Mobility) System Dynamics

The methodology of System Dynamics (SD) makes use of both qualitative and quantitative modelling approaches. SD uses causal relations between elements of the system, quantifying the relations of a system enables the exploration of the behaviour of a system over time (Pruyt, 2013). Hence, an SD model consists of a set of integral equations that are numerically solved. The equations represent behaviour such as accumulation, feedback and delays. With a stock-flow structure, these elements are modelled, and subsequent dynamic behaviour occurs when flows accumulate into stocks (Abbas and Bell, 1994). The concept of feedback is essential in this as it adds dynamic facets and prevents elements based only on linear behaviour (Auping, 2021). Examples of feedback in our model structure are found in the modal split, the number of (car) trips, the impact of COVID on trips, telecommuting behaviour and appreciation of public transportation.

SD is not an out-of-the-box option for the exploration of the future of mobility. As this paper showed the lack of exploratory nature in traditional transport models, we deviate from the normal route of providing decision-makers and transport planners model-based estimations. Using SD, we can provide a more complete prospect, displaying the dynamics of mobility impacts and the outcomes of changing uncertainties. There is an absence of prior SD research in this specific area which we can use as a basis for our model. Nonetheless, in the field of (urban) mobility, there are some examples of applications of SD as an exploratory transport modelling method.

Pfaffenbichler, Emberger and Shepherd (2010) developed an urban mobility SD model, which has been used in more than 15 cities and metropolitan areas to support future transport planning processes. Legêne, Auping, Homem de Almeida Correia and Van Arem (2020) used spatial system dynamics to evaluate the introduction and adoption of automated vehicles in urban areas. In the Netherlands, the first application was the development of the *ScnerioVerkenner* by Heyma, Korver and Verroen (1999), by which the first step towards a scenario planning tool was made. Nevertheless, the practical use of the ScenarioVerkenner is hardly seen nowadays. First, due to its development in the 1990s, meaning the model is currently outdated. Second, the fact that it was often used as a method to predict future demand and supply for infrastructure planning (Smits, van Maanen and Borgman, 1995). However, the methodology of system dynamics is more useful for observing model behaviour over time, and to a lesser extent, for the specific predictions of the future.

### 2.2. Transport modelling

To provide the developed model with a robust basis, the 4-step model, as presented in Figure 1, is used as a guideline for the structure of the model. The 4 steps consist of (i) trip generation, (ii) trip distribution, (iii) mode choice and (iv) route assignment (Ortúzar and Willumsen, 1990). As previous studies suggest potential effects within the mode attractiveness, the focus is aimed at the mode choice. Implementing a choice model in the system dynamics model enables the exploration of change in travellers' choices and thus travel behaviour after the pandemic. Nonetheless, the other phases in the 4 step model are included as well to ensure a complete transport modelling structure in the SD model. Trip generation is combined with trip distribution and is influenced by population growth to provide the input of trips. The assignment is subsequently simplified because detailed route assignments can be problematic in a system dynamics environment (Shepherd, 2014).

### 2.3. Exploratory modelling and analysis

For analysing the model outcomes and exploring the influences of uncertainty, Exploratory Modelling and Analysis (EMA) is used. Bankes (1993) introduced the concept of EMA in 1993. With the use of computational support, it is possible to perform a high number of experiments and analyse the uncertainties of a model (Kwakkel, 2017). The use of a high number of experiments (N >1000) in combination with the possibility to vary the range of input parameters

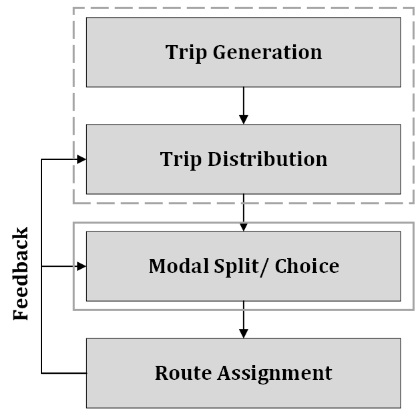


**Figure 1:** Point of interest in the 4-step model

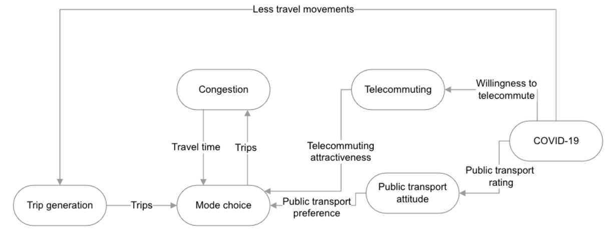


**Figure 2:** Overview of the system and sub-components

enables the exploration of the model outcomes in a base ensemble instead of a single base scenario. Within EMA it is possible to perform scenario discovery. With the use of a scenario discovery algorithm, computer-assisted scenario development is possible (Bryant and Lempert, 2010). Computational scenario discovery extends traditional scenario design where at first a storyline is developed and afterwards simulation takes place.

