Analysis of the Impact of Microcars on Carbon Emission and Traffic Congestion

A thesis submitted
to the TUM School of Life Sciences
Master's Program Sustainable Resource Management
in partial fulfilment of the requirements for the degree of
Master of Science

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April, 2025

Acknowledgments

I would like to express my deepest gratitude to all those who supported me throughout my thesis and academic journey.

First and foremost, I sincerely thank my thesis supervisor, Dr. Mohamed Abouelela of the Chair of Transportation Systems Engineering at the Technical University of Munich, for his invaluable guidance, constructive feedback, and continuous encouragement throughout the research process. His expertise and support have been instrumental in shaping the direction and quality of this work.

I also wish to thank the Chair of Transportation Systems Engineering and its department chair, Prof. Dr. Constantinos Antoniou, for providing the opportunity and resources to pursue this study. Their leadership and the academic environment they fostered at the Technical University of Munich were essential in enabling this research.

I am especially grateful to the Sustainable Resource Management Master's Program at the Technical University of Munich, where I received my education throughout my time here. The interdisciplinary curriculum and supportive academic community provided a strong foundation for this thesis and for my growth as a researcher.

I am also thankful to my friends and colleagues for their encouragement and camaraderie, which made this journey more meaningful.

Finally, I would like to express my heartfelt appreciation to my family for their unconditional support, patience, and belief in me throughout this entire endeavor.

Abstract

Rising congestion levels and environmental concerns such as energy consumption and pollutant emissions increasingly challenge urban transport systems. As a compact and energy-efficient alternative to conventional vehicles, microcars have drawn attention to their potential to enhance urban mobility and their market size is expected to grow. However, studies about the impact of introducing microcars on traffic and environmental performance are quite limited and, especially, no studies to date have explored its impact on a large-urban scale. This study investigates the microcar's impact into a large-scale urban transport network, Berlin City, through agent-based simulations using MATSim. A wide range of scenarios was tested by varying microcar replacement ratios, maximum speeds, and space requirements (PCE), with a focus on traffic performance indicators—mode share, average speed, congestion index, and travel duration—as well as environmental metrics including fuel consumption and CO_2 emissions. The results indicate that higher microcar replacement ratios generally lead to improved traffic flow and significant environmental benefits. However, the relationship between microcar penetration and performance gains is not always linear: while travel duration and environmental indicators improve steadily, other metrics such as mode share and average speed show nonlinear trends. Maximum speed shows limited influence, whereas PCE significantly affects traffic performance. With 100% microcar replacement, average speed increases by 4.3%, travel duration decreases by 9.8%, and carbon emissions drop by 11.4% compared to the base scenario. These findings demonstrate the potential of microcars to contribute to more efficient and sustainable urban transport systems.

Key-words: Urban mobility, traffic, microcar, micro electric car, simulation, MATSim

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List of Acronyms

CA	Cellular Automata
CNG	Compressed Natural Gas
CO_2	Carbon Dioxide
FEF	Fuel Efficiency Factor
gCO_2eq	Grams of Carbon Dioxide Equivalent
GHG	Greenhouse Gas
GTFS	General Transit Feed Specification
HBEFA	Handbook on Emission Factors for Road Transport
ICE	Internal Combustion Engine
kWh	Kilowatt-hour
LCA	Life Cycle Assessment
LEV	Light Electric Vehicle
LOS	Level of Service
LPG	Liquefied Petroleum Gas
MATSim	Multi-Agent Transport Simulation
MEV	Micro Electric Vehicle
NOx	Nitrogen Oxides
PCE	Passenger Car Equivalent
PMx	Particulate Matter (e.g., $PM_{2.5}$, PM_{10})
PT	Public Transport
QSim	Queue Simulation (MATSim module)
SUMO	Simulation of Urban Mobility
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
WTW	Well-to-Wheel

1 Introduction

Today's urban cities face emerging issues in their traffic systems: congestion issues and pollutant emissions. In urban areas with their ever-increasing populations and limited space for traffic infrastructure, congestion issues such as heavy traffic jams during peak times and parking shortages are inevitable problems. Additionally, mounting legislative and social pressures demand that governments and automotive manufacturers take action to reduce fuel consumption and mitigate environmental impacts, particularly carbon emissions.

To overcome these challenges, microcar, a class of vehicle, generally two-door, two-seater, and less than 3 meters in length (Tanveer et al., 2022), is an ideal alternative to internal combustion engine (ICE) cars, for it occupies less space for parking and on roads, and is convenient for short and medium distance trips that are typical in urban areas (Mu & Yamamoto, 2019). Also, Due to their lightweight and small design, microcars, especially electric microcars, also known as micro electric vehicles (MEVs), produce around 4–5 times fewer carbon emissions per traveled distance than ICE cars (Ehrenberger et al., 2022). Edwards et al. (2023) further describe the benefits of microcars, such as improving accessibility for older people and people living with disabilities and providing last-mile connectivity.

Microcars once considered a niche form of mobility, are increasingly recognized as a viable option for individuals or small families residing in densely populated urban areas. The global microcar market was valued at USD 4.5 billion in the year 2022 and is expected to grow at a rate of around 11 % during the forecast period (2023-2030), mainly due to the growing need for smaller vehicle coping with urban city traffic (e.g., congestion, parking space availability) and reducing the cheaper operation cost thanks to higher fuel economy of smaller cars (UnivDatos Market Insights, 2024).

To quantitatively assess and evaluate the impact of microcars on urban traffic systems, several studies have been conducted using traffic simulation tools and software. However, the number of studies is limited, and several challenges remain in evaluating the potential impacts of microcars on urban traffic systems:

1. **Behavioral Dynamics**: Some studies have simulated traffic scenarios with varying proportions of microcars and concluded that their introduction increases average vehicle speeds and reduces travel time, indicating congestion mitigation (Dray, 2022; Mu & Yamamoto, 2013a, 2013b). However, current studies assume fixed travel plans, overlooking how individuals may adapt their travel behavior in response to traffic changes caused by microcars. For instance, reduced congestion may encourage greater use of private vehicles or shift travel patterns, potentially creating new traffic dynamics. Simulations that incorporate dynamic behavioral changes are needed to understand these effects comprehensively.

2. **Scalability**: Most existing studies analyze the impact of microcars on small-scale scenarios, such as specific road segments or a few lanes in a virtual setting. While these studies provide valuable localized insights, they fail to capture system-wide implications, particularly interactions with other transportation modes such as public transport. Large-scale scenario analyses are essential for a holistic understanding of microcars' impacts on urban traffic systems.

3. **Microcar Configurations**: The diverse configurations of microcars—such as variations in speed, road occupancy, fuel efficiency, and emissions—are often overlooked. Systematic analyses are needed to identify how different microcar designs influence traffic dynamics, providing critical insights for optimizing microcar production and fostering sustainable urban mobility.

To address these gaps, this study aims to assess the impacts of microcars on traffic conditions and pollutant emissions in a large urban setting while accounting for individuals' dynamic traffic behavior. Specifically, it seeks to answer the following research questions:

- Q1: How does the introduction of microcars influence individual traffic behaviors and, accordingly, affect congestion, energy consumption, and emissions in an urban setting?

- Q2: How do microcars' maximum speed and space requirements impact simulation results?
- Q3: What is the optimal configuration and distribution of microcars in urban areas to minimize congestion, energy consumption, and pollutant emissions?

The findings of this study are expected to benefit stakeholders such as automotive manufacturers and urban policymakers. Specifically, the outcomes will:

- Enable policymakers to conduct quantitative analyses of microcar impacts in urban contexts.
- Help manufacturers identify microcar characteristics that improve urban traffic conditions.
- Assist decision-makers in identifying individuals most likely to benefit from microcars, guiding subsidies, and campaign strategies.

To achieve these objectives, the study employs the Multi-Agent Transport Simulation (MATSim) framework, an activity-based and extensible platform designed for large-scale traffic simulations (Horni et al., 2016). MATSim allows for incorporating dynamic individual behavior and multimodal transport interactions, making it suitable for this research. The study uses the well-documented Berlin urban network as a case study, using open-source data validated by the Technische Universität Berlin (Ziemke et al., 2019). Energy consumption and emissions are calculated by linking MATSim outputs to the database provided by the Handbook on Emission Factors for Road Transport (HBEFA).

This thesis is structured as follows: Chapter 1 includes the introduction, where the background, research objective and research questions are defined. Chapter 2 reviews relevant literature regarding the impact of introducing microcars into the traffic and existing traffic simulating models. Chapter 3 details the methodological framework. Chapter 4 presents the results, and

Chapter 5 and 6 discusses the findings, conclusions and implications of the study. Figure 1.1 shows the thesis framework.

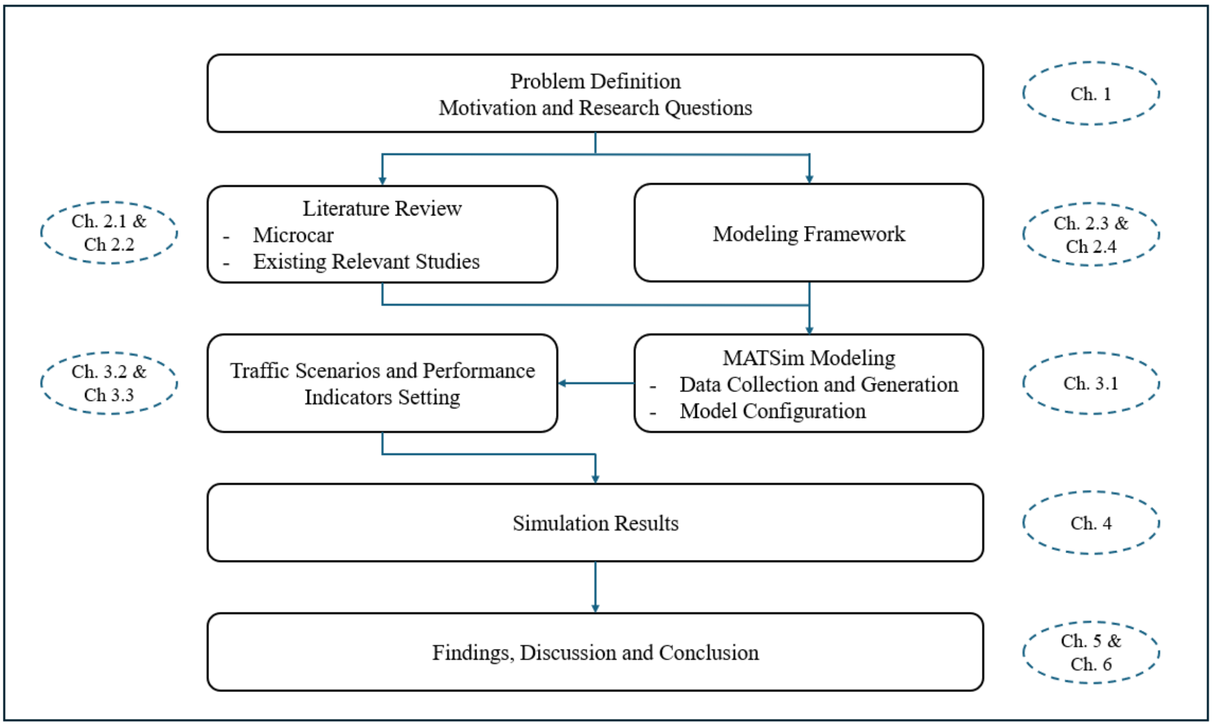

Figure 1.1. Thesis Framework

2 Literature Review

This literature review aims to provide a comprehensive overview of current research about the influence of microcars on traffic situations, evaluate the limitations of current research, and justify the selection of an appropriate traffic simulation model to achieve the study objective.

2.1 Microcars

The definition of a microcar varies, but it typically refers to a lightweight, two-seater, two-door vehicle less than 3 meters in length (Mu & Yamamoto, 2019; Tanveer et al., 2022). The terminology for microcars is not consistently defined. In this study, the terms "microcar," "micro-car," and "minicar" are used interchangeably. Similarly, the terms "electric microcar," "light electric vehicle (LEV)," and "micro electric vehicle (MEV)" are used interchangeably to refer to microcars powered by electricity.

Compared to conventional cars, microcars offer significant advantages in several ways. Internal combustion engines (ICEs) are not compact, and the large space occupied by ICE vehicles has contributed to worsening traffic congestion, particularly in major cities. A single occupant in a sedan requires approximately 15 m^3 of space, which is five times the requirement per person in a city bus and about 3.5 times that in a microcar such as the Renault Twizy (Karaca et al., 2018). Taking advantage of this small size and space occupancy, microcars can provide a driving experience with less traffic and parking congestion. Figure 2.1 shows the comparison of the size required for parking between a conventional vehicle and a microcar.

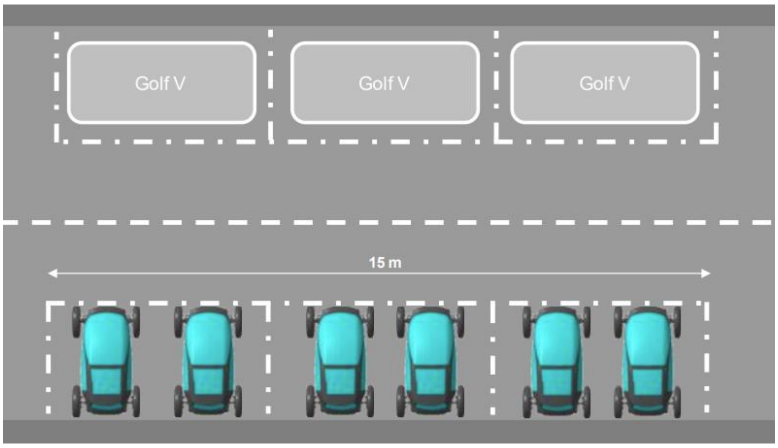

Figure 2.1. Comparison of space requirement comparison of L6e class cars vs C-Segment cars (Reske et al., 2017)

Beyond space-saving benefits, microcars also offer significant environmental advantages due to their lower energy consumption. Due to their lightweight and compact design, microcars are more energy-efficient than ICE vehicles. Ehrenberger et al. (2022) conducted a life cycle assessment (LCA) comparing light electric vehicles (LEVs) and passenger cars powered by gasoline, diesel, CNG/LPG, hybrid, and battery-electric systems. Their analysis considered fuel consumption, energy production, vehicle manufacturing, and battery production. The study found that ICE vehicles (gasoline, diesel, and CNG/LPG) emit approximately 220 g CO_2-eq per km, whereas LEVs produce only 40–50 g CO_2-eq per km. Moreover, substituting 50% of passenger car mileage with LEVs could reduce greenhouse gas (GHG) emissions by 44%.

The primary drawbacks of microcars compared to ICE vehicles are their limited range and lower passenger capacity (i.e., one or two seats). However, statistics show that the average daily distance traveled per person in Germany is 39 km (Federal Ministry for Digital Affairs and Transport, 2019)—less than one-third of the range achievable by modern electric microcars with a small battery configuration (Ehrenberger et al., 2022). Additionally, the average number of passengers per trip for all household vehicles is around 1.5 in the U.S., a decline from 1.87 in 1977 (U.S. Department of Energy [DOE], 2022; U.S. Department of Transportation [DOT], 1981). This low occupancy rate is a global trend. In 2015, the average vehicle occupancy was 1.42 in Germany, 1.50 in Japan, 1.55 in the UK, and 1.26 in China, respectively (Wolfram et al., 2020). These figures suggest significant potential for many private car users to adopt microcars without compromising the convenience of car ownership or travel experience.

