●●● Porter School of
the Environment and
Earth Sciences

The Raymond and Beverly Sackler
Faculty of Exact Sciences
Tel Aviv University

הפקולטה למדעים מדויקים
ע״ש ריימונד ובברלי סאקלר
אוניברסיטת תל אביב

בית הספר לסביבה ●●●
ולמדעי כדור הארץ
על שם פורטר

This dissertation was completed under the auspices of the Department of Geography and the human environment

Combatting Congestion: Robust Transportation Policy Evaluation in an Agent-Based Multimodal Simulation Model

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Submitted to the Senate of Tel Aviv University

June 2023

Abstract

This thesis investigates the challenges and potential solutions in large-scale transportation simulations using the Multi-Agent Transport Simulation of (MATSim) model. The study is divided into three parts, focusing on downscaling techniques and evaluating congestion mitigation policies with and without Demand-Responsive Transit (DRT)s.

In the first part, the research addresses hardware limitations and the need for effective downscaling techniques in MATSim. The findings demonstrate that downscaling up to 20% is qualitatively safe, based on the robustness of congestion patterns. The study also explores the performance of MATSim's parallel version, highlighting a modest improvement of 15-20% in calculation speed. The limitations and areas for future research are discussed, including the generalizability of downscaling findings and the need for investigating other transportation modes and models.

The second part of the dissertation examines the simultaneous implementation of parking prices and congestion charges as policy measures to mitigate urban traffic congestion, using the Jerusalem Metropolitan Area as a case study. The research demonstrates that a combined payment of approximately 10€ can reduce car arrivals to the city center by 25%, supporting modal shifts from driving to public transportation. Crucial differences between congestion charges and parking prices are identified, suggesting that the latter is more effective in managing congestion. Limitations in the MATSim model application for congestion management evaluation are acknowledged, and the need for further research on shared modes and income effects is emphasized.

The third part shows the impact of core-focused Demand-Responsive Transit (DRT) services on urban congestion and the effectiveness of entrance and parking fees in enhancing DRT's appeal. The findings reveal that unrestricted city center access leads to persistent congestion, with DRT services primarily attracting public transport users. However, when entrance and parking fees are imposed, DRT becomes more appealing to both car and public transport users, substantially reducing congestion. The study concludes that parking fees are more effective in managing congestion than congestion charges, given their simpler infrastructure and lower implementation costs. The research highlights the potential of combined policy measures to mitigate urban traffic congestion and promote sustainable transportation alternatives.

Overall, my research offers valuable insights into downscaling techniques and congestion mitigation policies in urban transportation systems, informing urban planning and policy development for more efficient and sustainable transportation.

Acknowledgments

First and foremost, I would like to express my deepest gratitude to my parents, Eyal and Nirit Ben-Dor. Their unwavering emotional and financial support has been the pillar of strength behind my academic pursuits. They had always encouraged me to strive for excellence and believed in my potential, even when I had doubts. Their love, patience, and sacrifices have been invaluable throughout this challenging journey.

I am extremely grateful to my academic mentors, Prof. Itzhak Benenson and Prof. Eran Ben-Elia, for their invaluable guidance, constant encouragement, and constructive critiques. Their profound knowledge, insightful perspectives, and unwavering dedication have been instrumental in shaping this thesis and my academic growth. I am fortunate to have been under their tutelage.

I would also like to extend my appreciation to Dr. Aleksey Ogulenko and Dr. Ido Klein for their insightful advice, helpful suggestions, and constant support throughout this journey. Their expertise and dedication have significantly contributed to the successful completion of this thesis.

My sincere gratitude goes to the Israel Smart Transportation Research Center (ISTRC) and the “Shmeltzer Institute for Smart Transportation” for their generous financial support. Their contributions have significantly alleviated the financial burdens associated with my research. I am also thankful for the valuable connections and resources they have provided, which have enriched my research experience.

I also want to thank Dr. Yelena Stolkin which during my first degree believed in me and her belief triggered a paradigm shift in my academic trajectory.

Lastly, I wish to acknowledge the Porter School and the Department of Geography at Tel-Aviv University. The nurturing environment it provided has been my academic home for many years. It has equipped me with essential skills, cultivated my curiosity, and fostered a love for learning that I will carry with me as I continue on my academic journey.

In conclusion, I extend my heartfelt gratitude to everyone who has been part of my Ph.D. journey. This milestone would not have been possible without your unwavering support, encouragement, and belief in my capabilities.

Thank you!

Golan Ben-Dor

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List of Abbreviations

ALS	Area Licensing Scheme
ABM	Agent-Based Modeling
BM-DRT	Bischoff and Maciejewski Demand-Responsive Transit
CPU	Central Processing Unit
DRT	Demand-Responsive Transit
ERP	Electronic Road Pricing
FIFO	First in First Out
GPU	Graphic Processing Unit
JHDA	Jerusalem's High-Demand Area
JMA	Jerusalem Metropolitan Area
JMATSIM	Jerusalem MATSim
JTMPT	Jerusalem Transportation Master Plan Team
LCC	London's Central Charge
MATSim	Multi-Agent Transport Simulation
MAS	Multi-Agent-Systems
MaaS	Mobility-as-a-Service
MOBSim	Mobility Simulation
ORS	One-Represents-Several
PHI	Peak Hour Interval
PT	Public Transit
Qsim	Queue-based simulation
SUMU	Simulation of Urban Mobility
SF	Sioux Falls
SAVs	Shared-Automated-vehicles
TAZ	Traffic Analysis Zones
TDM	Transportation Demand Management
TNC	Transportation Network Companies
TLVM	Tel-Aviv Metropolitan
UE	User Equilibrium

CHAPTER 1 Introduction

Background and problem statement

The transportation system is at the heart of every city. The match between the demand for travel and the supply of transportation services defines its ability to satisfy people's mobility needs. The current literature classifies transportation modes into three groups: (1) Private transportation—cars, two-wheel transport, walking; (2) Public Transportation (PT)—taxi, metro, bus, trams; (3) Emerging shared mobility—rented bikes, e-scooters, shared cars, ride-hailing, carpooling and ride-sharing (Tyrinopoulos & Antoniou, 2020).

The arrival of Automated vehicles (AVs) marks a significant leap in transportation technology. This disruptive innovation is underpinned by sophisticated Artificial Intelligence (AI) algorithms and advanced sensor systems coupled with information and communication technologies, enabling vehicles to navigate complex environments without human intervention. Their potential benefits are vast, from increased road safety due to reduced human error to improved traffic efficiency and accessibility for those currently unable to drive. However, while standalone AVs are set to revolutionize personal transport, a further transformative step lies in shared automated vehicles (SAVs)

SAVs are considered the next evolutionary step of AVs, incorporating a Demand-Responsive-Transport (DRT) architecture (Litman, 2017). There are several forms of the DRT: Micromobility (e-scooters/e-bikes); Ride-sharing services that facilitate shared rides among passengers with similar origins and destinations; carpooling like ride-sharing but with one of the passengers owning the vehicle; autonomous shuttles are self-driving vehicles that operate on fixed or flexible routes; on-demand taxi services (ride-hailing) allow passengers to request a ride using a mobile app (Ambrosino et al., 2016). This elaborate view extrapolates the growth of existing commercial Transportation Network Companies (TNC), like Uber, Lyft, and Via, which are serious candidates for introducing AV-based shared services (Fleischer et al., 2018).

There is a general belief that with the advancement of technology and proper regulation, a shift to DRT may bring a far-reaching decline in transportation-related externalities such as congestion, accidents, and air pollution (Fagnant & Kockelman, 2014). However, recent studies question this view. On the one hand, most ride-hailing users in the US are former PT users (Schaller, 2021), and it is unlikely that AV can further diminish car users' resistance to shared services. On the other hand, current TNCs are increasing traffic volumes, and distance traveled, thus increasing congestion (Qian et al. 2020).

Open questions and methodological approach

My thesis focuses on automated DRT services from a coevolutionary perspective. Will travelers adapt to SAVs, and will this new mobility architecture positively influence traffic congestion? What will the necessary regulatory policies be to promote a sustainable and viable SAV service for the operator and the customer? To answer these questions, I investigate a case study of the Jerusalem Metropolitan Area (JMA), with a 550 km^2 area and a 1.25 million resident population (ICBS, 2021).

Since AVs and SAVs are still far from wide deployment, I apply an agent-based simulation modeling approach to answer these questions. Specifically, I use the Multi-Agent Transport Simulation (MATSim) Modeling framework (Horni et al., 2016). MATSim operates at the spatiotemporal resolution of single travelers traversing street links at specific times to reach a designated geographical location, thus reflecting urban complexity and enabling large-scale regional simulations. Travelers in MATSim are simulated as agents—autonomous entities—that can observe, assess, and interact with their environment according to predefined rules. Agents can adapt and learn from their experiences, influencing and being influenced by other agents and the environment in complex ways. MATSim agents act according to predesignated daily travel plans and are adaptive to existing and new transportation modes (Horni et al., 2016). However, to properly simulate a large metropolitan area, the simulation must adequately represent reality, which is a challenge, especially for the JMA transportation system, which serves millions of daily trips. Simulating such an environment is difficult for any modern hardware. As part of my research, I built, validated, and calibrated the first MATSim model of the JMA.