The SD model in this paper is heavily dependent on COVID-related input, which is often based on estimations and best guesses from the literature. Therefore, the use of EMA allows analysing of model outcomes under different conditions, providing a stronger perspective on the future mobility impacts. The combination of EMA and our model is seen as valid as our goal is to observe the impacts on bandwidths to establish insight into the behaviour over time. Furthermore, the use of EMA in System Dynamics is often used and validated (Kwakkel and Pruyt, 2015), therefore providing a strong analysis method useful for our model.

# 3. COVID-19 mobility model

We developed a model to observe the impacts of mobility disruptions as a result of the COVID-19 pandemic. To observe the mobility impacts of COVID, we study the behaviour of the impacts over time in the near and distant future and explore the uncertainties causing the impacts.

## 3.1. Conceptual overview

The structure of our model is based on the elements in the 4-step model, emphasising the mode choice component. Figure 2 illustrates the different submodels and components in the model. The two Key Performance Indicators (KPIs) we focus on in this paper are *modal split* and *number of trips*. Both originate from the mode choice sub-model and are considered most useful for the observation of the impacts of COVID. The KPIs are influenced by input parameters and uncertainties in each sub-model.

*The five modes of transport*

Because there are numerous modes of transportation, a selection of the relevant alternatives is made. We include 5 main modes of transport, being: *car*, *public transport*, *bike*, *walking* and *tele-activity*. Tele-activity is a new addition to the mode choice and can be seen as the option to not travel for commuting or educational purposes. Both are referred to as telecommuting from now on as a collective term. With these five modes, we can determine the most important changes in mode attractiveness due to COVID.

*Telecommuting*

To cope with the adoption of telecommuting as part of our mobility system, we propose a new method of modelling working from home. The emphasis on telecommuting results from the literature where the significance of telecommuting in our future commute and travel behaviour is mentioned several times (Ton et al., 2022; Reiffer et al., 2022).

In prior SD models, Haghani, Lee and Byun (2003) & Malone, Verroen, Korver and Heyma (2001) included telecommuting by subtracting part of the trips not being made from the initial trip generation. The possibilities of including the choice of not making a trip into the mode choice are studied in this paper, resulting in a preference to model telecommuting as a novel alternative in the mode choice. In relation to previous SD mobility models, our model enhances the dynamic element of telecommuting. Without considerable changes to the model structure because the alternative is modelled similar as traditional modes of transport.

Adding the alternative telecommuting to the modal split enables the option to explore the attributes influencing the choice to work on-site or remote. The choice to work from home depends on numerous variables, most of which were discovered during the COVID-19 pandemic. In the aftermath of the pandemic, we learn more about the variables that influence the traveller's decision (Reiffer et al., 2022). Therefore, the inclusion of telecommuting as an alternative in the mode choice causes an enhanced ability to explore the behaviour of working from home.

### 3.2. Choice modelling

To observe the (future) hypothetical mode choice of travellers, we implemented the use of discrete choice models in our system dynamics model. The inclusion of the choice model enables the change in attractiveness over time to be observed (Train, 2003). The alternative a decision-maker chooses can be determined with the use of a logit formulation (Ortuzar and Willumsen, 2011). The decision-maker chooses the alternative that has the highest utility (McFadden, 1980), because of the utility maximisation theory we adapt for our designed choice model. The probability $P$ of the decision-maker choosing alternative $i$ is calculated with Equation 1.

Each alternative has a corresponding utility function which consists of attributes, such as travel cost, travel time and comfort. The attributes differ per alternative. Where applicable the utility or attributes are influenced by COVID variables.

$$P_i = \frac{e^{V_i}}{\sum_{r=1}^{n} e^{V_r}} \tag{1}$$

*Where:*

$P_i$ = *Probability of choosing mode i;*
$V_i$ = *Utility of mode i;*
$V_r$ = *Utilities of all the modes r;*
*n = Number of modes in consideration;*

### 3.3. Validation of input data

In order to validate the choice model, we use travel data from the pre-COVID situation to construct a solid base year. The base year data is derived from travel data originating from survey data in the annual study, *Onderweg in Nederland* conducted by CBS (2020). The pre-pandemic base year is used as a starting point for the trip generation. Subsequently, the designed choice model is calibrated on the base year input data, resulting in a validated choice model for the SD model.