Microcars, particularly lightweight four-wheeled vehicles, are categorized as L-category vehicles within the EU. According to Regulation (EU) 168/2013 (2013), quadricycles intended for public road use are classified into two subcategories: L6e (light quadricycles) and L7e (heavy quadricycles). L6e vehicles have a maximum design speed of 45 km/h and a running mass of no more than 425 kg (excluding the driver and propulsion batteries), while L7e vehicles can weigh up to 450 kg for passenger transport or 600 kg for goods transport, with some subcategories imposing additional speed limits. Despite their classification as a distinct vehicle segment, L-category quadricycles face growing market challenges. In Germany, the adoption of L6e and L7e vehicles has declined over the past decade. The number of newly registered quadricycles fell significantly from 11,659 in 2012 to 892 in 2021, and accordingly, the total fleet size has been shrinking since 2016, dropping from 118,325 vehicles in that year to 102,016 in 2022 (Edwards et al., 2023). This downward trend suggests that L-category vehicles face hurdles such as safety regulatory barriers despite their compact size and energy efficiency. On a broader scale, however, the global microcar market, including L6e and L7e vehicles and M1-category compact cars (e.g., Smart Fortwo), is growing. Valued at USD 4.5 billion in 2022, the market is projected to expand at an annual rate of approximately 11% from 2023 to 2030 (UnivDatos Market Insights, 2024). This growth is fueled by increasing urban congestion, limited parking availability, and the economic benefits of smaller, more fuel-efficient vehicles.

A range of microcar models are available on the market, offering various configurations in terms of speed, size, fuel type, and driving range. As shown in Table 2.1, L6e-category microcars, such as Citroën Ami and Renault Twizy 45, are limited to a maximum speed of 45 km/h and are generally compact in design. In contrast, L7e-category models, like Microlino and Renault Twizy 80, provide higher speeds and slightly longer driving ranges. Additionally, some models, such as Aixam City, utilize diesel, offering significantly extended ranges (450 km) compared to their electric counterparts.

Table 2.1. Microcar models and their configurations. Energy efficiency and driving range values shown in parentheses represent real-world user-reported data (Spritmonitor, n.d.).

Model	Category	Maximum Speed	Length	Fuel Type	Energy Efficiency	Driving Range
Citroën Ami (carwow, n.d.)	L6e	45km/h	2.41m	Electric	8.0(10.6) kWh/100km	75km
Renault Twizy 45 (Renault, n.d.)	L6e	45km/h	2.34m	Electric	5.8(10.4) kWh/100km	80km
Aixam City (Aixam, n.d.)	L6e	45km/h	3.00m	Diesel	3.1 L/100km	450km
Microlino (Microlino, n.d.)	L7e	90km/h	2.52m	Electric	7.3(10.7) kWh/100km	106-150km
Renault Twizy 80 (Renault, n.d.)	L7e	80km/h	2.34m	Electric	-9.1 kWh/100km	90km
Estrima Biro 60 Maxi battery (Estrima, n.d.)	L7e	60km/h	1.84m	Electric	NA	90km
Smart forTwo (ADAC, n.d.)	M1	130km/h	2.7m	Electric	12 kWh/100km	135(108)km

2.2 Studies on the Impacts of Microcars on Traffic

2.2.1 Search Methodology

To comprehensively review the existing research on traffic simulation of the impacts of microcars, a systematic approach was employed using Scopus, Web of Science, and Google Scholar as the primary search platforms. These databases were chosen for their extensive coverage of academic literature. The overview of the literature selection process is shown in Figure 2.2.

The initial step involved conducting database searches to identify potentially relevant articles. The search parameters were defined to include articles:

- Published in English,
- From 2010 onwards, to capture the most recent developments and trends,
- Containing the following keywords in the article:
  (microcar OR microcars OR "micro car" OR "micro cars" OR minicar OR minicars OR "mini car" OR "mini cars" OR "light electric vehicle" OR "micro electric vehicle" OR "light electric vehicles" OR "micro electric vehicles")

AND

(simulation OR simulate OR simulator OR simulations OR simulates OR simulated OR simulators)

AND

(traffic OR network OR networks OR transport OR transportation OR transports OR transportations).

- This long search string is designed to ensure comprehensive coverage of potentially relevant papers.

This search resulted in the identification of 4,930 articles from Google Scholar, 33 articles from Web of Science, and 1,700 articles from Scopus.

The next step involved narrowing down the search results by screening article titles to ensure relevance. Titles were assessed for the presence of the following terms:

- "microcar" OR microcars OR "micro car" OR "micro cars" OR "minicar" OR "minicars" OR "mini car" OR "mini cars" OR "light electric vehicle" OR "micro electric vehicle" OR "light electric vehicles" OR "micro electric vehicles" OR LEV.

This screening yielded 196 articles from Google Scholar, 18 articles from Web of Science, and 127 articles from Scopus. Subsequent screening involved reviewing both the titles and abstracts to confirm their relevance to the study's context, removing duplicates across the database, and finally reviewing the full text of the remaining articles to ensure their alignment with the study's objectives. This process left a total of 7 articles deemed suitable for the review.

A snowball approach was employed to complement the database search and account for potentially missed studies. This involved examining the reference lists of the seven selected articles, which led to the identification and inclusion of an additional article. Following this comprehensive screening and supplementation process, eight articles were ultimately included in the literature review.

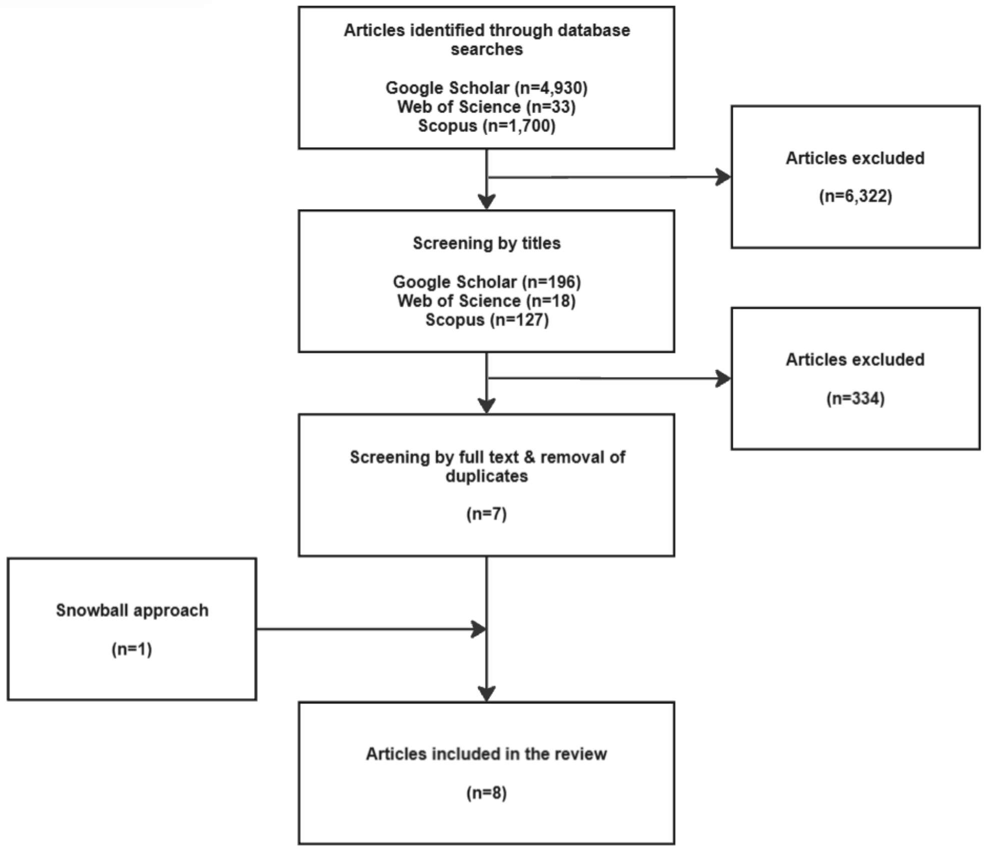

Figure 2.2. Overview of article selection

2.2.2 Reviews of Existing Studies

While engineering aspects (e.g., safety, battery management, motor systems, etc.) of microcars and micro electric vehicles are widely studied, studies focusing on the impacts of microcars using traffic simulation are limited. Following the selected literature review methodology, eight articles from four distinct research groups were identified as relevant to traffic simulations involving scenarios where microcars are introduced.

Rui Mu and Toshiyuki Yamamoto were among the first researchers to apply traffic simulation models to study the impact of microcars. In their 2012 study, they utilized a cellular automata (CA) simulation model to analyze traffic flow characteristics involving microcars. The simulation was conducted on a 400-meter urban highway and an arterial road with a traffic signal, focusing on scenarios combining conventional cars and microcars. The study varied both the proportion of microcars and the total traffic volumes in the lanes while also incorporating lane-changing behavior to evaluate its effects on traffic flow. The results demonstrated that higher proportions of microcars significantly improved average speeds under high traffic volumes, effectively reducing congestion. This pioneering research provided critical insights into the potential of microcars to enhance urban traffic efficiency.

Rui Mu and Toshiyuki Yamamoto (2013a) analyzed the influence of microcars on traffic networks using the VISSIM. This paper modeled the network based on the actual traffic system, the Kichijoji-Mitaka area in western Tokyo, encompassing 138 links and 57 nodes, to evaluate microcars' environmental effects and network performance under various scenarios. The study investigated the effects of three microcar speed assumptions (48–58 km/h, 40–45 km/h, and 25–30 km/h) and varying microcar proportions in traffic. From an environmental point of view, higher microcar proportions and lower speeds reduced emissions and increased fuel efficiency. Regarding travel efficiency, microcars positively impacted the average speed and reduced travel time when their desired speed was at least 40–45 km/h. However, speeds below 30 km/h increased congestion and travel times.

Rui Mu and Toshiyuki Yamamoto (2013b) further simulated a similar scenario (i.e., a 400-meter urban highway and an arterial road with a traffic signal with mixed traffic scenarios with conventional cars and microcars), using and comparing two simulation models: CA and microscopic simulation software VISSIM simulation models. The study found that higher proportions of microcars improved traffic flow and average speeds, particularly at densities exceeding 75 vehicles per kilometer. Both VISSIM and CA simulators confirmed that introducing microcars could relieve congestion, with CA being computationally more efficient.

Rui Mu and Toshiyuki Yamamoto (2019) analyzed the impact of microcars on traffic safety and environmental performance using a traffic CA model. They simulated traffic on a 700-meter urban highway and arterial road with a signalized intersection (i.e., an intersection with traffic lights) under both free-flow and congested conditions. The impacts of microcars differ depending on the traffic situation: (1) Microcars increased lane-changing and deceleration frequency in free flow but reduced them in congested traffic; (2) Microcars slightly worsened safety in free-flow highway conditions but improved it on arterial roads and in congested traffic; (3) Emissions increased in highway free-flow scenarios but decreased significantly on arterial roads due to smoother traffic. The study concluded that introducing microcars can improve urban traffic efficiency and environmental outcomes, particularly under moderate traffic densities.

Masry et al. (2022) investigated the potential impact of introducing exclusive microcar lanes using VISSIM microsimulation. The study examined two case studies: a hypothetical urban corridor and a suburban expressway in Greater Cairo, varying traffic compositions (i.e., microcar ratio from 0 to 50%), and lane configurations (mixed lanes, semi-mixed lanes where microcars are allowed to use any lanes in addition to their exclusive lane, and exclusive lanes). For the urban corridor, the results demonstrated that introducing microcars improved average travel times and increased throughput volumes, especially in semi-mixed configurations. The benefits were more pronounced at higher traffic volumes, with semi-mixed configurations outperforming exclusive lanes when microcars accounted for more than 30% of traffic. In the suburban expressway case, exclusive lanes didn't reduce as much travel times as mixed lane configurations unless microcar proportions reached 30%. This can be attributed to the underutilization of exclusive lanes with small proportions of microcars on the road. After confirming microcars' potential to reduce congestion and improve network efficiency, the authors drew an inductive conclusion that the increase in the share of microcars justifies installing dedicated lanes for microcars.

Tanveer et al. (2022) explored the effects of autonomous and manual vehicles, including a novel category of autonomous microcars, on heterogeneous traffic flow using a cellular automata (CA) model. The study aimed to understand the role of various vehicle types—autonomous microcars, manual microcars, autonomous cars, manual cars, autonomous buses, and manual buses—on traffic dynamics, emphasizing the potential of micro-autonomous vehicles (MAs) to alleviate congestion. The model focused on a one-way urban traffic network with a three-lane freeway segment of 10,000 meters. The simulation incorporated varying penetration rates of vehicle types and lane-change behaviors (aggressive and polite). Vehicle characteristics such as size, speed, reaction time, and lane-changing rules were integrated to replicate real-world traffic scenarios. Results demonstrated that MAs significantly enhanced traffic flow and road capacity compared to their manual counterparts, especially under higher penetration rates. For instance, networks with 80% autonomous microcars showed a 63% increase in flow capacity compared to those with predominantly manual cars. Aggressive lane-changing behavior further amplified the flow rate, while polite lane-changing had a limited impact. The study also highlighted the superior performance of autonomous microcars over autonomous cars in congested phases due to their smaller size and reduced reaction delays.

Santos (2023) and Dray (2022) both explored the transformative potential of Micro Electric Vehicles (MEVs) in urban traffic systems, using Avenida da Liberdade in Lisbon as their case study. Both studies employed the Simulation of Urban Mobility (SUMO) software to analyze the impacts of varying MEV adoption rates, ranging from 0% to 100%, replacing conventional ICE vehicles. Dray (2022) focused on traffic performance metrics, including average trip speed and trip duration. The study found that fully replacing conventional vehicles with MEVs increased the average trip speed by 8.9% and decreased the average trip duration by 8.1%. These results highlight the potential of MEVs to alleviate congestion and optimize urban traffic flow due to their smaller size and higher maneuverability. Santos (2023) extended the analysis by examining MEVs' environmental benefits, focusing on air quality impacts. The study demonstrated a strong correlation between MEV adoption rates and emissions reductions. At full MEV adoption, emissions of PMx, NOx, and CO_2 decreased by 31.2%, 26.1%, and 18.9%, respectively. Moreover, the study noted that the greatest environmental and traffic flow improvements occurred when MEV adoption exceeded 80%. Together, these studies emphasize the dual benefits of MEVs in urban contexts: improving traffic efficiency and reducing emissions.

2.2.3 Key Findings and Research Gaps of Existing Studies

The reviewed studies collectively highlight the impacts of microcars and micro electric vehicles (MEVs) on traffic efficiency, congestion mitigation, and environmental outcomes. Key findings from these studies are summarized as follows:

1. Traffic Efficiency and Congestion Mitigation

- Studies by Rui Mu and Yamamoto (2012, 2013a, 2013b, 2019) demonstrated that higher proportions of microcars improved average speeds and reduced congestion, particularly under high traffic volumes.

- Masry et al. (2022) showed that introducing semi-mixed lanes for microcars improved average travel times and throughput volumes, especially in scenarios where microcars accounted for more than 30% of traffic.

- Tanveer et al. (2022) found that autonomous microcars enhanced traffic flow and road capacity more effectively than manual microcars, particularly under higher penetration rates.