Thesis, takeaways, Contribution, and Organization

My research is comprised of three studies:

First, I investigate the robustness of the MATSim downscaling procedure (Ben-Dor et al., 2021)—the ability to adjust model parameters and simulate the dynamics of a full-scale system with only a fraction of travelers. By comparing traffic dynamics in the well-known Sioux Falls network downscaled and full-scaled traffic scenarios (Chakirov & Fourie, 2014), I demonstrate that 25% of travelers are sufficient for accurately representing traffic parameters. In the second section, I investigate whether socially acceptable congestion charges and parking fees can effectively reduce congestion in a highly congested city center. A possible reinforcement measure of the transition from private cars to shared services is a Pigouvian tax (Pigou, 1920), which exists in current transportation systems through either road or parking prices and may correct significant negative externalities like congestion, air pollution, and noise (Baghestani et al., 2020; Gu et al., 2018; Small & Yan, 2001; van den Berg & Verhoef, 2011; Yang & Huang, 2005). For the first time, I study a novel policy
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combining both congestion management measures to find an optimal charge level at a reasonable price of 7-12€/day for entering the city center. Such a charge would decrease daily arrivals by 25%. In the third section, I assess the effectiveness of shared DRT as a possible game-changer in the existing equilibrium between PT and private cars. I investigate the consequences of introducing shared DRT services and demonstrate that congestion charges or parking fees are necessary to make DRT effective.

As the first to comprehensively study simulation downscaling robustness, my research could pioneer a new study area with potential implications across various fields, such as crowd modeling and disease spread. Furthermore, it offers invaluable insights for transportation modelers to make informed decisions on the stability and representativeness of their models. Next, by combining parking prices, congestion charges, and DRT in the same simulated case study, I provide a fresh perspective on traffic congestion management and enhancing PT systems in the AV age. First, my work offers key policy takeaways, demonstrating that socially acceptable charges can effectively reduce congestion, providing robust pathways for policymakers to significantly improve traffic flow and urban mobility in their cities. Second, by investigating the role of DRT in the balance between PT and private cars, my research uncovers robust strategies to enhance PT and decrease reliance on private cars, particularly highlighting the necessity of congestion charges to make shared DRT an effective alternative. With methods and conclusions transferable to other locations, my work has broad relevance and significance for many cities worldwide.

The remainder of the thesis is structured as follows: Chapter 2 presents the research objectives; Chapter 3 presents an overview of agent-based modeling; Chapter 4 the research methodology, including MATSim; Chapter 5 presents an overview of the three studies. Chapter 6 investigates MATSim's downscaling, which is critical for large-scaling simulations such as JMA; Chapter 7 describes establishing the JMA case study and its MATSim scenarios of congestion charges and priced parking without DRT; Chapter 8 investigates the effects of the congestion charges and priced parking in Jerusalem with DRT. Finally, in chapter 9, I conclude the main findings of the research, highlighting and discussing the importance of the results and presenting my policy recommendations.

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CHAPTER 2 Objectives

My primary goal is to establish robust multiagent and multimodal simulation models that enable comprehensive investigations of introducing new transportation modes to urban transportation networks, namely SAVs. As a byproduct of this general aim, I built, calibrated, and validated an agent-based traffic simulation model for the city of Jerusalem as a workhorse to assess future transportation policies' sustainability.

Objective #1: Downscaling stability in agent-based transport simulations. Since multiagent simulations can become enormous and challenging to manage, the critical question is determining the sufficient fraction of a simulated traveler population to correctly and efficiently represent the proper system's dynamics. The choice of this fraction can influence the simulation's performance statistics and running time and therefore are critical to any prior investigation.

Objective #2: Modal choice sensitivity to congestion charges and parking fees. Congestion charges and parking fees are widely applied as policy measures to regulate road traffic in urban areas. An open question is how sensitive is the modal choice of the simulated system to different levels and combinations of these measures and whether there is an optimal level to regulate road traffic sufficiently.

Objective #3: Modal choice and network performance impacts of a metropolitan shared automated DRT introduction. Introducing shared DRT modes (SAVs) can disrupt the road network's performance and may severely impact travelers' modal choices. To determine an efficient operations policy, it is important to understand the scale of the expected impacts on congestion and mode choice and identify the potential winners and losers.

CHAPTER 3 Agent-Based Transportation Modeling for Policymaking – A Literature Review

This chapter reviews the literature that forms the thesis's theoretical foundation. I begin by exploring the essential role of transportation modeling in policymaking, highlighting its significant influence. The focus then shifts to Agent-Based Modeling (ABM), a computational approach that simulates the actions and interactions of autonomous agents and their specific application within the transportation realm. Detailed reviews are provided for the three studies at the start of their respective chapters.

3.1. The policymaking need for transportation modeling

In many cities worldwide, the mismatch between travel demand and transportation supply and the consequent congestion is a major problem for policymakers and transportation planners. Traffic congestion is a byproduct of urban agglomeration that creates tremendous economic and environmental externalities. These external costs are estimated at more than 1% of the EU GDP (European Union, 2019) and, according to the Israeli Ministry of Transport, resulted in a cumulative loss of 35 Billion ILS (Israeli Shekel, approximately €4.0) and a waste of 850 million hours in 2018 (Knesset Research Unit, 2018). Reducing travel time by even 10% can boost productivity by ~3% and up to 30% in highly congested regions (Christidis & Rivas, 2012). Transportation is also a leading energy consumer (~26%) and contributes a significant share of global emissions (~22%) (Timilsina & Shrestha, 2009; Raza et al., 2019; OECD-IEA,2016).

Considering their immediacy and spatiotemporal flexibility, most city dwellers use cars for everyday mobility (Handy et al., 2005). This trend has been recently reinforced during the COVID-19 pandemic, also in Israel, when travelers abandoned or reduced their use of public transportation and ridesharing in favor of cars, with many people opting to work from home (De Vos, 2020; Abdullah et al., 2020). People slowly started returning to PT post-pandemic; thus, the long-term pandemic travel behavior impacts could be limited (Hensher, 2020).

The decades-old, four-step travel model, a basic framework for determining transportation forecasts, remains dominant in transportation planning. This aggregated travel demand and trip assignment models network links, land use, and infrastructure (Rafiq and McNally, 2000) and is employed by many well-known software environments like Emme/2 or TRANSCAD. While the four-step model is suitable for static average modeling, not so is the case for within-day traffic congestion patterns or dynamic phenomena such as ridesharing (Bischoff et al., 2017).

More recently Activity-Based Models emerged, representing a comprehensive approach to understanding and predicting travel behavior. Unlike traditional trip-based models presented above, ABMs consider the entire sequence of activities and travel events an individual engages in over a day. They are grounded in the principle that travel demand is derived from individuals' needs or desires to participate in spatially distributed activities (Axhausen, 2005). This perspective allows for a better representation of travel complexity, including time-of-day effects, the influence of household and individual constraints, and the interdependence of activities and travel decisions. Activity-Based Models have the potential to provide more realistic and nuanced predictions of transportation demand, making them invaluable tools for transportation planning and policy-making (Bowman & Ben-Akiva, 2001). However, to date, the activity-based approach was only applied to derive travel demand, but the macroscopic simulation of road traffic and public transport mainly remained aggregated as before (Ettema and Timmermans, 2007)

The next evolutionary step is the disaggregate study of transportation problems using spatially-explicit Multi-Agent-Systems (MAS). The MAS's core is the agent-based model (ABM), which aims to quantitatively and qualitatively evaluate the dynamics of a society of autonomous agents with heterogeneous individual behavior. However, the larger the region, the higher the demand for model performance. Hence, studying transportation dynamics in areas with millions of travelers becomes a significant software and hardware challenge. That is, the modeler must balance the hardware limitations and the demand of correctly representing the heterogeneity induced by the variety of agents traveling and interacting in urban space. In other words, we must consider the transportation MAS and its scale-to-performance trade-off.

3.2. Agent-Based Modeling and its application in transportation

ABMs are bottom-up research tools for dynamically capturing aggregate macroscopic regularities entailed by a population of interacting disaggregate agents, their behavior, and the rules governing them (Epstein, 1999; Shalizi, 2006). Numerous ABM models have been applied in biology, economics, social sciences, business, system engineering, and more (Helbing, 2013). ABMs are beneficial for investigating what-if scenarios, with significant growth in socio-spatial system analyses, in general (Helbing, 2012) and transportation research, specifically (Bazzan & Klügl, 2014).

An *agent* is a discrete, autonomous entity with goals and actions with adaptable behavior to varying environmental conditions. Given their disaggregated nature focusing on individuals' spatiotemporal travel decisions, transportation ABMs capture the changes in individual travel behavior in reaction to policy measures, like road pricing or parking fees, as well as transportation innovations such as ridesharing, Mobility-as-a-service (MaaS[1]), automated vehicles, and more (Bonabeau, 2002). All three components of ABMs are essential for transportation planning: (1) Physical environment, which includes all transportation network components and land use defining origins and destination of trips and transportation supply; (2) Agents - vehicles and travelers who use these vehicles; and (3) agents' behavioral rules for mode choice, activities or departure time (Kagho et al., 2020).

Five major challenges for transportation ABM are considered (ibid):

1. *Data quality:* errors in synthetic/real population data, data collection process, data availability, etc., can threaten the validity of the simulation.
2. *Transparency*: Understanding the "black box" aspects of an ABM is crucial to understand the resulting outputs. By nature, ABM is a complex system with many parameters.
3. *Validation* - It is essential to show that the model can replicate reality in respect of real-world data on traffic counts, mode shares, trip distribution, and more.
4. *Reproducibility* - The complex nature of the ABM studies makes them harder to reproduce. Typically, traffic multi-agent simulations, once investigated, are not reproduced again.
5. *Cost of computation:* ABM usually demands many agents and, consequently, computing resources. For example, a MATSim simulation run for Paris, with a sample population of 10%, takes 5 hours on a modern computing cluster (Hörl et al., 2019a).