### 3.4. Distinction of trip types

Besides the nationwide impacts of COVID the more specific impacts, in certain areas, for different trip purposes and trip lengths, are of interest. The input data consist of base year trips on a detailed level. The trips are divided into trip types based on five trip purposes, five area types and four distance classes shown in Table 1. The trip types are modelled efficiently with the vectorisation of variables, essentially creating a copy of a variable and model structure.

Each trip type has separate attribute parameters and constants in their utility function. Subsequently, determining the mode attractiveness and the future number of trips for each combination (n=100) of trip types. This provides us with insight into the difference between, for example, a short commuting trip originating in an urban area and a long commuting trip originating in a nonurban area and the incentive to substitute that trip with a telecommute trip.

**Table 1**
Trip categories

| Trip purpose | Distance class | Distance [km] | Area type | Address density [Addresses/km^2] |
|---|---|---|---|---|
| Commuting | Short | <7.5 km | Very highly urban | >2500 |
| Educational | Middle short | 7.5 - 15 km | Highly urban | 1500 - 2000 |
| Social recreational | Middle long | 15 - 40 km | Moderately urban | 1000 - 1500 |
| Shopping & Personal care | long | >40 km | Little urban | 500 - 1000 |
| Other motives | | | Non-urban | <500 |

### 3.5. Experimental setup

The choice to model the input uncertainties under two sets of ranges results in the exploration of two sets of model ensemble outcomes. First, the COVID-19 base ensemble is constructed based on input ranges derived from the literature and travel behaviour (panel) data in the Netherlands. Second, due to the high magnitude of uncertainty regarding the input, the ranges are adapted and an additional ensemble is constructed for use in scenario exploration. With the exploration of both ensembles, we are able to observe the outcomes that are likely and on the other hand the more extreme/rare situations. With the results of both outcomes, this paper can relate to other mobility impact studies.

The SD model is designed with the system dynamics software package of Vensim (version: Vensim® 9.3.0), which provides a user-friendly graphical modelling interface (Ventana Systems, 2022). For the analysis of the model outcomes, and performing a high number of experiments, the EMA workbench (version: 2.1) is used. The EMA workbench is implemented in Python and features an integrated connector for the models in the Vensim package to be implemented in the workbench (Kwakkel, 2017).

The model experiments performed varies each of the input parameters within their range using a Latin Hypercube sampling (Kwakkel, 2017). This statistical sampling method generates a near-random sample of the input parameters. For the COVID-19 base ensemble, 1000 experiments are simulated, for the scenario exploration and wider ranges the experiments are increased to 5000, in order to perform scenario discovery.

## 4. Results

The attractiveness of modes of transport is expressed in their mode share over time. Based on the trip-based modal split, we study their increase or decrease in attractiveness post-COVID. The prognosis without the interference of COVID is additionally displayed, to observe the differences if the COVID pandemic never occurred. The results discussed in this paper are focussed on the near future, therefore, showcasing the model outcomes between 2019-2030. For the impacts over a longer period of time, the reader is referred to the complete study (Van Tol, 2022).

The initial modal split pre-COVID is shown in Table 2. The modal split is adjusted for the inclusion of a telecommuting alternative. Based on the studies from Hamersma et al. (2021) and Jongen, Verstraten and Zimpelman (2021) we were able to establish validated telecommuting input data.

**Table 2**
Modal split 2019

| | |
|---|---|
| Car | 47.01 % |
| Public transport | 5.74 % |
| Bicycle | 28.23 % |
| Walking | 15.88 % |
| Telecommuting | 3.13 % |

Figure 3 illustrates the modal split value of public transport in the near future. It can be established that in the presented time span the COVID-19 base ensemble (displayed in blue) is not able to equal the original prognosis (displayed in orange). Therefore, indicating that the future attractiveness of public transport appears not to recover by itself. Nevertheless, in an optimistic scenario, the 2019 pre-COVID level (5.74%) of attractiveness will be matched. As we observe a slightly higher density in model outcomes in the upper part of the ensemble in Figure 3, it is shown that the chances for recovery with such a gradient are higher.