2. Environmental and Safety Impacts

- Studies by Santos (2023) highlighted the environmental benefits of MEVs, noting significant reductions in PMx, NOx, and CO_2 emissions with higher MEV adoption rates. Full replacement of conventional vehicles with MEVs resulted in emissions reductions of up to 31.2% for PMx and 18.9% for CO_2.
- Microcars and MEVs were found to enhance fuel efficiency and reduce emissions, particularly in urban environments with moderate traffic densities (Rui Mu and Yamamoto, 2013a, 2019).
- The impact of microcars on safety varies by traffic conditions. While safety slightly worsened in free-flow highway scenarios, it improved in congested arterial roads due to smoother traffic flows and reduced lane-changing behavior (Rui Mu & Yamamoto, 2019).

3. Critical Parameters Influencing Performance

- Microcar Penetration Rates: Studies consistently found that the benefits of microcars and MEVs become more pronounced at higher adoption rates. For instance, Santos (2023) and Dray (2022) reported optimal environmental and traffic flow improvements when adoption exceeded 80%.
- Speed Assumptions: The effectiveness of microcars depends on their speed. Speeds of 40–45 km/h were found to optimize travel efficiency, while speeds below 30 km/h increased congestion and travel times (Rui Mu & Yamamoto, 2013a). Note that in this study, the range of microcar speed was set only between 25 and 58 km/h.
- Lane-Changing Behavior: Aggressive lane-changing behavior by autonomous microcars amplified flow rates, whereas polite lane-changing had a limited impact (Tanveer et al., 2022).

The studies underscore the transformative potential of microcars and MEVs in urban traffic systems. Their smaller size, energy efficiency, and environmental benefits position them as effective solutions to mitigate congestion and improve urban mobility. However, several research gaps remain that require further investigation:

The first gap is the consideration of behavioral responses to traffic changes. Existing studies predominantly focus on microcars' effects on traffic flow and environmental outcomes using simulation models such as Cellular Automata (CA), VISSIM, and SUMO. However, these studies lack a comprehensive exploration of individual behavioral responses to traffic changes introduced by microcars. Human driving behaviors, such as speed adjustment, lane-changing frequency, route choice, and mode choice, are dynamic and may evolve in response to microcars' presence on the road. For example, modified traffic situations by introducing microcars might encourage individuals to switch from other traffic modes (e.g., public transportation) to private vehicles, which could cause a new traffic situation (Dray, 2022). Without accounting for these behavioral adaptations, the current models provide only a partial understanding of microcars' overall impacts on transportation systems.

The second gap is the scalability of the study. The scope of previous studies has been limited to small-scale scenarios, such as short road sections (e.g., 400-meter or 700-meter urban highways) or isolated networks with a limited number of nodes and links. While these settings are valuable for controlled analysis, they fail to capture the complexity of large-scale urban traffic systems, where the dynamics of microcars could interact with more diverse road users, vehicle types, and infrastructure configurations. The lack of scalable simulation models capable of analyzing city-wide or regional impacts limits the applicability of the findings to real-world urban mobility planning.

The last gap is insufficient scenario analysis for microcar configurations. While some studies have considered variations in microcar speed and proportions, there is a lack of comprehensive scenario analyses that explore the interplay of critical parameters such as speed, distance occupied by microcars, and emissions. A more detailed exploration of these configurations is essential to provide appropriate recommendations for traffic policies and microcar design optimization.

Consequently, this study addresses these challenges—namely, individuals' behavioral responses to traffic changes, scalability, and comprehensive scenario analysis with varying microcar configuration parameters—by selecting an appropriate traffic simulation model and designing traffic scenarios for detailed analysis.

2.3 Traffic Simulator

In order to implement investigations about the impact of changes in traffic situations, there are two possible methods: carrying out experiments in a real traffic situation or conducting traffic simulation on the computer (Mu & Yamamoto, 2013a). Traffic simulation enables a better understanding of traffic events and provides the ability to construct virtual laboratories where they may conduct experiments for testing hypotheses (Barceló, 2010). This approach is particularly well-suited for exploring complex hypotheses that would be challenging or impractical to examine in real-world settings. For this study, traffic simulation is chosen as it aligns with the goal of analyzing varying microcar adoption rates and configurations (e.g., speed, size, etc.) on urban traffic conditions and pollutant emissions. Ideas of traffic simulation date back to the 1970s (Poeck & Zumkeller, 1976; Axhausen & Herz, 1989), and a wide array of computer-based traffic simulators have been developed. However, the diversity of available simulators presents a challenge for interdisciplinary researchers to identify the most suitable environment for their specific research needs. Selecting an appropriate simulation model requires a clear understanding of the purpose of the simulation and the required level of detail for dealing with their research objectives (Nguyen et al., 2021). In this subchapter, state-of-the-art traffic simulation models are reviewed to determine the most appropriate model for this study.

As introduced by Lucio Sanchez Passos et al. (2011) and further elaborated by Nguyen et al. (2021), traffic simulators can be categorized into four types based on their granularity of traffic modeling approach: 1) Macroscopic, 2) Microscopic, 3) Mesoscopic, and 4) Nanoscopic. Table 2.2 summarizes the characteristics, benefits, and limitations of the four simulation categories and their suitability for this study. Considering the objectives and characteristics of this study's analysis, microscopic traffic simulation is the most suitable among the four types of simulators. It can capture macro-level traffic flow measures such as speed, flow, and volumes in aggregates of a few minutes to one hour while also modeling driver behavior under various traffic conditions (Rao & Rao, 2015) (Kraschl-Hirschmann et al., 2011), enabling the analysis of traffic conditions such as congestion, and the representation of microcar-specific driving behaviors and emissions.

Table 2.2. Four types of traffic simulators and their suitability for this study

Type	**Description**	**Advantage**	**Limitation**
Macro	Models traffic flow as continuous variables	Low computational cost	Lacks individual vehicle detail
Meso	Simulates small vehicle groups with simplified interactions	Balances detail & efficiency	Limited vehicle dynamics
Micro	Models individual vehicles & interactions	Captures traffic dynamics	Computationally heavy for large networks
Nano	Simulates sub-vehicle mechanics & driver behavior	Highly detailed	Overly complex & expensive for city-scale

While numerous microscopic simulation models have been developed over the past decades, state-of-the-art research on traffic simulation has increasingly focused on agent-based models or multi-agent models (Huang et al., 2022, p. 3) (Nguyen et al., 2021). The agent-based model is used to simulate the behaviors and interactions of autonomous agents in the system and assess their overall impact on the system (Huang et al., 2022, p. 3). For example, travelers can be modeled as agents that interact and perceive information about their environments, such as other agents and traffic infrastructure, allowing for the implementation of decentralized knowledge and, thus, autonomous behavior based on situational conditions (Nguyen et al., 2021). The reasons for the increasing prevalence of such models are threefold: 1) the ability to capture the specific characteristics of heterogeneities in drivers' behavior and interdependencies among road users; 2) the capability to reflect and model new technologies (such as autonomous vehicles, vehicle-to-vehicle (V2V), and vehicle-to-everything (V2X)); and 3) advancements in computational power, which enable detailed microscopic simulations of transport processes, making agent-based modeling more feasible and effective (Huang et al., 2022, p. 3).

This study adopts an agent-based model to capture dynamic traffic behaviors that emerge from the interactions among individual agents in a system and their overall impact on traffic dynamics. Unlike other simulation models such as SUMO, VISSIM, and cellular automata (CA)—used in the studies reviewed in subchapter 2.2—agent-based models allow for a more detailed exploration of how these behaviors change under different microcar scenarios, such as varying penetration rates and vehicle configurations.

2.4 Multi-Agent Transport Simulation (MATSim)

Nguyen et al. (2021) conducted an extensive search for agent-based models and identified 38 fully agent-based models that are capable of large-scale scenario simulation. Among these options, Multi-Agent Transport Simulation (MATSim) is a leading simulation framework in transportation research (Müller et al., 2022). MATSim is a Java-based agent-oriented software framework. Initiated in 2004 at ETH Zurich, it is now being collaboratively developed by ETH Zurich, TU Berlin, and CNRS Lyon. The framework is designed with a broad focus, specializing in simulating large-scale transportation scenarios (Nguyen et al., 2021). MATSim employs a co-evolutionary algorithm, where each agent (i.e., person) iteratively optimizes its daily activity and travel schedule. This process involves competition among agents for limited space and time slots within the shared transportation system where individual travel decisions impact and are impacted by others. This dynamic approach enables agents to adjust their travel plans, such as route choice, time choice, mode choice, and destination choice, responding adaptively to changing traffic conditions (Horni et al., 2016; Ma et al., 2024).

For this thesis, the simulation model must meet several key requirements: it should be open-source, capable of incorporating individuals' dynamic responses to changing traffic conditions, and suitable for large-scale scenarios with flexible settings for traffic scenarios (e.g., mode composition) and vehicle configurations. Based on these criteria, MATSim was selected as the most suitable option.

MATSim has been utilized extensively across numerous projects, not only for academic research but also for practical applications within organizations. For instance, the Passenger Division of the Swiss Federal Railways (SBB) has been developing a comprehensive MATSim model of Switzerland since 2017 (*Show Case: SBB*, n.d.). This model now supports the company's decision-making processes for passenger demand planning. Additionally, MATSim has been widely applied to scenario analyses in various urban areas, including Berlin, Hamburg, Munich, Mexico City, Los Angeles, Santiago, Sweden, Paris, and more (*Open-Data MATSim Models*, n.d.). It has also been employed to simulate the impacts of emerging traffic services, such as car sharing and carpooling, as well as innovative transport modes like autonomous vehicles (Ciari et al., 2016; Hörl, 2017).

However, no studies to date have explored the introduction of microcars and their effects on traffic conditions and emissions using MATSim or any other agent-based simulation models.

3 Methodology

This chapter outlines the methodology employed for traffic simulation and emission modeling in the scenario analysis of microcar introduction. It is divided into three main sections:

The first section describes the methodology for traffic simulation modeling using the Multi-Agent Transport Simulation (MATSim). The Berlin open-source scenario is adopted as the base simulation framework, providing a foundation for the analysis. This section emphasizes the modifications and additions made to the original Berlin scenario while also explaining its initial configuration. Key areas of focus include demand generation (population and agent plans), vehicle configuration, scoring mechanisms, and replanning strategies.

The second section presents the simulated scenarios explored in this study. A key research gap addressed is the lack of comprehensive sensitivity analysis on the impact of microcars on urban transport. To fill this gap, this section examines a range of traffic scenarios, incorporating various microcar configurations, such as speed, space occupancy, and emissions. This ensures the analysis covers diverse and realistic scenarios to evaluate microcar integration effectively.

The third section introduces the indicators used to evaluate both traffic performance and emissions. It details the methodology and formulation of the network congestion index, as well as other metrics like speed and trip duration, to assess traffic conditions. Additionally, this section describes the emission modeling tool available in MATSim software, proposed and developed by Kickhöfer (2016) and Hülsmann et al. (2011).

3.1 Traffic Simulation Modeling

The MATSim process consists of generating initial demand, simulation-optimization loop (mobsim-scoring-replanning), and finally, analysis of the simulation output (Figure 3.1). Each step is described as follows (Horni et al., 2016):

1. Generating Initial Demand:

   The simulation begins with the initial demand derived from the daily activity chains (e.g., person A leaves home at 8:00, drives a private car from 8:05 to 8:35, works at a company for 4 hours, etc.) of the population in the study area. Activity chains are typically obtained from empirical data through methods like sampling or discrete choice modeling. Input data, such as road networks and vehicle configurations, are also prepared.

2. Iterative Simulation:
   The mobility simulation (mobsim) is the core of MATSim, where the transportation network is loaded, and agents execute their selected plans. MATSim adopts the computationally efficient queue-based approach for its traffic flow model. In this model, *A car entering a network link (i.e., a road segment) from an intersection is added to the tail of the waiting queue. It remains there until the time for traveling the link with free flow has passed and until he or she is at the head of the waiting queue and until the next link allows entering* (see Figure 3.1) (Horni et al., 2016)). For more details, please refer to Chapter 1.3 of (Horni et al., 2016)). At the end of each iteration, the performance of each agent's executed plan is recorded.
3. Scoring:
   After the mobsim phase, each agent's executed plan is evaluated and assigned a score. The score can be interpreted as an econometric utility and quantifies the agent's executed plan based on travel-related factors (e.g., travel time, cost, travel mode) and activity-related factors (e.g., activity duration, early departure, or late arrival). For example, staying home for 7 hours may yield a higher score than staying for 6 hours, while arriving at a theater after the movie's start time would result in a negative score. The scoring mechanism is based on econometric principles, encouraging agents to optimize their plans by balancing personal travel preferences and strategies.
4. Replanning:
   During the replanning phase, agents adapt their plans to improve their scores in subsequent iterations. A fraction of agents (e.g., 10%) modify their plans through changes in route choice, time choice, or mode choice, considering system constraints. MATSim offers various strategies to adapt plans, ranging from random mutations to approximate

suggestions to best-response modifications. For instance, routing often involves best-response optimization, where the currently optimal choice is selected, while time and mode replanning may rely on stochastic changes. This algorithm, called MATSim's co-evolution algorithm, achieves an equilibrium where the agents cannot further improve their plans unilaterally, which is more than the standard traffic flow equilibrium where activities are ignored.

5. Analysis:

   After completing all iterations, the simulation results are analyzed to derive insights into system performance and agent behavior. Outputs include travel times, network congestion patterns, mode shares, and spatial-temporal activity distributions. MATSim provides extensive tools for analysis, including traffic evaluation and emission calculations.

In order to execute traffic simulation on MATSim, the following essential input files are minimally required:

- network.xml: Defines the road infrastructure, consisting of nodes (intersections) and links (roads with attributes like capacity, length, and speed).

- population.xml: Provides travel demand information, including agents and their daily activity-travel plans.

- config.xml: Contains a list of simulation settings (i.e., configurations) that influence how the simulation behaves, such as scoring mechanisms and replanning strategies.

For this study, which investigates the impact of microcar-specific characteristics, an additional file, vehicles.xml, is required. This file configures vehicle-specific attributes such as speed, size, and emissions factors. These details are crucial for modeling the unique characteristics and environmental impact of microcars. Figure 3.2 summarizes the simulation process and input data provided from the input files.