Unequivocally, the confirmed leader among the open-source MAS transportation systems is MATSim - an event-driven multi-agent MAS environment that aims at modeling the co-evolution of travelers’ behavior and traffic conditions by imitating individual travel choices and behavior (Horni et al., 2016). MATSim agents adapt through reinforced learning and self-correction (McCarthy, 1987). It was developed for executing large-scale transportation simulations and can perform spatially explicit simulations of unlimited travelers (Abar et al., 2017). Recently, MATSim was compared to 83 different ABM in different fields and described as one of the most influential and developed simulation environments where the number of agents is only constrained by hardware ability. MATSim was the only transportation ABM ranked at the top level ("extreme scale") due to its ability to simulate millions of agents over vast urban networks and due to their adaptive behavior (Abar et al., 2017).

[1] MaaS is a consumer-centric mobility model, digitally integrating various transport services under a single platform (Jittrapirom et al., 2017).
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The spatial extent of a large-scale ABM is always problematic. A city can be too large to be fully simulated, and the larger the city, the lower the model performance. Downscaling - simulating the full spatial system with fewer agents can be applied in this case. To match the full-scale model, the downscaled version demands adjustment of the model parameters. Critically for my study, MATSim includes downscaling by design, practically employed in all real-world MATSim applications. The first study of the thesis is devoted to investigating MATSim downscaling by comparing the performance of the downscaled and full-scale solutions. This issue has hardly been addressed (see Chapter 6).

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CHAPTER 4 Methodology

The three studies I conducted as part of my research share a common methodology based on the MATSim simulation environment. In this chapter, I review its main attributes.

4.1. The Multi-Agent Transport Simulation (MATSim) environment—general view

MATSim is a popular open-source agent-based spatially-explicit environment that incorporates a human view of travel choice (Horni et al., 2016), including reinforced learning and self-correction (McCarthy, 1987). MATSim considers urban traffic as a collective outcome of the activities of individual travelers, which adapt to the transportation system by modifying their behavior. MATSim can simulate, with standard hardware, a population of a million and even more agents in a realistic GIS-based urban environment (Abar et al., 2017).

MATSim daily loop

MATSim simulates the *daily* dynamics of a transportation system by adjusting travelers' behavior and mode choices to emergent traffic conditions (Figure 4.1). This daily loop is repeated, allowing agents to "investigate" different travel options for maximizing their everyday utility. This process continues until the system converges to a User Equilibrium (UE), where the agents' average utility no longer increases. A typical "MATSim loop" starts with the "Initial Demand" step establishing the population of agents and the transportation network. Next, agents' activities, including their trips, are simulated using the MOBility Simulation (MOBSim) module. Once the daily activities are performed, agents are scored based on their performance—"Scoring"; agents' scores (i.e., utilities) are calculated using economic utility functions. In the "Replanning" stage, MATSim uses coevolutionary algorithms to improve agents' scores by changing their daily plans. The "MATSim Loop" ends with analyzing the events recorded during a daily simulation run.

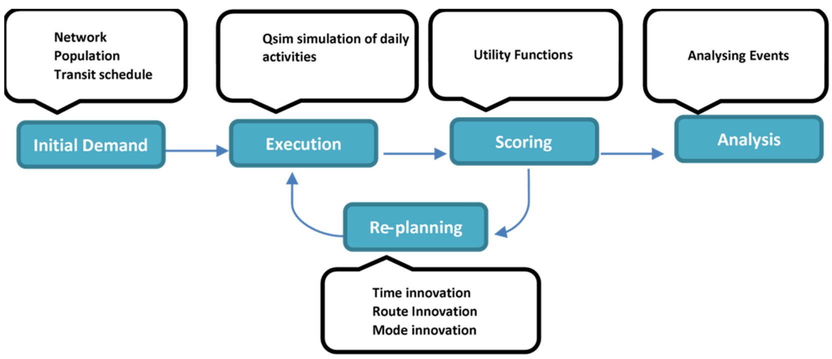

Figure 4.1. Flowchart of the "MATSim daily loop" (Horni et al., 2016).

The "MATSim loop" (Figure 4.1) starts with the "Initial demand" stage when all the input files are loaded, which includes the transportation network and a population of agents. The "Transit Schedule" that is necessary to simulate PT traffic is optional.

Transportation Network

A MATSim transportation network consists of nodes and connecting links. Agents traveling by car use the available road network consisting of links characterized by a list of *allowed modes (list of modes)*; the number of *lanes (one or more)*; *length (m)*; *flow capacity (vehicle/hour)* - the maximal number of vehicles that exit the link during an hour—*storage capacity (vehicles)* - the maximal number of vehicles that can be allocated on a link; *free flow speed*, *m/s*. MATSim considers road links as one-directional. MATSim supports a detailed transit implementation where each transit vehicle (bus, train, or tram) is assigned a size, maximal capacity, route, and daily timetable (Rieser, 2010). Transit vehicles are organized into the PT network, which consists of lines and stops. A PT line's route includes links and stops, including the origin and destination terminals. Stops are located at the inbound node of the link on which a physical stop is located.

Population and Plans

Each MATSim agent has its properties and spatially located activities combined into one or more travel plans. Travel plans consist of "Activities" and "Legs." An agent starts with one plan.

- Activities are performed at locations, e.g., at home, work, or shopping. Each activity has the desired start and end times and is explicitly located on the network.
- Legs are transportation modes an agent uses to reach its activities - "Walk", "Car", "Bus", "Rail".

MATSim generates the actual route of each leg as the shortest path (Dijkstra, 1959), which minimizes travel time by accounting for the traffic conditions at the hour of travel. "Car", "Bus" and "Rail" legs are simulated in the Qsim block of the "MATSim Loop" of Figure 4.1. Agents who use the "Walk" leg are teleported to their destination with a distance factor of 1.3 at a fixed speed of 0.83 meters per second (3 km/hour) and do not affect the network's capacity (Horni et al., 2016).

Figure 4.2 presents an example of a daily plan chain. An agent starts their first activity at "Home" and departs with a "Car" leg to "Work" intending to arrive there at 9:00. From Work, it continues to "Lunch" on foot, returns to "Work" also by foot, and travels by car back to "Home" towards 19:00.

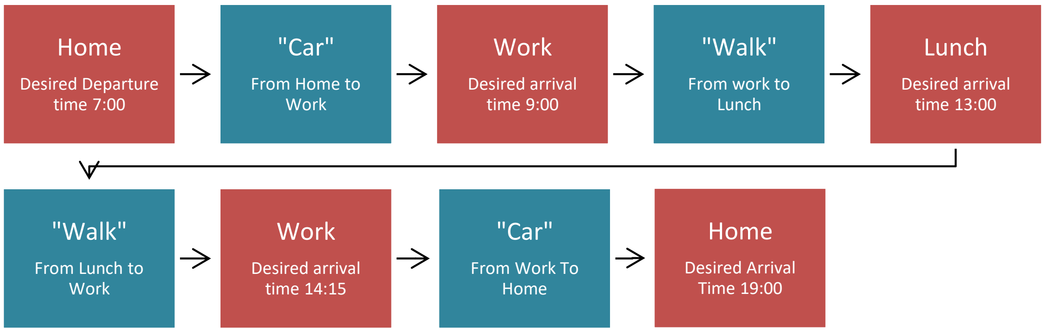

Figure 4.2. An example of an agent's daily plans: activities are marked by Red, legs by Blue.

4.1.1 MATSim approach to simulation of vehicles' mobility and interaction

MATsim aims at simulating millions of agents. To do so, it considers traffic flows at the mesoscale level and does not simulate car-following explicitly. The traffic simulation module of MATSim, QSim, employs a *First-In-First-Out* (FIFO) approach for simulating the traversal of road links. A link is considered a gate. The vehicle entering it at one end is added to the tail of the vehicle queue building up at the other end. The vehicle remains in this queue until it reaches the queue head (Figure 4.3). Thus, no vehicle can enter a link if the $storage\_capacity$—the maximal number of vehicles that can be physically allocated on a link, is exhausted.

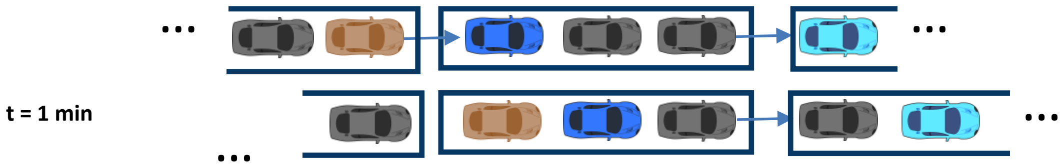

Figure 4.3. illustration of the QSim FIFO rule of vehicle advance on one link and between two consecutive links

The traversal time of a link depends on the current traffic conditions (Horni et al., 2016). The latter is defined by the $flow\_capacity$ – the maximal number of cars that can exit a link per time unit. Since both storage and flow capacity are limited, too many vehicles queueing on a limited capacity link generate traffic congestion.