First of all, one of the reasons is that telecommuting and PT are competitors, as illustrated in Figure 4. This is not surprising as commuters are a considerable share of public transport passengers. The decay of PT is not in full relation to the increase in telecommuting, indicating other factors impact the decrease of attractiveness as well. We witness that the mode share of telecommuting stabilises at various levels, contrary to the PT mode share, indicating different behaviour (Figure 3 & Figure 4). Furthermore, the absolute change in percentage points in the modal split value is different.

Secondly, the valuation of public transport in the years after COVID is still of considerable essence. Although telecommuting is responsible for a significant loss in the future number of public transport passengers, the increased attractiveness of other alternatives, car and bicycle remain (Figure 5 & Figure 6). Indicating travellers tend to use the (re)discovered alternatives to substitute PT. The bicycle is in the future mainly used as an alternative for short PT trips and the car is used for longer distances as an alternative for PT trips.

In order to determine the more in-depth causes of why public transport recovery proceeds slow, the various trip purposes were examined in more detail. It was found that PT travel with social-recreational purposes encounters, similar to commuter travel, a slow road to recovery. The attractiveness of social-recreational travel is expected to recover faster in the near future compared to commuting trip purposes. However, the original no-COVID trend was depicted to be higher, eventually showing similar progress of recovery for both commuting and social-recreational travel. This shows that, in addition to the lack of travellers who work from home, public transport also lacks the essential social-recreational travellers.

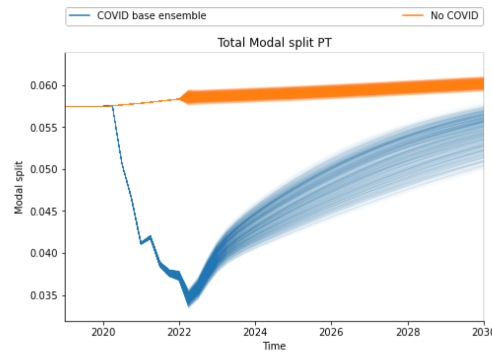


**Figure 3:** Public transport mode share

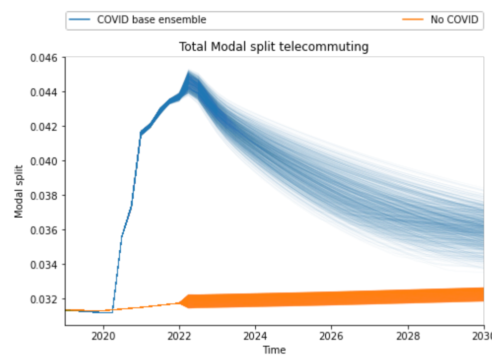


**Figure 4:** Telecommuting mode share

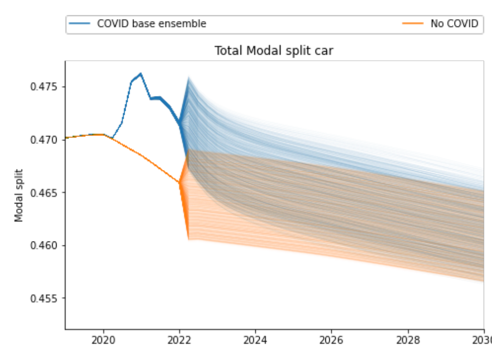


**Figure 5:** Car mode share

## 5. Conclusion & discussion

*Comparison with other research*

Our outcomes are in line with research from Francke and Bakker (2022) regarding the slow recovery. However, the authors predict a faster road to recovery than our results suggest. The effect of travellers' aversion towards the use of public modes did not improve as quickly as estimated by Francke and Bakker (2022). The attractiveness of other