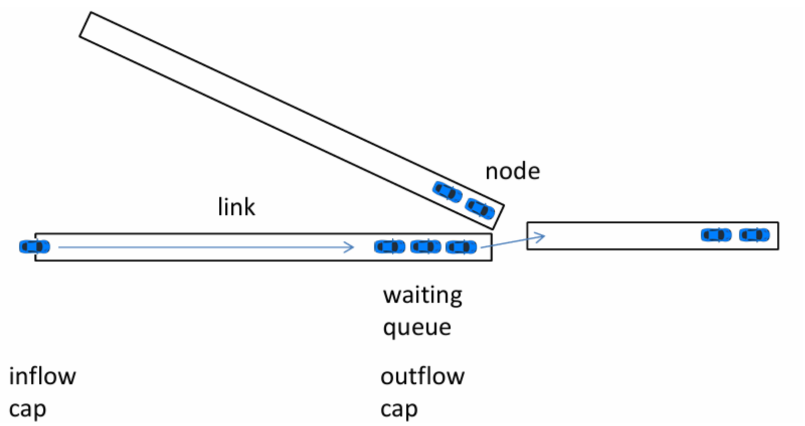

Figure 3.1. Traffic flow model (Horni et al., 2016)

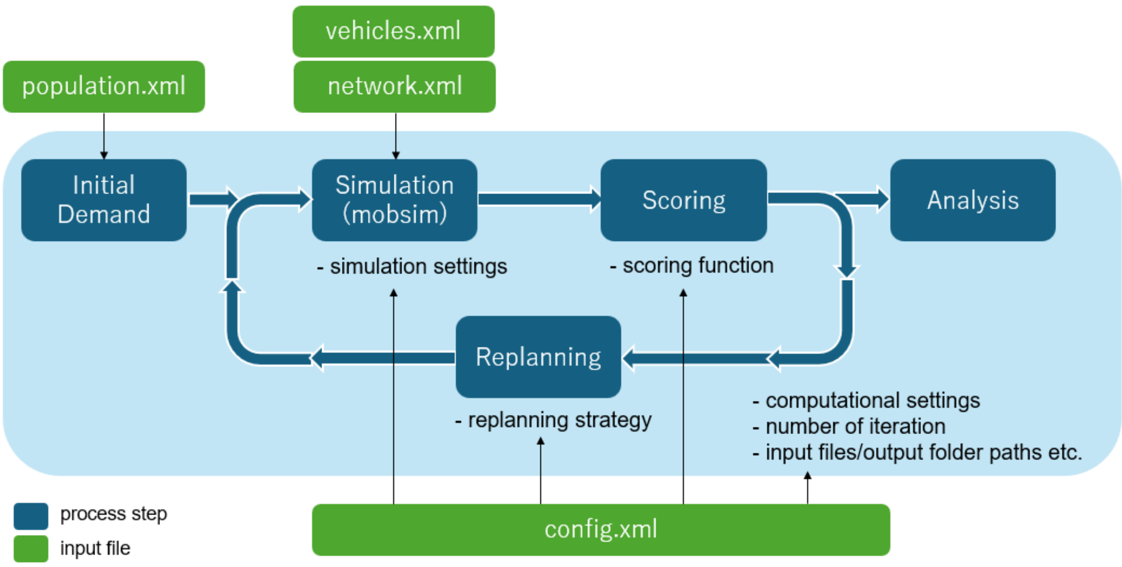

Figure 3.2. Overview of MATSim process and important input files

To evaluate the impact of microcar introduction, we first need to select a study area and gather input data that accurately reflects real traffic conditions. This will help us establish a base scenario, which serves as a reference for comparing different scenarios involving microcars. For this study, Berlin was selected as the study area, and the Open Berlin Scenario (Ziemke et al., 2019) was chosen as the base scenario for the urban traffic simulation. The input data for the Open Berlin Scenario was developed entirely from open data sources. The simulation results have been validated against real-world traffic data, including mode share, travel distances, and travel durations, demonstrating a strong correlation with the real-world travel survey. With its validated accuracy and large-scale setting, the Open Berlin Scenario provides a highly suitable foundation for this study. The following subsections describe the methodology used to generate each input data and configure the simulation for this study.

3.1.1 Network

The network used in this study is based on the network.xml file from the open Berlin scenario (Ziemke et al., 2019), as illustrated in Figure 3.3. The network is generated based on OpenStreetMap data and represents all road categories within the Berlin city boundaries and all main roads in the surrounding state of Brandenburg. For public transport, additional links and nodes are added based on General Transit Feed Specification (GTFS) data. In the latest version of the open Berlin scenario directory at this moment (v6.4), the network consists of 119,174 nodes and 283,885 links. Of these links, 11,133 are bike-only links, 5,643 are car-only (car, freight, ride, truck) links, 197,185 are car-bike-mixed links, and 69,924 are public transportation (pt) links.

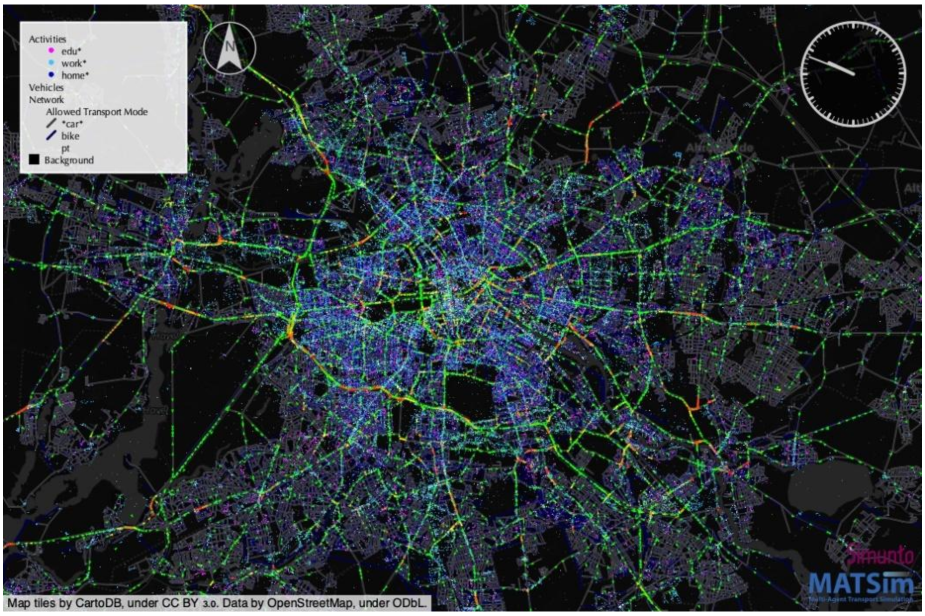

Figure 3.3. Car network (grey) and public transit network (blue) in Berlin (Matsim-Scenarios, n.d.)

3.1.2 Vehicle Configuration

The vehicle configuration file defines vehicle-specific parameters that affect the behavior of vehicles on the traffic network. Key parameters are maximum velocity, passenger car equivalent (PCE), network mode, and flow efficiency factor. PCE is the number of passenger cars a single vehicle is equivalent to (Sun et al.). That is, PCE represents the relative longitudinal road space occupied by a vehicle compared to a standard private car, which has a PCE of 1.0. For instance, a vehicle with a PCE of 0.5 occupies half the road space of a standard private car, while a vehicle with a PCE of 2.0 occupies twice the space. The network mode determines the links on which a vehicle is allowed to travel. This is based on the allowed network modes specified for each link in the network file. The flow efficiency factor (FEF), also known as the flow capacity factor, is used to adjust the contribution of different vehicle types to the flow capacity of a link. Flow capacity defines the outflow capacity of a link—i.e., the maximum number of vehicles that can leave the link per time step (e.g., vehicles/hour). The FEF represents the equivalent number of passenger cars that a single vehicle type accounts for in outflow calculations. For example, A vehicle with an FEF of 0.5 occupies half the capacity of a standard passenger car.

Table 3.1 lists the vehicle types defined in the Open Berlin Scenario along with their specific parameters. The vehicle type "Ride" refers to cars used as passenger transport. For the ride mode, agents are routed on the network, and their teleportation time is derived from the (congested) travel time of the car mode along that route.

Vehicle types such as "Golf1.4," "vwCaddy," and "mercedes313" are registered in the vehicle input file for commercial purposes, including traffic services or goods delivery (Table 3.2). The PCE values are defined to reflect the relative size and impact of different vehicles: the PCE for the bike mode is smaller than a passenger car, while the PCE for the truck mode is larger, accounting for vehicle size and required safety distance. The flow efficiency factor for all vehicle types is uniformly set to 1.0.

For this study, the microcar was introduced as a new vehicle type. The maximum velocity and PCE were set within a range of 50 km/h to 120 km/h and 0.5 and 0.7, respectively. A sensitivity analysis was performed to evaluate the impact of different values for these parameters. The specific scenario settings for the sensitivity analysis are detailed in the next section. The flow efficiency factor for microcars was set to 1.0, which is consistent with all other vehicle types.

Table 3.1. Overview of Vehicle-specific Configurations

Vehicle type	**Max. speed**	**PCE**	**Network mode**	**FEF**
bike	11km/h	0.2	bike	-
car	140km/h	1	car	1
ride	140km/h	1	car	1
golf1.4	140km/h	1	car	1
vwCaddy	140km/h	1	car	1
mercedes313	140km/h	1	car	1
freight	80km/h	3.5	truck	1
truck	80km/h	3.5	truck	1
light8t	80km/h	2	truck	1
medium18t	80km/h	3	truck	1
heavy40t	80km/h	4	truck	1
microcar	50-120km/h	0.5-0.7	microcar	1

Table 3.2. Commercial vehicles defined in the vehicle file in this study

Vehicle Category	Image
VW Golf 1.4 Trendline[a]	
VW Commercial Vehicles Caddy Maxi 2.0 TDI[b]	
Mercedes 313 CDI[c]	

[a]Photo retrieved from ADAC, n.d.-a. [b]Photo retrieved from ADAC, n.d.-b. [c]Photo retrieved from Wikipedia, 2013.

3.1.3 Demand Dataset Generation

The accuracy of travel demand data is crucial for a realistic representation of the population and their urban mobility interactions (Alvarez Castro et al. 2024) and for accurate evaluation of the impact of microcar introduction to the urban traffic network. In this study, we adopt the demand dataset provided and validated by the Open Berlin Scenario as the base scenario demand. The simulation results using this dataset have been validated against real-world traffic survey data, ensuring that the base scenario provides a reliable foundation for developing a microcar-integrated demand dataset. For details on the methodology to generate this base demand dataset, please refer to (Ziemke et al., 2019).

The Open Berlin scenario includes population samples of 10%, 3%, and 1% of the Greater Berlin dataset. Ben-Dor et al. (2021) found that traffic simulation results, particularly travel duration, using population samples below 10% can significantly deviate from the full-scale model. Figure 3.4 presents the total travel duration for each population scenario. The results indicate that the 3% and 10% samples produce similar total travel durations, whereas the 1% sample shows a significant deviation from the other two. To balance computational efficiency with accuracy, this study selects the 3% sample, ensuring reliable results while reducing processing time.

To generate new demand datasets incorporating microcar users, a systematic process was applied to identify potential agents who could switch from passenger cars to microcars:

1. Identify all agents from the 3% sample dataset.
2. Select agents who travel by car, either for private or business purposes.
3. Exclude business users operating large vehicles, such as trucks and vans, as these are not suitable for microcar replacement.
4. Exclude agents whose daily travel distance exceeds 90 km, given the limited range and efficiency of microcars for long-distance trips (Refer to Table 2.1).
5. For private car users, exclude agents from households with more than two members since microcars are typically designed for one or two passengers.

6. After applying these filters, the remaining agents were identified as those with the potential to transition to microcars.

The overall process of identifying eligible agents is illustrated in Figure 3.5. To create new demand datasets, the travel mode of these eligible agents is replaced with microcars at varying replacement rates: 25%, 50%, 75%, and 100%. The selection of agents who switch to microcars follows a prioritization process:

1. Private car users are given precedence over business users.
2. Lower-income agents are prioritized over higher-income agents, reflecting the assumption that affordability considerations play a crucial role in the adoption of microcars.

All travel plans that use public transportation ("pt") remain unchanged for two key reasons:

1. To ensure that the mode share between cars, public transportation, walking, and biking remains consistent with the base scenario, allowing for a meaningful comparison.

2. MATSim's replanning phase allows agents to optimize their travel plans over multiple iterations. This means that public transport users can still switch transport modes if necessary, just as private vehicle users can.

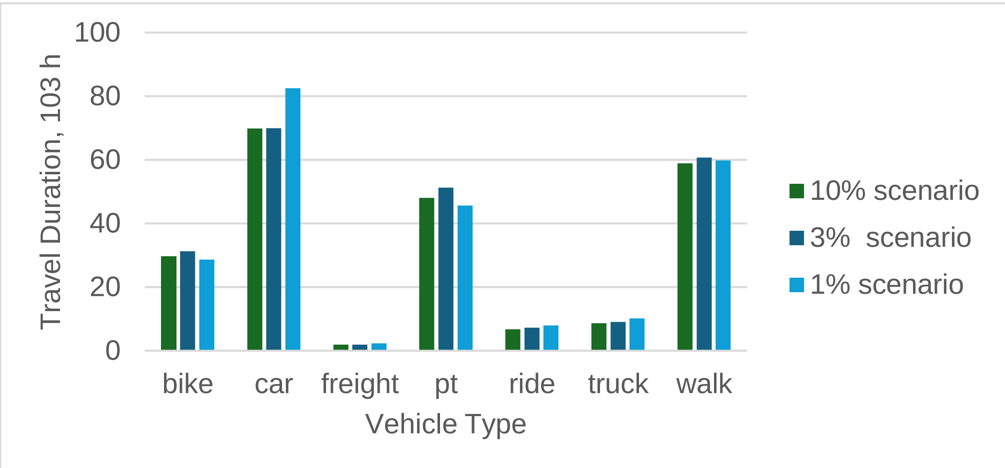

Figure 3.4. Total travel duration of scenarios with different population samples. The travel durations for the 10% and 1% population scenarios are scaled to a 3% sample by applying multiplication factors of 0.3 and 3.0, respectively.

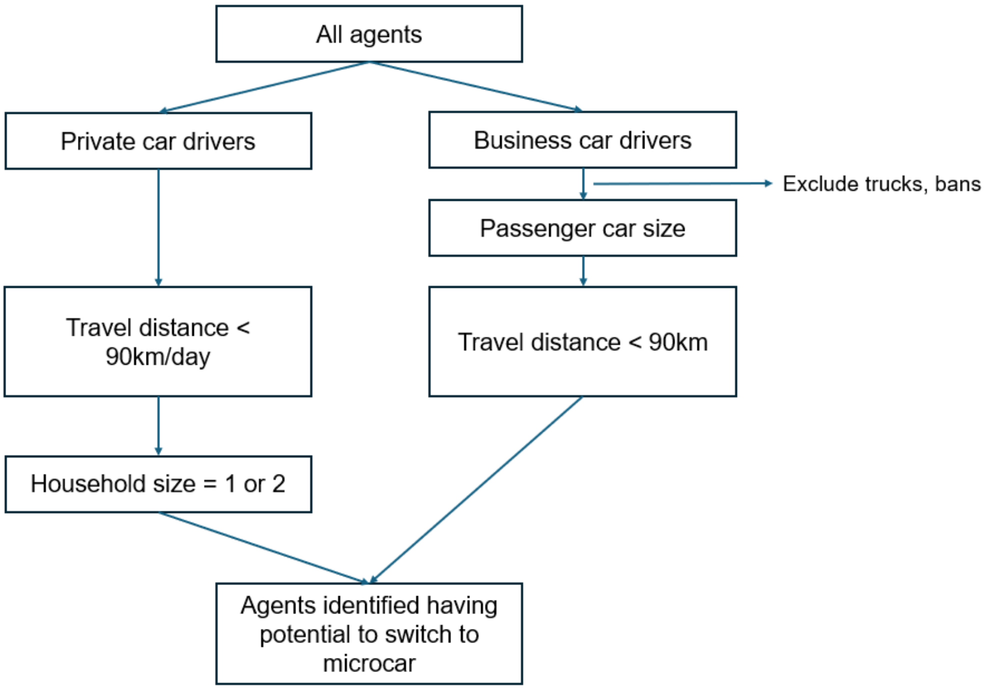

Figure 3.5. The process of identifying agents that have the potential to switch to microcars

3.1.4 Scoring Function and Replanning Strategies

In MATSim, the quality of an agent's plan is described by a score S_{plan}, which is computed as the sum of all activity (i.e., work, stay at home, shopping, etc.) utilities plus the sum of all travel utilities. In general, performing activity utilities increase the overall score (positive utility), while travel utilities decrease it (negative utility) (Balać et al., 2018). The formula to calculate the score S_{plan} of an agent called the Charypar-Nagel Utility Function, is as follows (Charypar et al., 2005; Horni et al., 2016) (Eq. (1)):

$$S_{plan} = S_{act} + S_{trav} \qquad (1)$$

Where S_{act} is the total utility obtained from the agent performing the daily activities (normally positive), while S_{trav} is the total utility obtained from the agent traveling following activities (normally negative).