Figure 4.4 illustrates how $flow\_capacity$ and $storage\_capacity$ influence the traffic flow. For example, consider three connected links with the following capacities:

link1: $storage\_capacity\ =\ 3\ car,\ flow\_capacity = 2\ car/min$

link2: $storage\_capacity\ =\ 6\ car,\ flow\_capacity = 2\ car/min$

link3: $storage\_capacity\ = 3\ car,\ flow\_capacity = 1\ car/min$

The following events will happen between t = 0 and t = 1 (looking from left to right): since $flow\_capacity$ of link1 is 2 cars/min, two cars will try to exit link1 and proceed to link2; since $flow\_capacity$ of link2 is also 2 cars/min, two cars will try to exit link2 and proceed to link 3; and, since $flow\_capacity$ of link3 is 1, one car will exit it. Looking from right to left: Possible transitions from link2 to link3 would not be fully executed since only one unit of the storage capacity on link3 will be emptied. At the same time, the transitions from link1 to link2 will be executed in full since, after one car, the unexploited $storage\_capacity$ of link2, that would transfer to link3, will be equal to 3 cars.

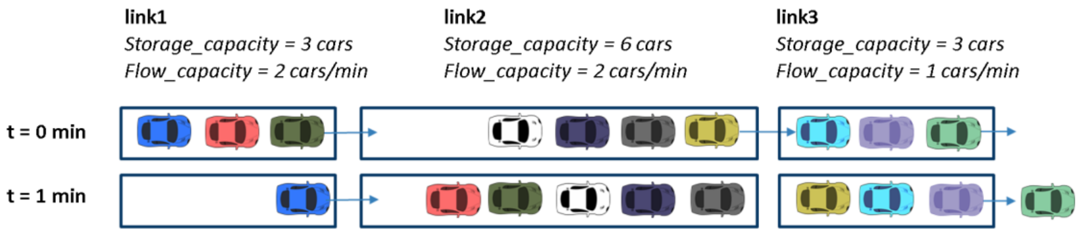

Figure 4.4. Illustration of the effects of MATSim link storage capacity and flow capacity on the simulated traffic flow

The queue-based approach substantially improves QSim's performance compared to other microsimulations that explicitly account for vehicle interactions (Abar et al., 2017). In particular, the QSim approach prohibits the volume-to-capacity ratio (V/C) from exceeding 1. In contrast, the traditional static traffic assignment models that use an impedance function, like EMME (Gao et al., 2010), TransCad (Ji et al., 2002), or Cube (Vorraa, 2009) permit conditions where V/C is above 1.

Recently, a new mobility simulator HERMES (Graur et al. 2021) was proposed as an alternative to QSim. Hermes is a mobility framework that capitalizes on the fact that events in large-scale simulations are concentrated in sparse areas, making the traversal of the entire graph inefficient. It employs an event-driven execution to process only events at a specific iteration, contrary to QSim's approach. Hermes incorporates optimized code paths, data structures, pre-computation, memorization, and efficient code, enabling efficient large-scale simulations without compromising extensibility. Consequently, it is twice as fast as QSim. Hermes focuses on core functionality and supports simulating different vehicle types and private and public transport, similar to QSim. However, it did not support extensions like dynamic vehicle routing necessary to simulate DRT. In Chapter 8, I discuss how I incorporated HERMES to be used with DRT simulations.

Agents plans are input for MATSim, and below are some Activity-based models which are exploited in MATSim, like ALBATROSS (Arentze et al., 2000), FEATHERS (Bellemans et al.,2010); or CEDMAp (Sener et al., 2006). Plans are implemented with the MOBSim module and are compared based on scoring. MOBSim executes agents' plans and enables their adaptation to evolving traffic conditions by changing plans. To simulate agents' adaptation, MOBSim selects, at each iteration, some share of them for possible innovations: change of route, mode, or departure time. The performance of each agent is *scored* using pre-established utility functions. The agents for whom the innovation improves the score accept the change, while agents for whom the innovation decreases the score reject it.

Changes in agents' behavior entail traffic changes, and the underlying assumption of MATSim is that, in a series of iterations of the same travel day, this process of system-travelers' co-adaptation will converge to a User Equilibrium (UE), a steady state when no agent can improve its score by changing its behavior. The MATSim *daily loop* (Figure 4.1) is reiterated until UE is achieved. Figure 4.5 displays a typical MATSim evolution of scoring that stabilized at the ~1250th iteration.

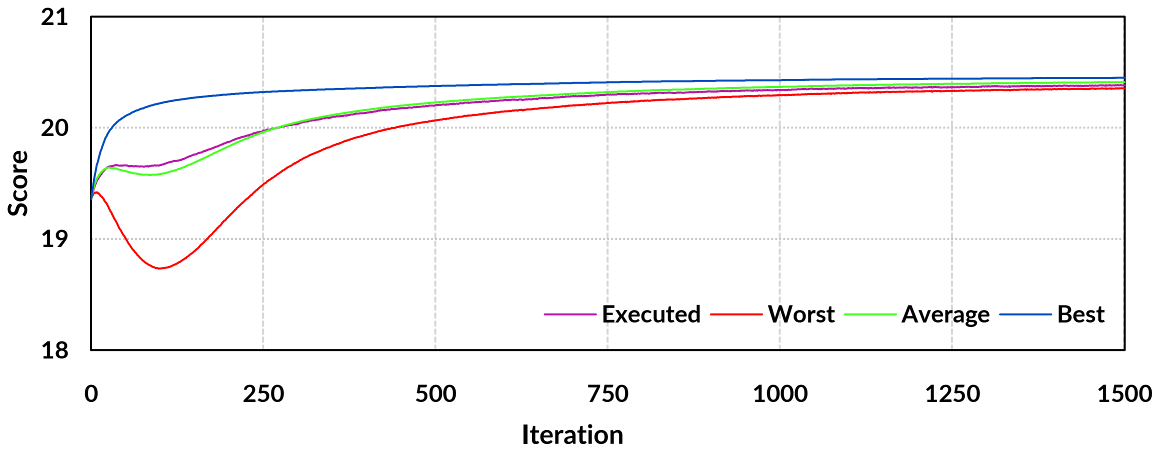

Figure 4.5. The typical evolution of MATSim's average population scores for the Sioux Falls scenario (Chakirov & Fourie, 2014). "Executed" is the average score for all executed agents' plans, "Worst", "Average" and "Best" are the average scores for the corresponding sets of agents' plans.

It is important to stress that MATSim focuses on the daily dynamics and does not consider the long-term consequences of the agent's modal shift, like a change of car ownership or a change of job.

4.1.2 Simulation of agents' behavior in MATSim

MATSim agent's goal is to perform its daily plan. Plan's performance is *scored* at the end of the day, and an agent varies its plan to increase the daily score. Agent's daily behavior is scored using the Charypar-Nagel function (1) that sums up utilities of all daily activities and trips (Horni et al., 2016)

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

Here, $S_{act,q}$ is the utility of activity q, $S_{trav,mode(q)}$ is a (dis)utility of the travel that follows activity q using the chosen transportation $mode(q)$, N is the number of activities, and K is the number of travel legs between them. Note that a trip to activity q may consist of several legs, e.g., a transit trip with transfers. The expression for $S_{act,q}$ is as follows:

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{late.ar,q} + S_{early.dp,q} \tag{2}$$

where $S_{dur,q} \geq 0$ is the utility of performing activity q that depends nonlinearly on the marginal per-hour utility of the activity $\beta_{dur} \geq 0$, activity's duration in hours $t_{dur,q}$, and the typical duration of this kind of activity $t_{typ,q}$:

$$S_{dur,q} = \beta_{dur} \cdot t_{typ,q} \cdot ln\left(\frac{t_{dur,q}}{t_{typ,q}}\right) + 10\beta_{dur} . \tag{3}$$

$S_{wait,q} \leq 0$ refers to the (dis)utility of waiting time if arriving before the activity is possible, e.g., too early to a closed store, $S_{late.ar,q} \leq 0$ is the penalty for arriving too late, e.g., being late to work, $S_{early.dp,q} < 0$ is the penalty for early departure from an activity, like leaving work early to pick up children from school. Expression (3) is designed in a way that each activity obtains its typical duration $t_{typ,q}$, the same utility value $10\beta_{dur}$ – the utility of 10 hours of activity. In this way, the utility function emphasizes the accurate execution of the daily plan; the ln function guarantees that the activities with longer than typical duration do not dominate over the shorter ones.

Performing a trip leg scores negatively and trip disutility $S_{trav,mode(q)}$ depends on transport mode, travel time, fares, and transfers:

$$S_{trav,mode(q)} = C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,mode(q)} + \beta_m \cdot \Delta m_q + \beta_{transfer,q} \cdot x_{transfer,q} \tag{4}$$

Here, $C_{mode(q)} \leq 0$ is a dimensionless constant that represents (dis)utility of using a $mode(q)$; $\beta_{trav,mode(q)} \leq 0$ is the marginal (dis)utility of time spent traveling with a $mode(q)$ following activity q, per hour; $t_{trav,mode(q)}$ is the travel time in hours; $\beta_m \geq 0$ is the marginal utility of money, per monetary unit; $\Delta m_q \leq 0$ represents the change in the agent's monetary budget caused by fares or tolls for the complete leg q; $\beta_{transfer} \leq 0$ is a dimensionless penalty for transfer that may occur during the trip, and $x_{transfer,q}$ is an indicator variable of whether a transfer occurred between the previous and current leg. Note that all disincentive policies that I investigate below contribute directly to the term Δm_q only. The parameters which I use for the JMA simulations are described in section 6.1.2.