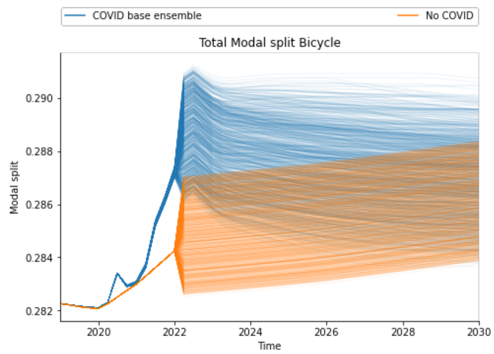


**Figure 6:** Bicycle mode share

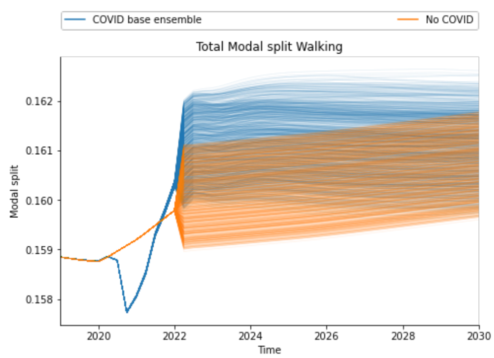


**Figure 7:** Walking mode share

alternatives, telecommuting, car and bicycle and the effect of negative attitudes remain influential factors.

The factor of telecommuting inevitable influences the loss of public transport travellers. This is in line with Hamersma et al. (2021), who suggested that mostly telecommuting is keeping travellers out of PT. In addition to Hamersma et al. (2021), we extend the results by showing the outcomes over time. We can conclude that the number of future travellers substituting their trip with working from home is slightly less than argued by Hamersma et al. (2021), for the underlying reason that we study the coherence of effects. Hence, we assume the shift in attractiveness to other modes has a minor dampening effect on telecommuting.

*Research question*

In this paper, we proposed the following research question: *What are the long-term impacts of COVID-19 on passenger mobility in the Netherlands as a result of changing travel behaviour?*

It can be concluded that our travel behaviour has changed as a result of the COVID-19 pandemic. The primary effect is the absence of travellers in public modes of transportation due to, first of all, our preference for working more on a remote basis and, secondly, travellers' increased preference to use the car or bicycle in the post-COVID era. This is substantiated by the remaining negative attitude towards public modes of transportation.

*Unexpected findings*

Public transport in the near future struggles to get back on top. Because we analysed the cohesive impacts, it was shown that besides the role of telecommuting, the attitude towards different modes of transport is still of considerable influence after the pandemic. In association with the negative PT attitude, the attractiveness of modes other than PT remains high in the post-COVID era. In contrast to other research, the role of travellers' attitudes in the future is undervalued (Francke and Bakker, 2022) or primarily focussed on travellers' attitudes during COVID (Ton et al., 2021).

Nonetheless, the effects of telecommuting are substantial for public transport. As shown in the analysis of the results, there is a strong connection between tele-activities and the use of public transport. Zooming in on the commuter and, to a limited extent, educational travel, it is illustrated that public transport and telecommuting are competitors and seek the same type of traveller. This has consequences for the future, as inherently, remote working keeps travellers out of PT. Therefore, the possible promotion of public transport in the future must be focused on attracting new travellers.

For telecommuting, it was already shown before the pandemic (Van der Loop, Willigers and Haaijer, 2019) that small amounts of telecommuting had a significant effect on congestion reduction. As a result, there is a high incentive to keep telecommuting at a certain minimum level. When telecommuting and PT are stimulated through either policy or behavioural change, conflict might arise. Potential measures need to be aligned to prevent opposing interventions. It is impossible to design a policy for one without considering the other.

*Model considerations*

It is found to be beneficial to explore telecommuting as a new alternative. Since the pandemic, remote working is embedded in our behaviour and has changed our concepts of commuting. The choice to avoid travelling has become easier for commuters and has impacted our mode and travel choice. With the inclusion of telecommuting in the mode choice, we could observe the dynamic progress of telecommuting over the years.

Furthermore, the developed SD model was found to be appropriate for the application to the case of COVID-19. Our approach and model were tested and validated by comparing our outcomes with mobility impacts found in the literature. Therefore, providing the possibility of applying the model to mobility disruptions wider than COVID. The objective of SD is different to traditional transport models, where SD models thrive outcomes with a different level of accuracy. It is, therefore, essential to notice that we do not desire to pinpoint a value from the presented plots to estimate the modal split or number of trips at a specific moment in time. Rather, we desire to observe the behaviour and the course of change of KPIs.

*Future research*

Finally, our model and research leave room for improvement and future research. Due to several simplifications in the current model, the future extensions focus on model additions to improve the model's explanatory power. Future research points primarily in the direction of quantifying the policy recommendations. The potential adjustment of travel behaviour with the use of measures or interventions is touched upon briefly in this paper. It would be beneficial to implement control measures or policy interventions in the SD model regarding the stimulation of PT, such as pricing, increased supply or positive image, to determine the subsequent effect on attractiveness.

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