Eq. (2) presents the formula for the travel utility:

$$S_{trav} = \sum_{modes\ used} (\beta_m \cdot C_{m,mode}) + \sum_{q=0}^{N-1} S_{trav,mode(q)} \tag{2}$$

Where,

$$S_{trav,mode(q)} = C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,q} + \beta_m \cdot \gamma_{dist,mode(q)} \cdot d_{trav,q} \tag{3}$$

- N: the total number of trips by the agent.
- $C_{mode(q)}$: the mode-specific constant (normally negative). This captures mode attractiveness or inconvenience that is not explained by other parameters like travel time or cost. (unit: utils/day)
- $C_{m,mode}$: the mode-specific daily monetary constant that refers to the monetary amount an agent pays per day to use a mode such as vehicle ownership and insurance
- β_m: the marginal utility of money (unit: utils/monetary unit). The value of this factor is 1.0, common in all modes.
- $\beta_{trav,mode(q)}$: the marginal utility of time spent traveling by mode. Note that time spent traveling takes away from time that could have been used for other activities (e.g., work, leisure, home). Therefore, this opportunity cost is already included in the scoring function as part of the marginal utility of performing activities (i.e., loss of $S_{act,q}$). However, different travel modes impose different levels of discomfort, stress, or convenience, so this $\beta_{trav,mode(q)}$ captures these mode-specific additional factors. (unit: utils/time unit)
- $t_{trav,q}$: the travel time between activity q and q+1
- $\gamma_{dist,mode(q)}$: the mode-specific monetary distance rate that indicates the monetary rate paid per unit of distance (unit: monetary unit/distance unit. e.g. Euro/km)
- $d_{trav,q}$: the distance traveled between activity q and q+1

Table 3.3 shows the values of parameters for mode-specific calculations. The parameter values, except for those for microcars, are adopted from the Open Berlin Scenario, where the calibration of the values was conducted to fit the observed traffic data (Ziemke et al., 2019). For microcars, the mode-specific parameters were established as follows:

- $C_{mode(q)}$: The microcar choice is assumed to be less attractive than a normal car as they are neither as fast nor big as normal cars, but more attractive than a bicycle as they ensure protection from the external effects for different weather conditions and stable as an automobile (Karaca et al., 2018). Therefore, its value was set at -6.80, positioned between the values assigned to bikes and passenger cars.
- $\gamma_{dist,mode(q)}$: This parameter represents the cost per unit of distance traveled (€/m) and is estimated based on the energy efficiency of microcars available in the market. While manufacturers report energy efficiencies ranging from 5.8 to 8.0 kWh/100 km, real-world data from users suggests an actual efficiency of around 10–11 kWh/100 km (Table 2.1). This discrepancy is likely due to real driving conditions, including harsh temperatures, road conditions, battery degradation, and increased energy consumption over time. For the study, 10.7 kWh/100 km was adopted to represent the actual energy efficiency of e-microcars. According to Bundesnetzagentur & Bundeskartellamt (2024), the average electricity price for households in Germany in 2024 was 0.4159 €/kWh. Using these values, the monetary cost per meter is calculated as:

$$\frac{10.7kWh \times 0.4159€/kWh}{100{,}000m} = 4.50 \times 10^{-5}€/m$$

- $C_{m,mode}$: This parameter represents the fixed costs of vehicle ownership. As the value for the passenger car is already given and calibrated by the Open Berlin Scenario, the value for a microcar was estimated by getting the ratio of the total cost of ownership of a microcar and a passenger car:

$$C_{m,microcar} = \frac{Total\ cost\ of\ ownership\ of\ a\ microcar}{Total\ cost\ of\ ownership\ of\ a\ passeger\ car} \times C_{m,passenger\ car}$$

According to the report by Agora Verkehrswende (2022), the average total cost of ownership of an electric microcar is €26,666.02, while that of a diesel medium passenger car is €44,111.24 in Germany. Therefore, the parameter value is:

$$C_{m,microcar} = \frac{€26,666.02}{€44,111.24} \times 5.00 = 3.02$$

Table 3.3. Mode-specific parameters for scoring

Mode	$\mathbf{C_{mode(q)}}$	$\mathbf{C_{m,mode}}$	$\boldsymbol{\beta_{trav,mode(q)}}$	$\boldsymbol{\gamma_{dist,mode(q)}}$
walk	0	0	0	0
bike	-0.872	0	0	0
freight	0	0	0	-4.0E-4
truck	0	0	0	-4.0E-4
pt	0.432	-3.00	0	0
ride	-1.154	0	-6.88	-1.49E-4
car	-0.488	-5.00	0	-1.49E-4
microcar	-0.680	-3.02	0	-4.5E-05

In the Berlin Open Scenario, agents are categorized into five subpopulations based on their role in the transport system: “person,” “freight,” “goodsTraffic,” “commercialPersonTraffic,” and “commercialPersonTraffic_service.” These classifications distinguish between private individuals and business or service-related trips. Each subpopulation follows a distinct replanning strategy, which determines how agents adjust their daily travel behavior over simulation iterations.

In this study, the “person” subpopulation, which represents private individuals, is subject to a comprehensive set of replanning strategies that allow various types of change in travel behavior:

- ReRoute strategy (weight: 0.15), which allows them to change route

- TimeAllocationMutator strategy (0.15), which allows them to shift activity start and end times
- SubtourModeChoice strategy (0.15), which enables them to alter their mode of transport within a single trip chain, selecting among car, microcar, pt (public transportation), bike, walk, or ride
- ChangeExpBeta strategy with a weight of 1.0, ensuring that they progressively adopt more optimal travel decisions based on accumulated experience in the simulation.

The inclusion of various innovative strategies for private individuals is particularly important to this study, as it provides agents with the ability to flexibly shift toward a better travel plan adapting to traffic conditions if the new plan offers a higher perceived utility than their current transport option.

For business and service-related agents classified under “freight,” “commercialPersonTraffic,” and “commercialPersonTraffic_service” subpopulations, only the ReRoute strategy (weight: 0.15) was allowed for innovation strategy because changes in activity and travel time or modes are unrealistic for these subpopulation categories. Additionally, they adopt the ChangeExpBeta strategy with a weight of 1.0.

3.2 Simulation Settings and Traffic Scenarios Studied

To comprehensively assess the impact of replacing passenger cars with microcars, a sensitivity analysis is conducted based on three key factors: (1) the replacement ratio, (2) the maximum speed of microcars, and (3) the passenger car equivalent (PCE) of microcars. The base scenario represents the condition where no passenger cars are replaced by microcars. The overview of sensitivity analysis settings is shown in Table 3.4.

The first sensitivity analysis investigates the effect of different replacement ratios, which define the percentage of passenger cars substituted by microcars. The replacement ratios considered are 25%, 50%, 75%, and 100%. The second sensitivity analysis evaluates the influence of microcar speed on traffic conditions. The maximum microcar speed varies across six levels: 50

km/h, 70 km/h, 90 km/h, 120 km/h. The third sensitivity analysis examines the impact of microcar PCE. For the definition of PCE, please refer to Chapter 3.1.2. By adjusting the PCE values, the study evaluates how the size of microcars influences congestion levels. The PCEs considered are 0.5, 0.6, and 0.7. By varying these three parameters, a total of **48 simulation scenarios** are analyzed. Table 3.5 summarizes the key parameters and values used to configure the simulation model.

Table 3.4. Parameter Values of a Sensitivity Analysis

Parameter	**Values**
Microcar Replacement Ratio (%)	25, 50, 75, 100
Max. Speed of Microcar (km/h)	50, 70, 90, 120
PCE of Microcar	0.5, 0.6, 0.7

Table 3.5. Main parameters and values for the simulation model

Parameter	**Value, constraint, and assumptions**
Population sample	3% of the Berlin population
Network	Berlin City, consisting of 119,174 nodes and 283,885 links
Number of iterations	300
Controller	QSim
Transport modes	car, ride (car passenger), truck, freight, bike, walk, pt (bus, tram, train), microcar
Replanning Strategies	For "person" subpopulation: • Reroute (weight: 0.15) • TimeAllocatorMutator (0.15) • SubtourModeChoice (0.15) • ChangeExpBeta (1.0) For other subpopulations: • Reroute (0.15) • ChangeExpBeta (1.0)

	Innovative strategies are applied until the first 90% (270) of iterations Refer to section 3.1.4. for more details
Parameters for scoring function	Refer to section 3.1.4.

3.3 Indicators Evaluated

3.3.1 Traffic Performance

At present, there are no unified evaluation metrics for evaluating traffic conditions, and therefore, studies on the evaluation of traffic performance have been using different metrics. Rao & Rao (2012) conducted a comparison between different metrics to assess urban traffic, including Speed, Travel time, Delay, LOS (level of service), and volume, and concluded that the metrics based on speed performance are the most appropriate.

(He et al. 2016) adopted the speed performance index to measure the road traffic state and further developed the road network congestion index based on the speed performance index to evaluate the level of traffic congestion state.

The speed performance index R_v is expressed in Eq. (4)

$$R_v = \frac{v}{V_{max}} \times 100 \tag{4}$$

where,

- v: the average travel speed, km/h
- V_{max}: the maximum permissible road speed, km/h.

Using the speed performance index R_v, the road segment congestion index R_i is expressed as Eq. (5). The value of R_i is between 0 and 1, and the smaller the value of R_i, the more congestion of road segment.

$$R_i = \frac{\overline{R_v}}{100} \times \frac{t_{NC}}{T_t} \tag{5}$$

where,

- $\overline{R_v}$: the average of speed performance index
- t_{NC} the duration of non-congestion state, which is the duration when the speed performance index R_v is over 50, minute
- T_t: the duration of the observation period, minute

Finally, the road network congestion index R is given by integrating all the road segment congestion indexes R_i by weighing them with the length of the road segment L_i (Eq. (6)).

$$R = \frac{\sum_i R_i L_i}{L_i} \qquad (6)$$

This index provides a comprehensive evaluation of the overall congestion state of the network, taking into account the variation of roads existing in the network, such as the maximum permissible road speed and the length. It enables a comparative analysis of congestion levels across different networks with varying conditions. MATSim integrates the calculation of this index as an additional plugin, and the result can be visualized using SimWrapper.

In the context of studies about the impact of microcar introduction on traffic situations, travel time and travel speed performance indexes are used as common metrics, as reviewed in Chapter 2.2.

Considering the metrics used in existing studies and the capabilities and resources available on MATSim, the following metrics are chosen:

- Mode share of cars and microcars among all transport modes
- Average travel speed
- Travel duration
- Network congestion index

The mode share of cars and microcars is used to evaluate the impact of microcars on individuals' preference for private car use compared to other transport modes. The next two metrics are selected to enable comparability with previous studies on the impact of microcar introduction, while the final metric is chosen to accurately assess traffic congestion levels by accounting for road characteristics such as speed limits and road length.

3.3.2 Environmental Performance

Energy consumption and emissions are calculated using the emission modeling tool provided as a package in MATSim, developed by proposed and developed by Kickhöfer (2016) and Hülsmann et al. (2011). This tool computes vehicle energy consumption and emissions by linking MATSim simulation outputs to emission factors from the Handbook on Emission Factors for Road Transport (HBEFA).

The tool considers two types of emissions: warm emissions and cold-start emissions. Warm emissions occur during driving and depend on factors such as speed, acceleration/deceleration, stop duration, road gradient, and vehicle characteristics (e.g., vehicle type, fuel type, and engine capacity). Cold-start emissions are generated during the engine warm-up phase and are influenced by factors like distance traveled, parking time, ambient temperature, and vehicle characteristics.

HBEFA provides emission factors for various pollutants, including CO_2 equivalent, NOx, SO_2, CH_4, NH_3, and more. In this study, CO_2 equivalent (g/traveled distance) was chosen to evaluate the overall emissions of the Berlin traffic system. Among the different emission factor types in HBEFA, this study adopts well-to-wheel (WTW) emissions for calculations. This approach is crucial for accurately assessing electric vehicle emissions—otherwise, their emissions would be considered zero since they do not produce exhaust emissions while driving.

Cold-start emissions were excluded from the analysis (i.e., set to zero) for two reasons:

1. Lack of sufficient data on cold-start emissions in HBEFA.
2. Their relatively minor contribution to overall emissions compared to warm emissions.

As HBEFA lacks data on energy consumption and emissions specific to microcars, these values were independently calculated and integrated into the HBEFA dataset. In the HBEFA database, values for carbon emissions and energy consumption are provided for each road type, road-specific maximum speed, and traffic conditions (either Free-flow or Stop & Go). In this study, the carbon emissions data for microcars were referenced from (Ehrenberger et al., 2022) and estimated by aligning them with the values for electric vehicles in HBEFA regarding carbon emissions and energy consumption. The estimation process is as follows:

1. The study by (Ehrenberger et al., 2022) conducted an LCA of electric microcars and calculated carbon emissions based on their maximum speed. Utilizing these values, the carbon emissions under Free-flow traffic conditions were estimated as follows:

- ~40 km/h: 50 gCO_2eq/km
- 40–90 km/h: 45 gCO_2eq/km
- 90–130 km/h: 49 gCO_2eq/km

2. The HBEFA database provides carbon emissions and energy consumption values for electric passenger cars (e-passenger cars) under different traffic conditions. By applying the ratio of carbon emissions in Free-flow to those in Stop & Go conditions for e-passenger cars to microcars, the carbon emissions under Stop & Go conditions were estimated.
3. In the HBEFA database, the ratio of carbon emissions (gCO_2eq/km) to energy consumption (MJ/km) for e-passenger cars remains constant. By applying this ratio to microcars, the energy consumption was estimated based on their carbon emissions.

An example of this estimation process is illustrated in Figure 3.6.

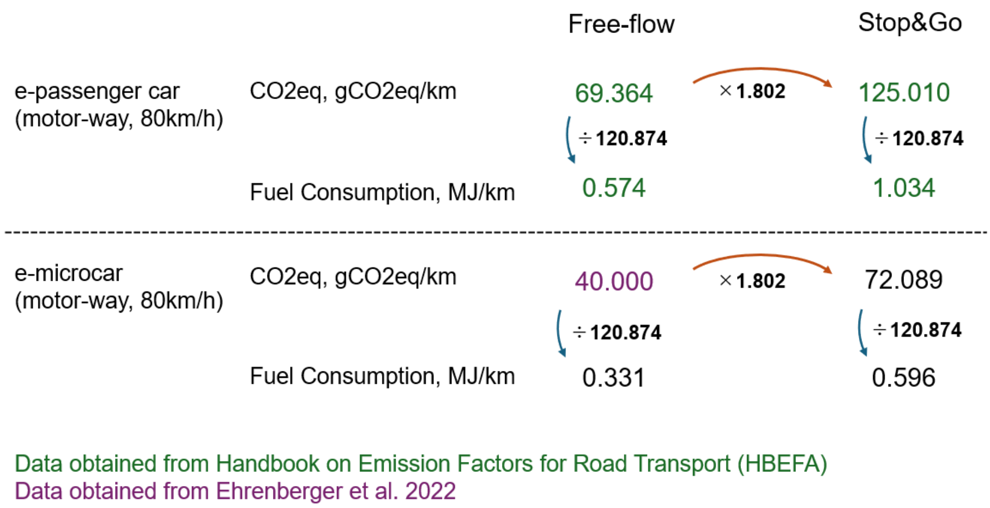

Figure 3.6. Example of estimation process of carbon emissions and fuel consumption of a microcar

4 Results

This chapter presents the simulation results, focusing on the effects of three key parameters: the microcar replacement ratio, the maximum speed of microcars, and their Passenger Car Equivalent (PCE) value. The analysis examines how these parameters influence a range of performance metrics, including the mode share, average speed and travel time of cars and microcars, congestion index, carbon emissions, and fuel consumption.