4.1.3 Agent adaptation to traffic conditions

In the 'Replanning' stage, a fixed fraction of agents is selected randomly for plan innovation. The latter can be the change of the (1) route of a current mode; (2) transportation mode; (3) departure time. MATSim travelers are programmed to behave *proactively*, exploring various travel options. The daily plan is scored at the end of the day after execution and is stored in the finite agent memory. Those agents who were not selected for innovation pick one of the stored plans for the next daily iteration. The plan is chosen according to a logit choice model:

(1) Each plan j in the agent's memory gets its score S_j. Let S_0 be the best score,

(2) The weight of the best plan is set as $w_0 = 1$, the weight of each other plan j as $w_j = e^{\beta(S_j - S_0)}$, where β reflects agents' ability to distinguish between plans based on their scores (by default, $\beta = 1$),

(3) Plan j is selected for execution with the probability $p_j = w_j / \sum_j w_j$.

Since agents' daily plans are typically balanced regarding the ratio between the overall activities duration and total travel time, the main component of the plan's score – utility of performed activities does not vary much from iteration to iteration. Thus, the main factor that defines the difference $S_j - S_0$, and, consequently, the probability of picking plan j, is the travel disutility of a plan j.

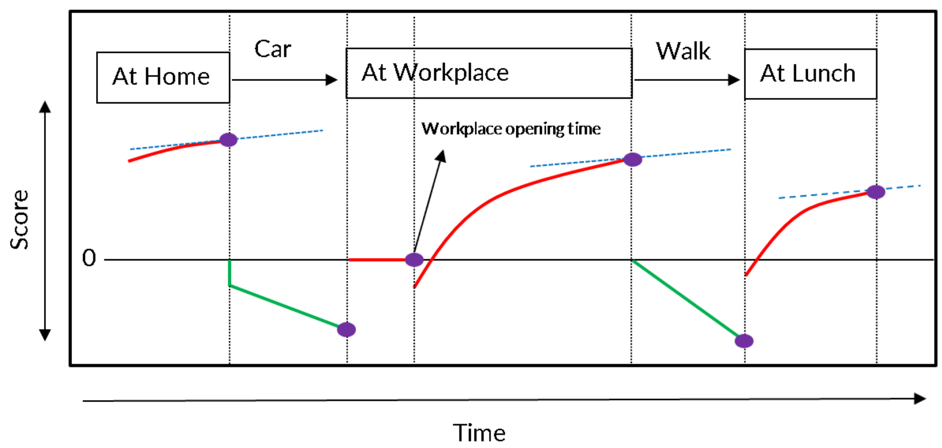

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Figure 4.6. Example of the "Charypar-Nagel" agent scoring function change during a day. The scoring of agent activities is shown in Red and of the legs in Green. Purple dots denote the end/start time of activities; blue lines denote the marginal utility of each activity.

CHAPTER 5 Studies Overview

My research comprises three studies that are built on top of each other. The first study investigates the robustness of MATSim downscaling[2] procedures based on querying the Sioux Falls (SF) scenario (Chakirov and Fourie, 2014), a well-documented transportation planning testbed. To understand the collective dynamics of complex and heterogeneous urban systems, the agent population should be sufficiently large, and the larger it is, the lower the model performance. The MATSim downscaling principle aims to overcome this problem by adjusting the model parameters to guarantee that the downscaled system's dynamics will replicate the full-scaled one's dynamics (Horni et al., 2016, Bischoff and Maciejewski, 2016). Unlike other ABMs, MATSim downscaling is a widely-exploited intrinsic procedure (Bischoff and Maciejewski, 2016; Ciari et al., 2004; Bekhor et al., 2011; Tchervenkov et al., 2018). Several studies have investigated downscaling, including (Hemdan et al. 2018, Horni et al., 2011; Zhuge et al., 2017; Llorca and Moeckel, 2016); nonetheless, systematic studies of MATSim downscaling implications are still lacking.

The second study focuses on two related congestion mitigation policies—congestion charges and parking pricing[3]. The ABM framework is considered an adequate testbed to assess their coevolutionary effects on travel behavior and transportation network (Kaddoura et al., 2020). Several ABM studies investigated congestion charges (Zheng et al., 2012; Agarwal & Kickhöfer, 2015; He et al., 2021, Kaddoura et al., 2020a) or parking prices (Waterson et al., 2001; Coppola, 2002; Benenson et al., 2015 and more). However, to the best of my knowledge, none considered them simultaneously. Here I develop the Jersalem MATSim scenario (JMATSim) to study their combined impacts on mode choice and traffic volumes entering the city center to find optimal charge levels to reduce traffic-related externalities.

The third study utilizes the JMATSim model to investigate another emerging issue—automated shared DRT (Bischoff et al., 2017)[4]. Here, I combine all three mechanisms – congestion charges, priced parking there, and an on-demand shared-taxi service. I investigated the sensitivity of the network performance and the associated travel behavior (mode choice) to the DRT fleet and the served area sizes to determine a balanced set of carrot-and-stick measures for a robust modal shift from private to shared and PT modes.

[2] published under: Ben-Dor et al, 2020 and Ben-Dor et al 2021.
[3] published under: Ben-Dor et al 2022b.
[4] published under: Ben-dor et al 2022c and Ben-Dor et al 2023

CHAPTER 6 - Study 1: MATSIM downscaling robustness

Chapter 6 is the first study of the thesis. It starts with a theoretical background on downscaling robustness and then delves into the investigation of downscaling robustness. This chapter was published in a peer-reviewed journal.[5]

6.1. Background

6.1.1 Downscaling of large-scale transportation ABMs

Parry and Bithell (2012) analyzed the state of large-scale agent-based modeling in social science, ecology, military, and telecommunications listing four major approaches to cope with systems that exceed the abilities of the current hardware. The first two approaches do not account for the specificity of the models:

- *Hardware upgrading* – Advantage: No re-programming is needed. Disadvantage: it can be costly.
- *Parallelization* – Disadvantage: requires advanced computing skills for coping with the overhead of communication between the cores. Solutions are problem-dependent and can be yet inefficient. (Gasser, 2005). Advantage: If successful, it can be employed on the cloud with a practically unlimited number of cores.

Parallelization

The ABM mobility simulators have the same problem. They represent traffic either as a dynamic queue, e.g., MATSim (Horni et al., 2016) and, more recently, POLARIS (De Souza et al., 2019) or as a partially or fully implemented high-resolution car-following model, e.g., SUMO (Krajzewicz et al. 2006), Cube (Vorraa, 2009) and SimMobility (Nahmias-Biran et al., 2020; (Adnan et al., 2016). Parallelization demands essential re-programming for all these approaches. Dobler et al. (2010) were the first to establish the parallel version of MATSim's software. They demonstrated improved performance for 12 cores or less; however, the increase in cores did not decrease the simulation runtime.

Computing through a Graphics Processing Unit (GPU) using a computer graphics card pushes this threshold further but is also limited (Saprykin et al., 2019). Multi-core versions are claimed by POLARIS (De Souza et al., 2019) and SimMobility (Adnan et al., 2016). SimMobility employs the boost threads library that synchronizes access to the data shared by multiple threads and the message-passing interface library. POLARIS's central framework is the

[5] Ben-Dor, G., Ben-Elia, E., & Benenson, I. (2021). Population downscaling in multi-agent transportation simulations: A review and case study. Simulation Modelling Practice and Theory, 108, 102233.
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discrete-event engine DEVE that organizes the agents to execute in a desired order, with multiple threads managing the agents without interference (Auld et al. 2016). Aimsun, a commercial software for microscopic agent-based simulations that accounts for car-following and lane-changing, applies a multi-core CPU parallelism and decreases simulations runtime with up to 8 cores (Heywood et al. 2018). SUMO, a popular agent-based tool for simulating car-following and lane-changing, has some parallelization routines (Krajzewicz et al. 2006). I do not employ the parallel version of MATSim in my study.

Downscaling

The complexity of agents' behavior and the associated non-linear phenomena in ABMs can be exhibited differently by the system as a whole and its parts (Parry and Bithell, 2012). However, considering the available hardware, large agent-based systems should be simulated with an agent population smaller than the city's population (Parry, 2009). Parry and Bithell (2012) point to the *One-Represents-Several (ORS)* scaling approach compared to *Modeling the whole system with a fraction of the agent population*. Advantages: No need to re-program agents' behavioral rules. Disadvantages: Demands careful scaling of the model infrastructure.

ORS downscaling demands adjusting the model parameters to guarantee that the dynamics of the downscaled system remain the same as those of the full-scaled one (Bischoff & Maciejewski, 2016a). As far as I know, MATSim is only the ABM software with an intrinsic downscaling procedure (Horni et al., 2016). Downscaling in MATSim demands straightforward adjustments of the network parameters and is widely applied (Balmer et al., 2008; Bekhor et al., 2011; Bischoff & Maciejewski, 2016; Bischoff & Maciejewski, 2016b; Boesch et al., 2016; Erath et al., 2012; Gao et al., 2010; Kickhofer et al., 2016; Maciejewski & Bischoff, 2017; Tchervenkov et al., 2018; Waraich & Axhausen, 2012). However, studies of the downscaling *effects* on model dynamics are yet limited in scope, and therefore, I aim to close this gap.