To illustrate these relationships, two types of visualizations are provided for each metric. First, a 3D plot shows the trends in the absolute values of each metric and the percentage changes relative to a baseline scenario without microcar integration. These percentage changes reflect each metric's relative increase or decrease compared to the base case. Second, a 2D histogram presents all scenario results side by side, allowing for a more precise comparison.

4.1 Microcar Impact on Traffic Performance

Figures 4.1 and 4.2 illustrate the combined mode share of cars and microcars among all transportation modes, showing how introducing microcars influences individuals' preference for private over public transport.

As microcars are increasingly introduced into the network, the mode share of cars and microcars rises, though at a decreasing rate, meaning that the initial introduction has the most significant impact on the increase in the mode share of cars and microcars. Interestingly, the maximum speed of microcars has a minimal influence on mode share. In contrast, microcars' Passenger Car Equivalent (PCE) plays a more substantial role—smaller microcars (lower PCE) lead to a higher mode share. This effect becomes more pronounced with higher replacement ratios. For instance, at a 25% replacement rate, a scenario with a PCE of 0.5 yields a 0.5% greater mode share than one with a PCE of 0.7. At full (100%) replacement, the difference grows to 1.1%.

The maximum observed increase in mode share is 9.39% above the base scenario, occurring when the replacement ratio, maximum speed, and PCE are set to 100%, 50 km/h, and 0.5, respectively.

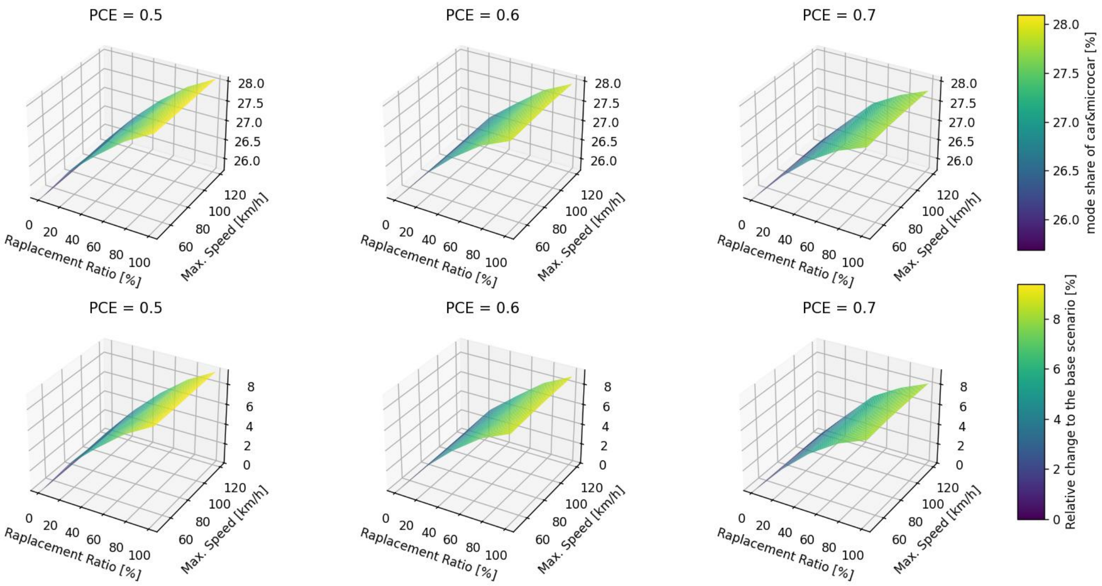

Figure 4.1 - a. 3D plot of mode share of cars and microcars across different scenarios (top three graphs) b. Percentage change compared to the base scenario across scenarios (bottom three graphs)

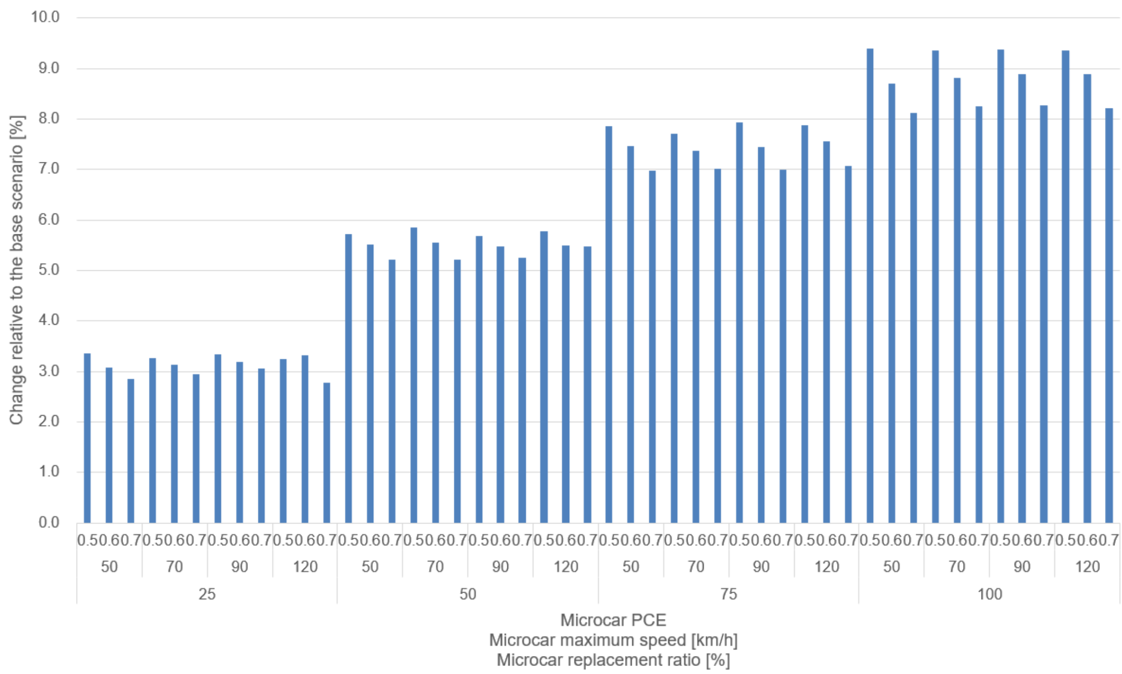

Figure 4.2. 2D histogram of mode share of cars and microcars in percentage change compared to the base scenario

Figures 4.3 and 4.4 present the average speed of cars and microcars across various scenarios, measured in kilometers per hour. These figures exclude other modes, ensuring a focused analysis of private vehicles.

Average speed generally increases at an increasing rate with higher microcar replacement ratios, and this increase becomes more rapid at higher levels. The impact of microcar maximum speed varies depending on the microcar replacement ratio. The influence of the microcar's maximum speed varies: up to 50% replacement, the influence of the microcar's maximum speed is limited, and the average speed peaks when the microcar speed is 90 km/h. Beyond 50% replacement, the average speed increases at a decreasing rate as the microcar's maximum speed increases. The impact of microcar PCE is significant, especially in high microcar replacement scenarios—lower PCE values (i.e., smaller car size) lead to higher average speeds. The average speed remains similar to or even lower than the base scenario when microcars have low speeds (50 km/h) and high PCE (0.7).

The highest recorded average speed is 39.2 km/h, an increase of 1.6 km/h (4.28%) over the base scenario, achieved with a 100% replacement rate, 90 km/h speed, and 0.5 PCE.

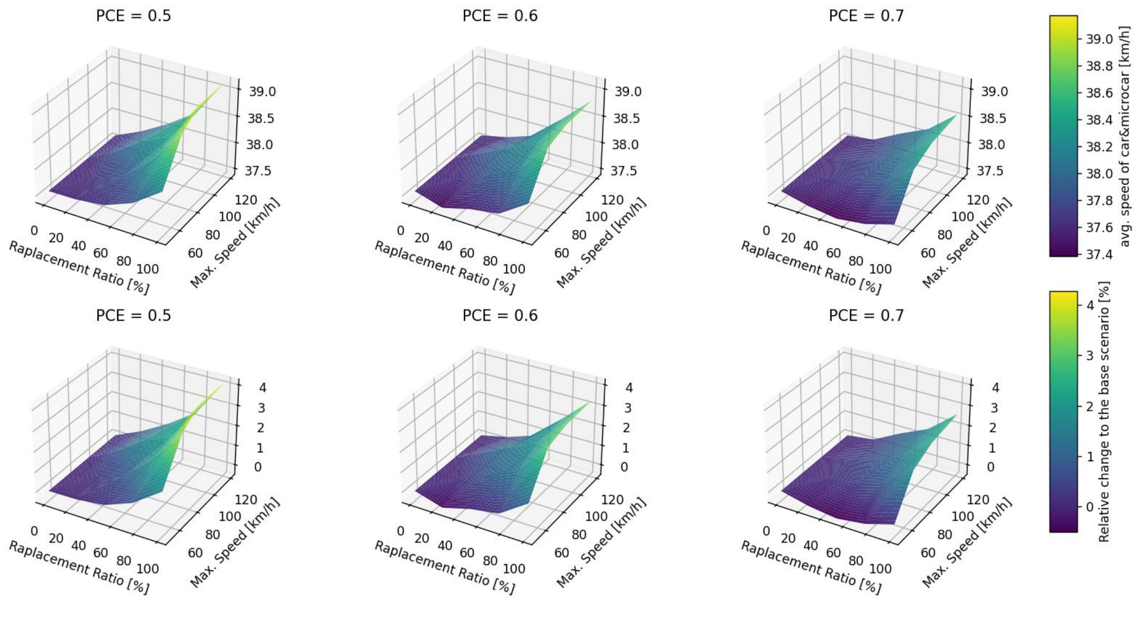

Figure 4.3 - a. 3D plot of the average speed of cars and microcars across different scenarios (top three graphs) b. Percentage change compared to the base scenario across scenarios (bottom three graphs)

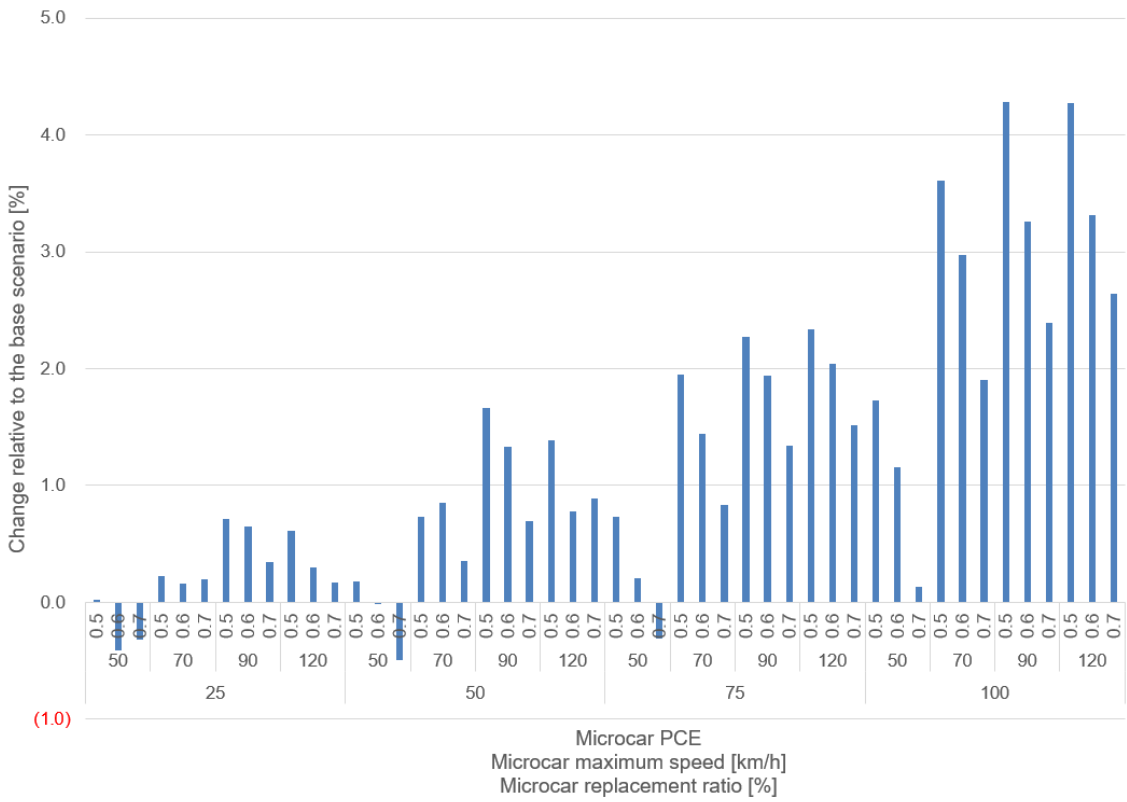

Figure 4.4. 2D histogram of the average speed of cars and microcars in percentage change compared to the base scenario

Figures 4.5 and 4.6 display the overall congestion index, measured on a scale from 0 (high congestion) to 1 (no congestion).

Across most scenarios, the congestion index changes marginally (between 0.1% and 0.3%) compared to the base scenario. However, when microcars have a low maximum speed (50 km/h), the congestion index decreases with increasing microcar replacement and PCE; the congestion level is worse than the base scenario. In contrast, scenarios with higher microcar speeds (90 or 120 km/h) generally result in improved congestion levels, particularly when the PCE is low. In such cases, the congestion index can improve by more than 0.3% compared to the base scenario.

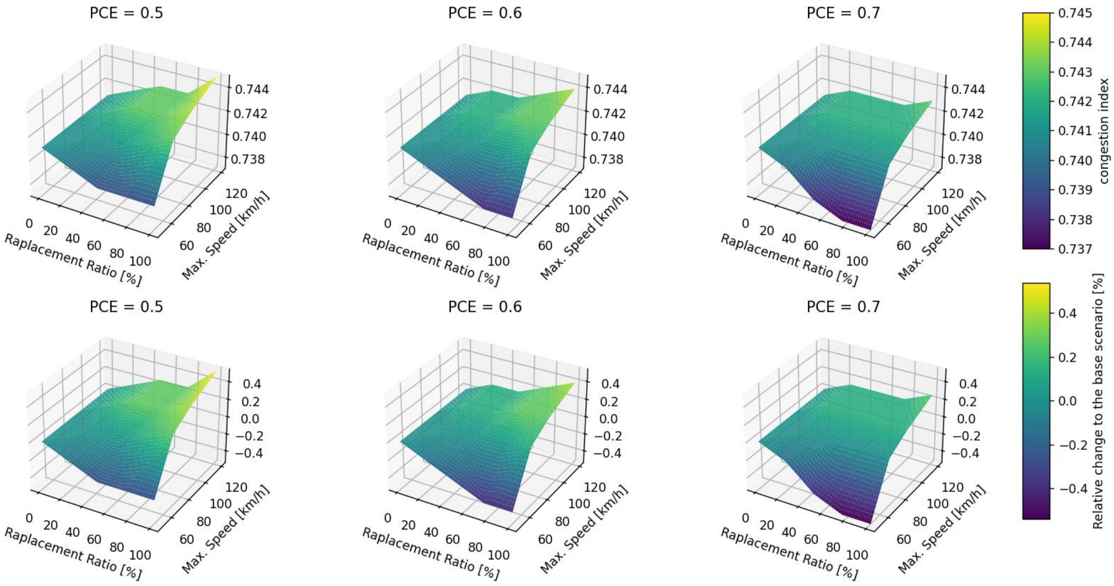

Figure 4.5 - a. 3D plot of congestion index across different scenarios (top three graphs) b. Percentage change compared to the base scenario across scenarios (bottom three graphs)

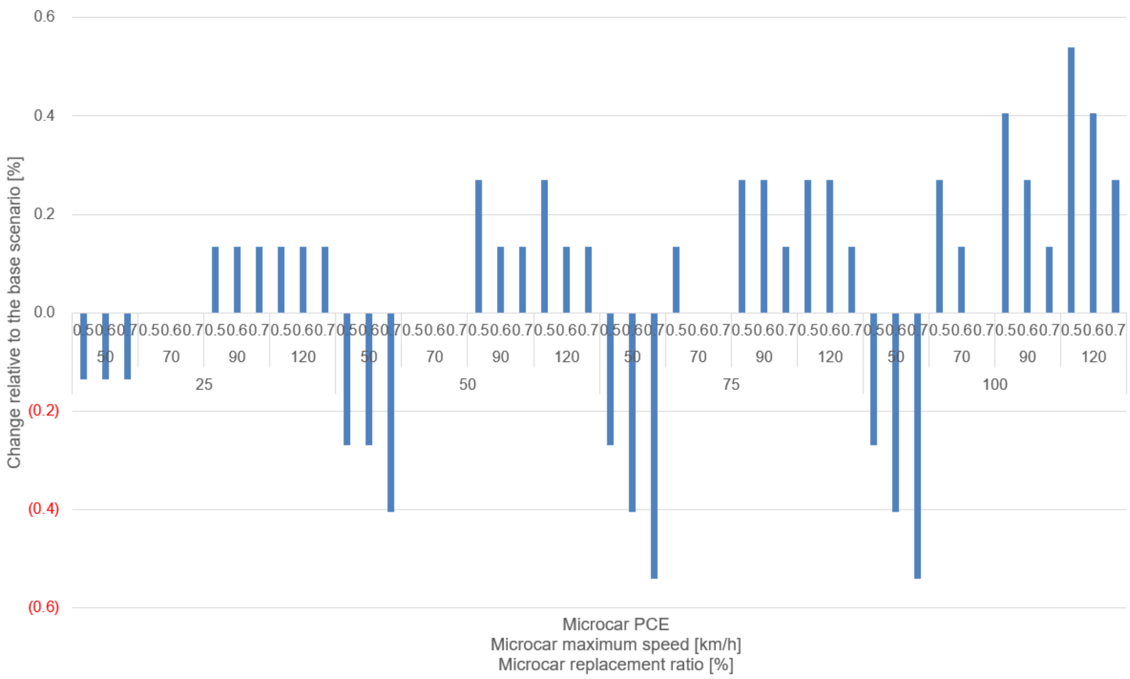

Figure 4.6. 2D histogram of congestion index in percentage change compared to the base scenario

Figures 4.7 and 4.8 present the average daily travel duration per agent for cars and microcars, measured in hours. Other transport modes are excluded to isolate the impact on private vehicles.

Travel duration decreases almost linearly with an increasing microcar replacement ratio. At 100% replacement, the reduction approaches 10%. Maximum speed has limited influence except in low-speed scenarios (50 km/h), where durations are longer. PCE again emerges as a key factor: lower PCE values result in shorter travel times, especially at higher microcar replacement levels. At 100% replacement, the gap between low (0.5) and high (0.7) PCE scenarios can reach 2%.

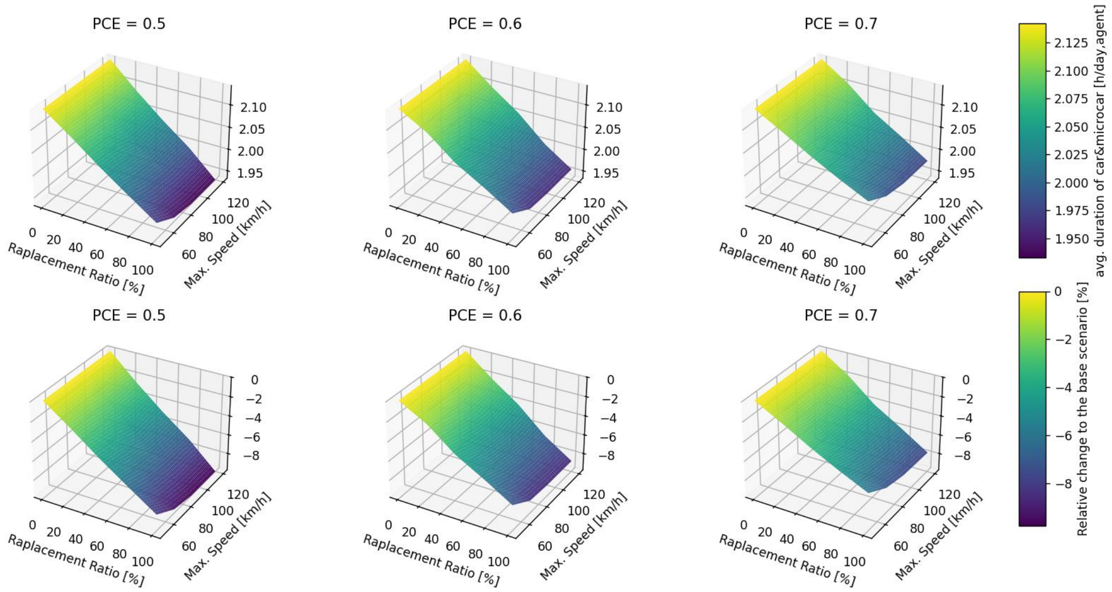

Figure 4.7 - a. 3D plot of average travel duration of cars and microcars across different scenarios (top three graphs) b. Percentage change compared to the base scenario across scenarios (bottom three graphs)

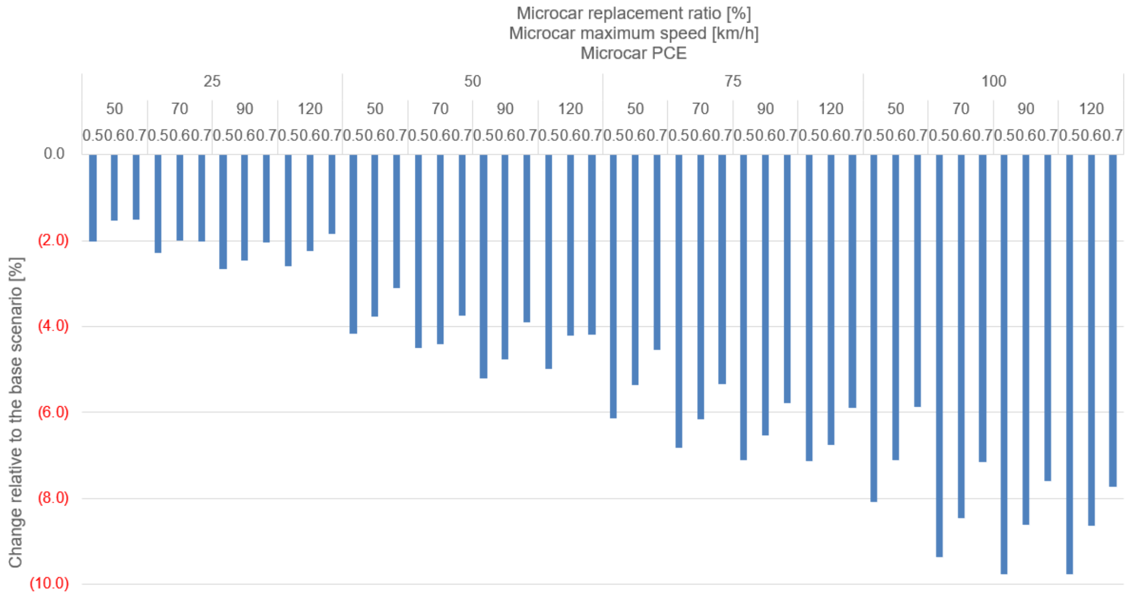

Figure 4.8. 2D histogram of average travel duration of cars and microcars in percentage change compared to the base scenario

4.2 Microcar Impact on Environmental Performance

Figures 4.9 and 4.10 illustrate the impact of microcar introduction on carbon emissions, while Figures 4.11 and 4.12 present the impact on fuel consumption within the study area. Public transport modes (i.e., train, tram, and bus) are excluded from these calculations.

The results indicate that both carbon emissions and fuel consumption decrease linearly with the microcar replacement ratio. As discussed in Subchapter 4.1, introducing microcars leads to a modest increase in private car use. However, the figures here suggest that this shift has little impact on overall emissions and fuel consumption. Instead, the reductions are primarily driven by the improved energy efficiency of microcars. The influence of microcar maximum speed and PCE on these environmental indicators is negligible. When all eligible car users identified as potential microcar adopters are switched to microcars (i.e., 100% replacement), daily carbon emissions in the study area are reduced by 2,812 tons (–11.4%), and fuel consumption decreases by 36.8 terajoules (–12.6%) as the whole network compared to the base scenario.

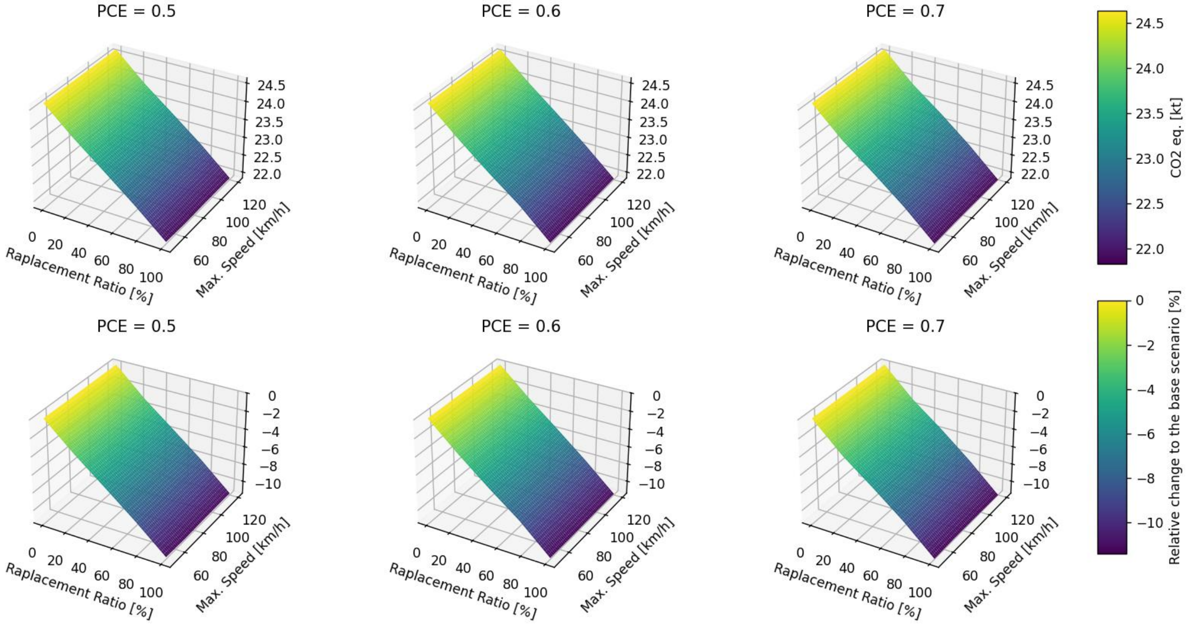

Figure 4.9 - a. 3D plot of CO_2-equivalent emissions in the Berlin area in kilo ton across different scenarios (top three graphs) b. Percentage change compared to the base scenario across scenarios (bottom three graphs)

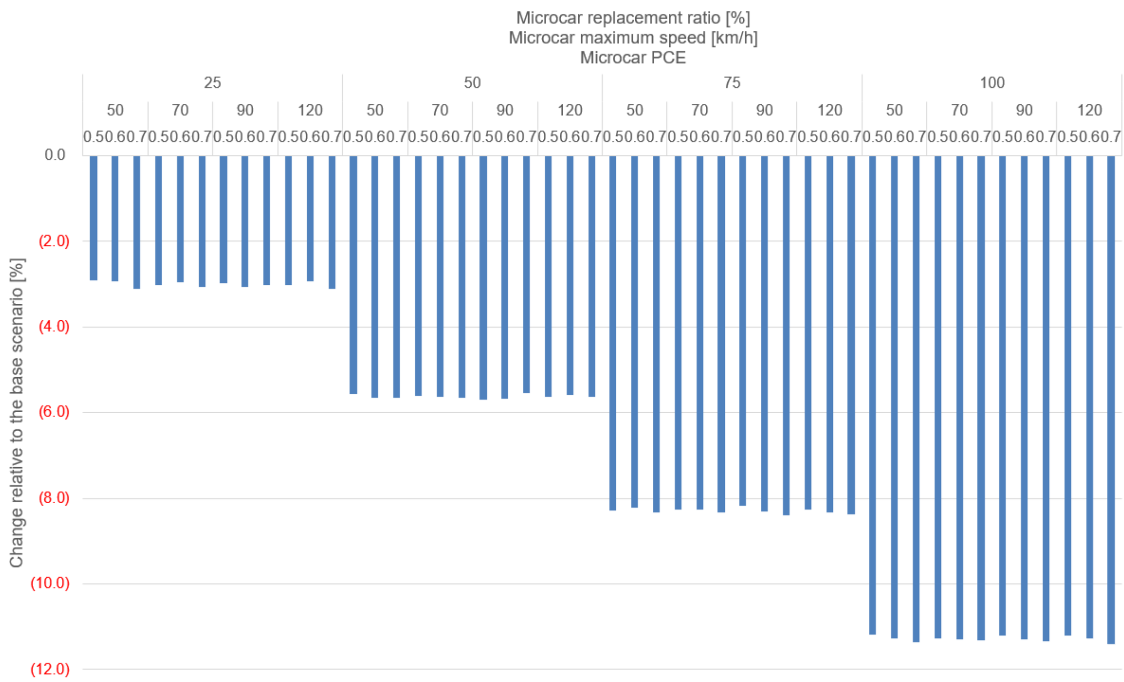

Figure 4.10. 2D histogram of CO_2-equivalent emissions in the Berlin area in percentage change compared to the base scenario