To project the results obtained in the downscaled simulation to the full-scale model, one must be sure that these are unbiased, i.e., over several runs, the average value of any output statistic is similar to that of the same statistic in the full-scale model. In addition, even for unbiased statistics, their variation should be known to estimate the number of repetitions necessary to assess the statistic with the required precision. As shown in Table 6.1, the values of the downscale ratio (*k)* can vary between 1% and 25%, and in 16 out of 31 studies, the choice of *k* is motivated by the desired computing time, while in 7 other papers by some common agreement

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Table 6.1. MATSim downscaling applications and their attributes

#	Authors	Year	Scenario	Research goal	Total Pop [100%]	Downscaling justification	values of *k* [%]	Network size [Nodes/Links]	PT
1	Illenberger et al	2007	Berlin, Germany	Perfection of re-planning procedure	1,700,000	N/A	10%	N/A	N/A
2	Balmer et al	2008	Greater Zürich, Switzerland	Model performance	1,816,930	Common choice	10%	24,180/60,492	No
3	Horni et al	2009	Switzerland	Perfection of travelers' choice model	2,284,010	N/A	10%	N/A	N/A
4	Dobler	2010	Berlin, Germany	Parallelization of MATSim	1,600,000	N/A	1%	11,000/28,000	N/A
5	Dobler	2010	Canton Zurich, Switzerland	Parallelization of MATSim	400,00	N/A	25%	73,000/163,000	N/A
6	Gao et al	2010	Greater Toronto, Canada	Bridging between EMME/2 and MATSim	5,570,000	Common choice	5%	16,337/ 40,549	N/A
7	Bekhor et al	2011	Tel-Aviv, Israel	Traffic simulation	3,200,000	Performance	10%	7,879/ 17,118	N/A
8	Horni et al	2011	Zurich city center, Switzerland	Study of output variance	680,000	Performance	10%	24,180 / 60,492	N/A
9	Erath et al	2012	Singapore	National traffic modeling	4,300,000	Performance	25%	12,420/26,972	Yes
10	Waraich et al	2012	Zurich, Switzerland	Parking search	1,800,000	Common choice	1%, 10%	1 million	No
11	Kickhöfer et al	2013	Munich, Germany	Effect of travel costs on emissions	2,093,530	Performance	10%	17,888/41,942	No
12	Röder et al	2013	Brussels, Belgium	Cordon pricing for a highway	860,214	N/A	1%	10,861/19,830	No
13	Dobler et al	2014	Canton Zurich, Switzerland	Bicycle and pedestrian traffic	1,800,000	N/A	25%	24,000/60,000	Yes
14	Hülsmann et al	2014	Munich, Germany	Air pollution assessment	2,093,530	Performance	1%	17,888/41,942	No
15	Nicolai et al	2014	Zurich, Switzerland	Accessibility analysis in Zurich	336,290	Performance	10%	24,180/60,492	No
16	Bösch et al	2015	Zurich, Switzerland	Extension of MATSim multimodal capabilities	N/A	Performance	0.1%,1%, 10%	N/A	Yes
17	Simoni et al	2015	Zurich city center Switzerland	Road pricing	1,800,000	N/A	10%	550/1224	No
18	Ziemke et al	2015	Berlin, Germany	Population model calibration	1,105,037	N/A	1%	11,345/24,335	No
19	Balać et al	2016	Zurich, Switzerland	Activity re-planning	N/A	Performance	1%	N/A	N/A

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20	Bischoff et al	2016	Berlin, Germany	Introduction of automated taxi	N/A	Performance	10%	N/A	N/A
21	Bösch et al	2016	Switzerland	National scenario	N/A	N/A	1%, 10%, ,100%	N/A	Yes
22	Fourie	2016	Zurich, Switzerland	Perfection of the QSim	2,000,000	N/A	10%	N/A	No
23	Gavin McArdle et al	2016	Dublin County, Ireland	Perfection of travelers' choice model	600,000	Performance	25%	N/A	No
24	Hülsmann	2016	Munich, , Germany	Detecting air pollution hotspots	2,093,530	Performance	1%	17,888/41,942	No
25	Kickhofer et al	2016	Santiago, Chile	Traffic simulation	6,650,000	Performance	65%	N/A	No
26	Ordóñez	2016	Singapore	Effects of iteration step exceeding one day	3,742,500	N/A	%1	N/A	No
27	Saadi et al	2016	Liège, Belgium	River flood impact on transportation	1,094,791	Performance	1%	24,372/55,959	No
28	Hörl	2017	Île-de-France, France	Introduction of automated vehicles	1,000,000	Performance	10%	N/A	Yes
29	Maciejewski et al	2017	Berlin, Germany	Congestion of automated taxis	N/A	Common choice	10%	N/A	N/A
30	Bassolas et al	2018	Barcelona, Spain	Traffic simulation	2,300,000	Performance	10%	9,217/17,690	Yes
31	Tchervenkov et al	2018	Switzerland	Externalities of mobility (emissions, congestion, noise)	N/A	Common choice	10%	N/A	N/A

6.2. MATSim approach to downscaling

The fundamental principle of downscaling in MATSim is "One Represents Several" (ORS), i.e., every agent is considered as representing K other agents, and model parameters are modified accordingly to preserve the dynamics of the full-scale model. It is not evident that the ORS concept will guarantee, irrespective of K, that the downscaled simulations will replicate the dynamics of the full-scale model. The ORS downscaling has become popular and is recently added to the POLARIS model (De Souza et al. 2019). The inherent MATSim downscaling makes it an excellent candidate for investigating ORS effects on the model's outcomes. The latter is evidently crucial for the ever-increasing audience of MATSim's users. My study offers general guidelines on applying the ORS downscaling.

ORS downscaling in MATSim is defined by parameter K – the number of agents in the full-scale model represented by one agent of the downscaled model. In what follows, I characterize the downscaled model by the *downscaling ratio k*, the fraction of the traveler

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population that is considered in the downscaled simulation, i.e., k = 1/K. For example, in a 10%-downscaled model, 10% of the real population of the region is considered. I will interchangeably call the downscaled scenario "k-downscaled" and "k*100%-downscaled", e.g., "0.1-downscaled" or "10%-scenario". In these terms, the full-scale model that operates with the area's entire population is 100%-downscaled.

To implement ORS downscaling in MATSim, each link's flow and storage capacities are adjusted proportionally to k. In a full-scaled model, these capacities are established as:

$$flow\_capacity\_full = \frac{capacity\_value\_of\_link}{capacity\_period\_of\_network} \quad (5)$$

$$storage\_capacity\_full = \frac{length\_of\_road\_link * number\_of\_lanes}{effective\_cell\_size} \quad (6)$$

The $capacity\_value\_of\_link$ in equation *(5)* is established for all links of a given network applying standard traffic engineering methods of and calculated (per hour) according to the Highway Capacity Manual (Highway Capacity Manual, TRB, 2000). Since traffic changes in MATSim, are considered per second, the $capacity\_value\_of\_link$ is normalized using $capacity\_period\_of\_network$ = 3600. The $effective\_cell\_size$ in equation (6) is the minimal length of a road lane a vehicle occupies calculated in MATSim as the length of the vehicle (in meters) multiplied by 1.5. The vast majority of MATSim applications set the $effective\_cell\_size$ equal to 7.5 m, and I adopted this value as well.

When downscaling, the flow and storage capacities are adjusted. The adjustment of the flow capacity is linear, whereas that of the storage capacity is non-linear:

$$flow\_capacity\_downscaled = flow\_capacity\_full * k \quad (7)$$

$$storage\_capacity\_downscaled = full\_storage\_capacity * k^{0.75} \quad (8)$$

For example, in a 10%-downscaled model, according to (3), $full\_flow\_capacity$ is multiplied by k = 0.1 and, according to (7), $full\_storage\_capacity$ is multiplied by $k^{0.75}$ = $(0.1)^{0.75}$ = 0.1778. The exponent of 0.75 in *(8)* was proposed by Nicolai (2012) to avoid network breakdowns related to excessively congested links (Rieser & Nagel, 2008) and confirmed by (Llorca, and Moeckel, 2019).

In a full-scale simulation, MATSim randomizes the order in which agents are considered for performing their daily plans and selected for innovation. This randomization is controlled by a *global random seed* set at the beginning of the full-scale model run. In a downscaled simulation, besides adjusting storage and flow capacities, MATSim randomly selects k*100% agents that represent K agents in the full-scale model by activating a *downscale random seed* (Horni et al., 2016).

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The ORS approach may be incorrect since (1) road links are connected, and we are interested in the dynamics of congested network traffic, and (2) agents in MATSim are adaptive, and the traffic state influences their choice of routes, departure times, and daily plans. Intuitively, decreasing the downscaling fraction *k*, results in fewer cars representing traffic on a link and in a decrease in the system's robustness to variations in agent behavior. Consequently, the level of traffic on the congested and, especially, non-congested links may well become non-robust to the decrease in k, and traffic dynamics for low k will not replicate sufficiently well the dynamics of the full-scale model.

6.3. The effect of downscaling on model simulations

Basically, the variation of the global average characteristics of a full MATSim scenario is very low. Hemdan et al. (2018) estimated the Coefficient of Variation (CV) of several global statistics based on three repetitions of the full MATSim Sioux Falls simulation (84,110 agents) and reported close to zero CV of the modal shares (car, walk, transit); 0.08%-0.60% for the average travel time; 0.25% for the average morning peak traffic flow (veh/h). The average network morning peak density (veh/km) had the largest variability, with CV = 2.13%.