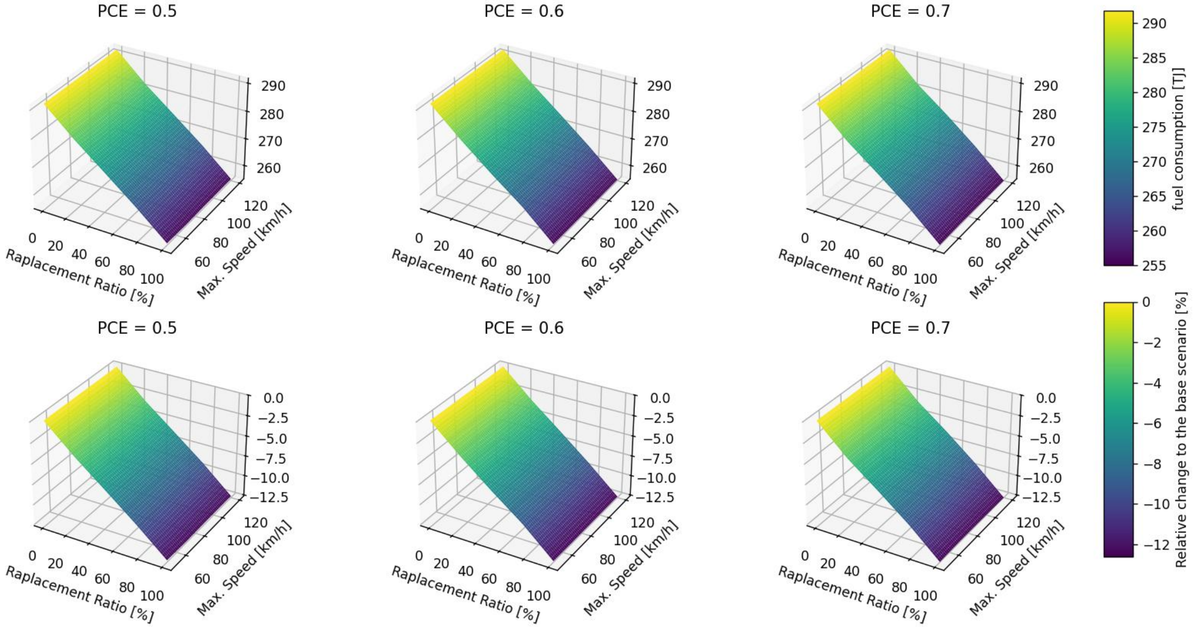

Figure 4.11 - a. 3D plot of fuel consumption in the Berlin area in terajoule across different scenarios (top three graphs) b. Percentage change compared to the base scenario across scenarios (bottom three graphs)

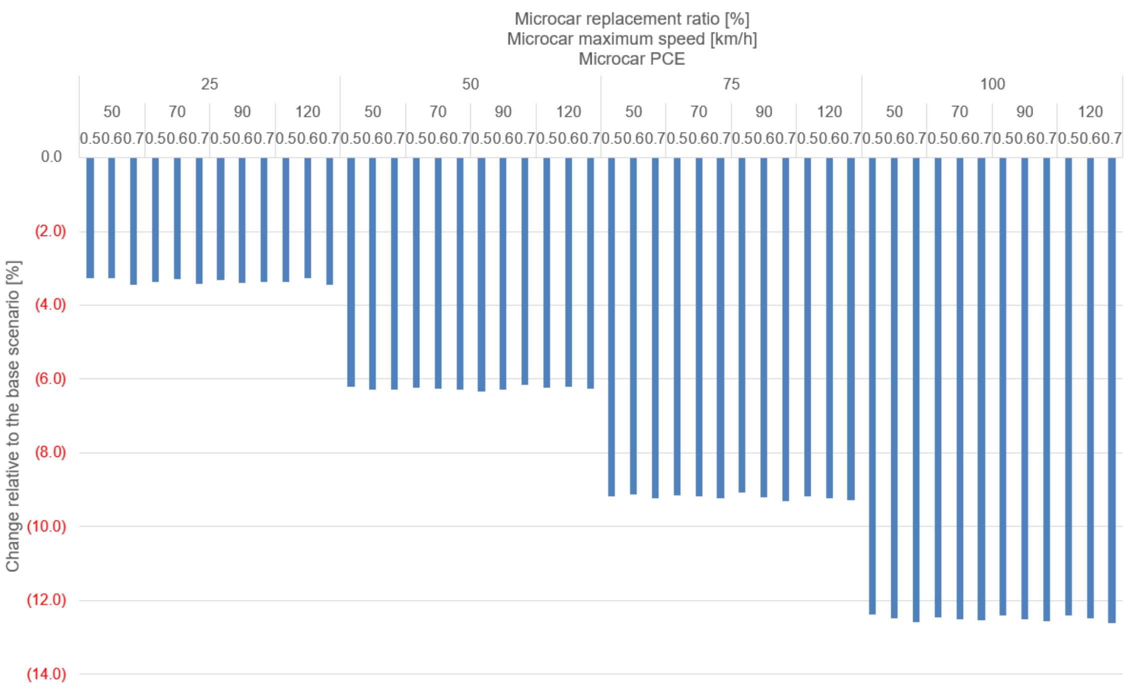

Figure 4.12. 2D histogram of fuel consumption in the Berlin area in percentage change compared to the base scenario

4.3 Optimal Scenario Analysis

Table 4.1 provides a comparative summary of the best- and worst-performing scenarios across all evaluation metrics.

For traffic performance, the optimal scenario is defined by a microcar replacement ratio of 100%, a maximum speed of 90 km/h or 120 km/h, and a PCE of 0.5. This combination yields the most favorable outcomes: a 4.3% increase in average speed, a 9.8% reduction in average travel duration, and a 0.5% improvement in the congestion index.

In terms of environmental performance, the optimal scenario occurs with a 100% replacement ratio, a maximum speed of 120 km/h, and a PCE of 0.7. Under this configuration, carbon emissions decrease by 11.4%, and fuel consumption drops by 12.6% compared to the base scenario. However, as discussed in Subchapter 4.2, the maximum speed and the PCE of a microcar have a minimal impact on these environmental metrics.

On the other hand, the worst-performing scenario in terms of traffic outcomes is generally associated with a maximum microcar speed of 50 km/h and a PCE of 0.7. This configuration results in a slight decline in average speed and congestion index (–0.5%), indicating reduced traffic performance. Additionally, the mode share increases by 9.4%, reflecting a shift toward private vehicle use without corresponding improvements in efficiency.

For environmental performance, the base scenario—where no microcars are introduced—performs the worst, with the highest levels of carbon emissions and fuel consumption. This highlights that any level of microcar adoption leads to environmental benefits, regardless of performance parameters.

Table 4.1. Comparative summary of best-performing and worst-performing scenarios across all metrics

	base	best scenario			worst scenario		
	value	value	change relative to the base scenario	variable combination*	value	change relative to the base scenario	variable combination*
avg. speed of car&microcar [km/h]	37.6	39.2	4.3%	[100%, 90km/h, 0.5]	37.4	-0.5%	[50%, 50km/h, 0.7]
mode share of car&microcar [%]	25.7	25.7	0.0%	base	28.1	9.4%	[100%, 50km/h, 0.5]
avg. duration of car&microcar [h/day,agent]	2.14	1.93	-9.8%	[100%, 120km/h, 0.5]	2.14	0.0%	base
congestion index	0.741	0.745	0.5%	[100%, 120km/h, 0.5]	0.737	-0.5%	[100%, 50km/h, 0.7]
					0.737	-0.5%	[75%, 50km/h, 0.7]
CO2 eq. [kt]	24.6	21.8	-11.4%	[100%, 120km/h, 0.7]	24.6	0.0%	base
fuel consumption [TJ]	292	255	-12.6%	[100%, 120km/h, 0.7]	292	0.0%	base

*The variable combination represents the values of microcar replacement ratio [%], microcar maximum speed [km/h], and microcar PCE in the scenario

5 Discussion

5.1 Key Findings and Research Question Reflections

This study explored the impact of microcar introduction on traffic performance and environmental outcomes in a large urban setting using agent-based simulations. The results reveal several important findings:

- The introduction of microcars positively influences urban traffic conditions in general, although the extent and nature of these effects vary across performance indicators:
    - Travel duration and environmental performance (CO_2 emissions and energy consumption) show a linear decrease as the number of microcars increases, indicating consistent improvements.
    - Mode share of cars and microcars increases at an accelerating rate, with the most significant shift occurring during the early stages of microcar adoption.
    - Average speed of cars and microcars increases at a decelerating rate, suggesting that while benefits continue to accumulate, they do so more gradually as the number of microcars increases.
    - Congestion index shows only marginal variation, implying a relatively limited response to the increasing number of microcars.
- Although the introduction of microcars leads to a slight increase in private vehicle mode share, overall energy consumption and carbon emissions consistently decline with higher microcar adoption—primarily due to their superior energy efficiency.
- Microcar maximum speed shows a limited impact on most metrics. However, its influence on average speed and congestion levels becomes more pronounced at higher replacement ratios (i.e., at 75% and 100%). Introducing microcars with too low maximum (i.e., below 50km/h) speed can worsen the congestion level and average speed of the network.

- PCE, representing the road space taken by a microcar, has a significant influence on traffic performance. Lower PCE values result in improved speed and shorter travel duration.

These findings address the research questions posed in Chapter 1:

- **RQ1: How does the introduction of microcars influence individual traffic behaviors and, accordingly, affect congestion, energy consumption, and emissions in an urban setting?**
  → The introduction of microcars improves average travel speed and reduces congestion and travel time. Although it slightly increases private vehicle use, this does not negate the environmental benefits—emissions and energy use decrease across all microcar replacement scenarios.

- **RQ2: How do microcars' maximum speed and space requirements impact simulation results?**
  → The space requirement (PCE) significantly impacts traffic performance. Smaller microcars contribute more effectively to traffic efficiency. The maximum speed, in contrast, has a marginal effect on performance and emissions, especially at low microcar replacement ratios. When the maximum speed of microcars is too low (e.g., 50 km/h), it can hinder traffic flow and reduce network efficiency. These findings suggest that microcar manufacturers should preserve a reasonable maximum speed and prioritize compact vehicle design to maximize the positive impact of microcars on urban traffic conditions.

- **RQ3: What is the optimal configuration and distribution of microcars in urban areas to minimize congestion, energy consumption, and pollutant emissions?**
  → Optimal traffic performance is achieved at 100% microcar replacement, particularly when combined with a maximum speed of 90–120 km/h and a PCE of 0.5. In terms of environmental outcomes, full replacement also results in the greatest reductions in CO_2 emissions and fuel consumption. Notably, the influence of microcar speed and PCE on

environmental benefits is minimal, suggesting that the observed efficiency gains are primarily driven by the extent of vehicle replacement rather than specific vehicle configurations. It is also important to highlight that these optimal traffic and environmental outcomes occur despite the mode share of cars and microcars reaching its highest level at 100% replacement. This finding supports the adoption of microcars in urban areas and can help alleviate concerns about their potential negative impacts on traffic conditions.

5.2 Interpretation in the Context of Previous Studies

The findings of this study align with previous research as follows:

- Similar to Mu & Yamamoto (2012, 2013a, 2013b), this study confirms that increasing the number of microcars improves average speed and travel time.
- While existing research primarily used simplified or small-scale models (e.g., VISSIM or CA), this study extends the analysis to a large-scale, behaviorally dynamic urban network, providing system-wide insights.
- By utilizing real-world traffic data and the thoroughly calibrated base scenario, the study ensures a realistic and reliable outcome.
- In line with Santos (2023) and Ehrenberger et al. (2022), the results confirm that microcars significantly reduce carbon emissions and fuel consumption, reinforcing their role in sustainable urban mobility.
- This study builds on Tanveer et al. (2022) by highlighting the importance of vehicle size (PCE), validating that smaller vehicles improve traffic efficiency even without advanced automation.
- Unlike existing studies that assumed fixed behavior, this analysis considers the adaptive behavior of individuals through MATSim, capturing how individuals adjust mode, route, and time in response to traffic dynamics.

5.3 Study Limitations and Directions for Future Research

Despite offering valuable insights, several limitations should be acknowledged:

- Simplified emission assumptions: The emission and energy consumption for microcars were estimated due to a lack of well-established data. Therefore, more detailed emission factors (e.g., cold starts, weather effects) were not fully captured.
- Assumed agent behavior: While MATSim captures dynamic responses, other factors (e.g., attitudes toward safety, microcar comfort) are not modeled and may affect microcar adoption.
- Uncertainty in microcar adoption assumptions: This study assumes that individuals with shorter car travel distances and smaller household sizes are more likely to adopt microcars. However, this identification algorithm should be refined using real-world data or user surveys to capture actual adoption patterns and preferences.
- Uniform replacement logic: Although a simple prioritization process was applied (e.g., travel distance, household size), the study did not take into account spatial or temporal features for microcar distribution.

Taking these study limitations into account, future research could build upon this work by conducting pilot studies or collecting real-world data to refine microcar emission profiles and better understand behavioral adoption patterns. In addition, exploring synergies with emerging mobility innovations such as shared microcar services or autonomous vehicle technologies, could help understand more advantages of microcars, particularly regarding the optimization of parking and curb space usage.

6 Conclusion

In response to growing challenges in urban traffic systems—particularly congestion and pollutant emissions—microcars have gained attention as a space- and fuel-efficient alternative to conventional vehicles. This thesis examined the impact of introducing microcars into an urban transport network through a large-scale agent-based simulation using MATSim. The analysis focused on four key performance areas: transport mode share, average travel speed, congestion levels, and average travel duration, alongside environmental indicators such as fuel consumption and carbon emissions. A range of scenarios varying microcar replacement ratios, maximum speeds, and space requirements (PCE) were tested to evaluate their combined effects on system-wide transport efficiency and sustainability.

The findings indicate that increasing the microcar replacement ratio leads to consistent improvements in traffic performance and environmental outcomes. Notably, average travel speed increases and travel duration decreases, particularly when microcars are smaller (lower PCE). While introducing microcars slightly increases the overall mode share of private vehicles, this shift does not significantly hinder traffic flow or negate the environmental benefits. On the contrary, both fuel consumption and carbon emissions decrease substantially with higher levels of microcar adoption, underscoring their potential as a low-emission urban mobility solution.

Among the tested variables, PCE emerged as a key driver of traffic efficiency, with smaller vehicles contributing more effectively to smoother traffic flow. Maximum speed had a relatively limited impact, becoming more influential only at high replacement ratios. However, traffic performance deteriorates across scenarios when the maximum speed is too low (e.g., 50 km/h). The optimal scenario for traffic performance involved a 100% replacement rate, microcar speeds of 90–120 km/h, and a PCE of 0.5. For environmental performance, 100% replacement alone was the dominant factor, with maximum speed and PCE of microcars playing a minimal role.

This study also contributes methodologically by utilizing a behaviorally dynamic, data-calibrated simulation environment that overcomes many limitations of past studies. By integrating real-world traffic data and a well-calibrated base scenario, the analysis provides realistic and generalizable insights into the effects of microcar adoption.

However, several limitations must be acknowledged. Microcar adopters were identified based on simplified assumptions regarding travel distance and household size, which may not fully capture real-world adoption behavior. Geographical, psychological, and economic factors influencing adoption were beyond the scope of the simulation model. In addition, emission profiles for microcars were estimated due to the lack of detailed empirical data.

Future research should aim to address these gaps by incorporating survey data or real-world pilot studies to improve the accuracy of microcar adoption modeling. Additionally, investigating the integration of microcars with shared mobility systems or autonomous vehicle technologies could provide further insights, especially concerning parking space management and network effects.

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Declaration of Originality

I declare that this thesis is my own work and that, to the best of my knowledge, it contains no material previously published, or substantially overlapping with material submitted for the award of any other degree at any institution, except where due acknowledgment is made in the text.

Date and Signature of student 22 April 2025 Aoyagi Ikuma.