Intuitively, the global statistics' variance and bias in a downscaled simulation should be higher than in the full-scale model. Zhuge & Shao (2016a), Zhuge et al. (2016b), and Zhuge et al. (2017) investigated car traffic simulation for Baoding, China, and compared the daily averages of agent scores, travel distance, V/C, and travel speeds for the 20%, 10%, 5%, and 1%-runs. They report that downscaling from 20% to 10% had no influence on these four statistics. However, downscaling of 5% and 1% increased the average travel distance by 30% and biased average scores. At the same time, the city-wide average V/C remained the same for all *k*. Llorca & Moeckel (2019) investigated the effect of downscaling on the distribution of agent travel times and daily scores in a traffic simulation of Munich. They performed one simulation run for the values of *k* between 0.01 to 1 and demonstrated that travel time distributions for *k* within the range of (0.05, 1) remained like that of *k* = 1. For *k* < 0.05 the deviation from the travel time of the full-scale model became substantial. The average daily score slightly increased with the decrease in *k,* and for *k* = 0.05 was ~5% higher than that obtained for *k* = 1. They concluded that the lower threshold for *k* is 5%. Horni et al. (2011) estimated the variance of the hourly traffic volume in 30 repetitions of a 10%-scenario for the City of Zurich. They demonstrated that the CV of the hourly link volumes varied up to 10%-20%. Adjusting the capacities according to the ORS downscaling principle and equations (3) – (4) is insufficient for the multi-modal traffic. The problem lies in adjusting the number of PT vehicles' we cannot decrease it in proportion to k since it will automatically increase waiting time. In case the PT vehicles use dedicated bus lanes, the solution is simple - represent the PT lines by separate network and reduce their passenger capacity

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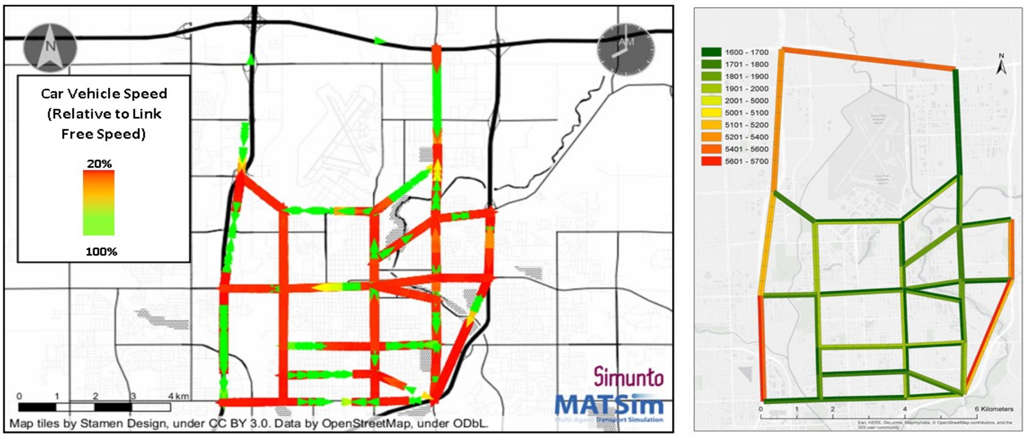
proportionally to *k* (Kickhofer et al., 2016). However, this solution cannot work in cities where cars and PT vehicles drive compete over the same road space. In this case, I linearly adjust PT vehicle capacity and length and modify the queueing model of QSim, allowing PT vehicles to override the link flow capacity restrictions (Ben-Dor et al., 2017).

To summarize, the open questions that demand systematic research of the downscaling are as follows: What is the bias, variance, and tradeoff between them of the downscaled simulations' statistics? In this chapter, I investigate the impacts of downscaling based on the well-known Sioux Falls test case scenario, focusing on unimodal scenarios with private cars.

6.4. Sioux Falls as a testbed for studying downscaling.

The City of Sioux Falls (SF), South Dakota's road network, is a popular test case long used in transportation planning investigations and was adapted to MATSim by Chakirov & Fourie (2014). The scenario has been widely applied since 1970 to the present day in different case studies from dedicated bus lanes (Ben-Dor et al., 2018), road pricing optimization (Kaddoura et al., 2014), and automated vehicles (Wang et al., 2018) to unmanned airborne drones (Rothfeld et al., 2018). Two versions of the SF road network exist – the 2014 simplified version that contains only major roads and the 2017 version containing all links and junctions in the city (Hörl, 2017). In this study, I use the 2014 network. This network was selected as it is well-studied and documented, and its simplified topology allows an easier understanding of its emergent traffic patterns and dynamics.

The SF network has 334 links and 282 junctions (Figure 6.1). The road links are of two types: *Urban Road* – two-lane links with a flow capacity of 800-1,000 cars per lane per hour, and *Highway* - three-lane links with a flow capacity of 1,700-1,900 cars per lane per hour. The storage capacity of the road links in equation (8) was estimated by (Chakirov & Fourie, 2014) according to the attributes of the SF road network – link length and the number of lanes.



(a) (b)

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Figure 6.1. Sioux Falls 2014 road network and (a) morning peak traffic flow at 08:00 for 168,220 agent population; (b) flow capacities on links (vehicles/hour).

Uncommon to many MATSim studies, travel plans are available for 100% of the population in the SF scenario. In addition, this scenario is small enough (population and network) to simulate the full-scale model with standard computer hardware. The daily plans were constructed based on micro-census and land-use data and included three types of activities: staying at home, being at work, and secondary activities (ibid). The total number of travelers (agents) is 84,110, characterized by age, gender, and car ownership. However, with this number of agents, the level of traffic congestion observed on the road network is relatively low. To generate higher congestion, I cloned each Sioux Falls agent, including their own travel plans, and reconsidered 168,220 agents as the full, i.e. k = 1 scale model. The initial modal split in SF is roughly 78% car use and 22% transit. However, as noted before, in my analysis, I assumed that all agents drive cars.

I investigated downscaling by varying k between 1 and 0.01, i.e., I consider scenarios with the number of agents varying between 168,220 and 1,682. To downscale the simulation, I normalized $flow\_capacity\_downscaled$ and $storage\_capacity\_downscaled$ according to equations *(7)* and *(8)* above. To estimate the variance of the model outputs, each scenario was repeated 10 times with a different random seed. Repetitions of the full-scale model were run, each with a different global seed, while those of the downscaled models with different random seeds. In all scenarios, I applied the same scoring functions as proposed by Chakirov & Fourie (2014). All simulations were run with 3000 iterations, a sufficient number for convergence to UE. The results in this study are based on the last iteration of each simulation (3000). Plan innovations - re-routing and change of departure time were applied in each run for 1% of randomly selected agents from the 1st up to the 2700th iteration. During these iterations, the agents store the five best plans in memory; whenever a new plan is adopted, the worst one is forgotten. In the remaining 300 iterations, innovations were switched off.

6.5 The number of iterations necessary for converging to User Equilibrium

Figure 6.2 presents the dynamics of the executed scores of all agents averaged over 10 runs in the full-scale model. In most runs, convergence to UE happened around the 400th iteration, with some sporadic deviations of the scores in some runs up to around the 800th iteration, likely caused by the transfer from one UE to another. Further on, the system reaches a final UE where the average score remains stable (STD $\approx$ 0) in all 10 runs.

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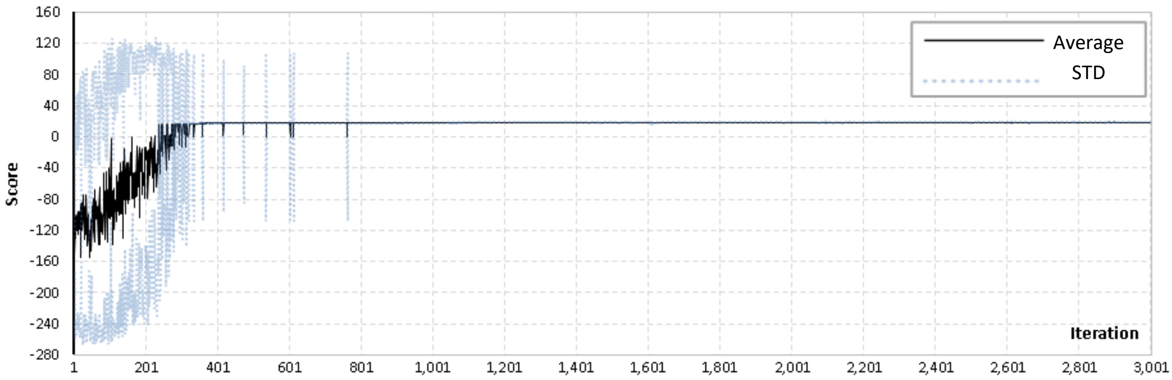

Figure 6.2. Average (black) and average ± STD (light gray) of the executed scores in the full-scale model (over 10 repetitions), by iterations.

In the downscaled simulations, the number of iterations necessary to reach the final UE state was similar to the full-scale run, where it was between 600 and 800. I thus assert that ~800 iterations are sufficient for convergence to the final UE in the SF scenario. If the number of iterations necessary to reach the system UE does not depend on *k,* then it can be estimated in one "long" simulation.

6.6 The choice of statistics for analysis of simulation output

Conceptually, some statistics of MATSim outputs should automatically scale, i.e., linearly change with the decrease of *k*, while others should remain constant. Examples of potentially scalable statistics are the number of departures or the traffic volumes per time unit that should change linearly with the decrease of *k*. Non-scalable statistics include the average of agents' scores or the average travel distance that should remain the same regardless of *k*. When comparing the output statistics of downscaled and full-scaled models, V multiplies the scalable statistics by 1/*k*, whereas non-scalable ones remain as is.

In what follows, I investigated the effects of downscaling, at different spatiotemporal resolution levels, on four non-scalable statistics: (1) **executed scores** (reflecting the co-adaptation level of agents), (2) **travel distance**, (3) **trip duration** and (4) **volume-to-capacity (V/C) ratio**; and two scalable statistics: (1) the **hourly number of car departures** (number of agent departures) and (2) **traffic volumes** (number of traveling agents) (Table 6.2). The values of the last two statistics obtained in the downscaled runs are then multiplied by 1/*k*. Each of the statistics is considered per day and per hour.

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Table 6.2. Investigated statistics of simulation outputs

Output statistic	Description	Category
Agent executed scores	Daily average	Non-scalable
Travel distance	Hourly average travel distance	Non-scalable
Trip duration	Hourly average travel time	Non-scalable
Volume-to-capacity (V/C) ratio	volume (V) to flow capacity (C) per hour	Non-scalable
Hourly number of car departures	Number of agent departures	Scalable
5-minute traffic volumes	Number of traveling agents	Scalable

The downscaling effects are examined at the full aggregation level, i.e., spatially, over the entire network and temporally, over the entire day, as well as at higher spatiotemporal resolutions - hourly or aggregated by peak/off-peak periods of the day. The spatial distribution of traffic flows is investigated based on the hourly car volumes, aggregated over the entire network and disaggregated by individual links by the peak/off-peak periods of the day.

The peak hour is defined as an hour of the maximal traffic volumes (M), and the *Peak Hour Interval* (PHI) is defined between the moment when the number of cars on the network exceeds the value of $M/2$ and until it declines back again to $M/2$ (Rollo & Schulz, 1970). Based on the full scenario, morning PHI was set to [06:30, 11:00], and evening PHI to [17:00, 19:45] (Figure 6.3). The period between the morning and evening peaks (11:00-17:00) was considered an off-peak period. I did not include night traffic after 19:45 and before 5:00 in the analysis.

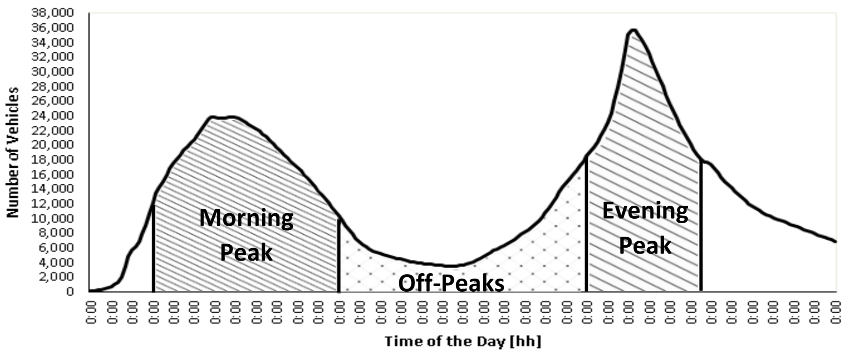

Figure 6.3. Traffic volumes per hour, and morning and evening Peak Hour Intervals

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6.7 the similarity between downscaled and full-scale runs

In what follows, I denote output statistic *c* obtained in a *k*-downscaled run *i*, as c_i^k, and its average, standard deviation, and coefficient of variation as m_c^k, s_c^k and CV_c^k, respectively. The baseline for comparison between the full-scale and downscaled simulation runs was a set of output statistics averaged over 10 repetitions of the full-scale model: average m_c^1, standard deviations s_c^1 and coefficients of variation CV_c^1.

To compare the downscaled and full-scaled runs, I estimated the relative bias b_i^k between the statistic c_i^k of the downscaled run I and the full-scale run average m_c^1:

$$b_i^k = \frac{c_i^k - m_c^1}{m_c^1} \qquad (9)$$

Below, I present the relative bias averaged over 10 repetitions of the downscaled scenario - m_b^k and its standard deviation -s_b^k. I consider the dependence of a certain statistic on *k,* varying *k* between *k* = 1 to *k* = 0.01 (in decreasing direction). Output statistic is therefore regarded as robust to *k*-downscaling if its average relative bias m_b^k is close to 0 and, to account for the decrease in population size, its STD s_b^k is close to $CV_c^1/\sqrt{k}$.

6.7.1. Excluding outlier simulation runs

How certain can I be that, given *k*, the statistics of two downscaled simulation runs will be similar? Intuitively, in different runs, when *different samples represent k < 1, the population of agent*s. These agents follow their specific plans; thus, the model could converge each time to a different UE. Even for *k* = 1, despite converging to the same UE (Figure 5.1), similar average scores can represent different distributions of population scores and could entail differences in other statistics as well.

To understand whether different simulation runs converged to the same UE and that the average and STD that characterize the distribution of the output statistics were reliable, I searched for possible outliers by analyzing the distribution of the average scores in a UE state for each *k* separately. I classified a run as an outlier if the average score in the UE state was beyond Tukey's fences (Tukey, 1977) constructed based on all 10 runs for a given *k*:

$$[Q_1 - w(Q_3 - Q_1), Q_3 + w(Q_3 - Q_1)] \qquad (10)$$

where w = 2.5, and Q_1 and Q_3 are the 25th and 75th percentiles, respectively.

Note that for the normal distribution of scores, the probability of obtaining a score outside Tukey's fences with w = 2.5 is less than $5*10^{-5}$.

`

There were no outliers within the runs for *k* = 1, while 3 out of 100 simulation runs with *k* < 1 had converged to UE with average scores at the border or beyond Tukey's fences with w = 2.5: One for *k* = 0.5 (w = -2.48); one for *k* = 0.4 (w = -3. 21); and one for *k* = 0.05 (w = 2.84). Some of the statistics for these three runs were also beyond Tukey's fence with w = 2.5. These runs were naturally excluded from the analysis and were substituted by an additional run for the same value of k. After excluding the outliers, the STD of the relative bias for all statistics was $CV_c^1/\sqrt{k}$ or lower.

6.8 Analysis of the MATSIM downscaling approach

6.8.1. Statistics of the downscaled vs the full-scaled model

The values of m_c^1, s_c^1 and CV_c^1 for the selected statistics in the full-scale runs are presented in Table 6.3. One can observe that the values of CV_c^1 never exceed 5% and remain below 2.5% for most of the statistics.

Table 6.3. The average, STD, and CV of output statistics for the fullscaled (*k* = 1) SF simulation were estimated based on 10 repetitions with different global seeds.

Output Statistic	Average	STD	CV
Executed Scores	18.82	0.04	0.19%
Travel Distance (km)	5.22	0.0037	0.07%
Trip duration (mm:ss), Morning Peak (06:30 – 11:00)	52:33	02:23	4.54%
Trip duration (mm:ss), Evening Peak (17:00 – 19:45)	57:58	00:46	1.31%
Trip duration (mm:ss), Daily Off-Peak (11:00 – 17:00)	35:39	00:47	2.20%
Hourly Departures, Morning Peak (06:30 – 11:00)	20,680	114	0.55%
Hourly Departures, Evening Peak (17:00 – 19:45)	30,055	91	0.30%
Hourly Departures, Daily Off-Peaks (11:00 – 17:00)	20,480	60	0.29%
5-minute traffic volumes, Morning Peak (06:30 – 11:00)	18,591	891	4.79%
5-minute traffic volumes, Evening Peak (17:00 – 19:45)	26,122	332	1.27%
5-minute traffic volumes, Day Off-Peak (11:00 – 17:00)	7,145	154	2.15%

The output statistics of the full-scale runs, by hours of the day and by links, are presented in Figures 6.4 and 6.5. Figure 6.4 presents the mean and STD of the hourly number of departures and traffic volumes and the CV of these statistics, which remained below 10%.

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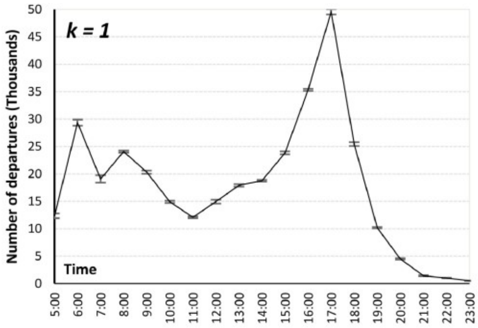
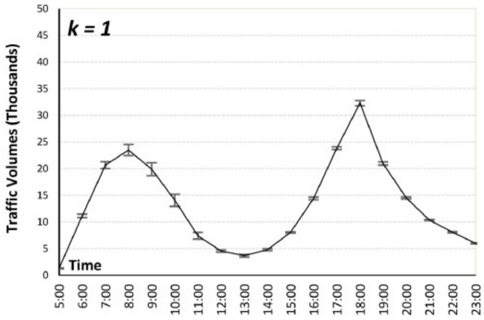
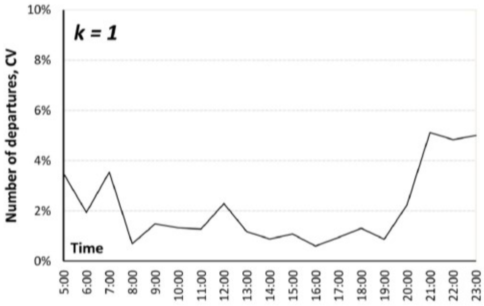


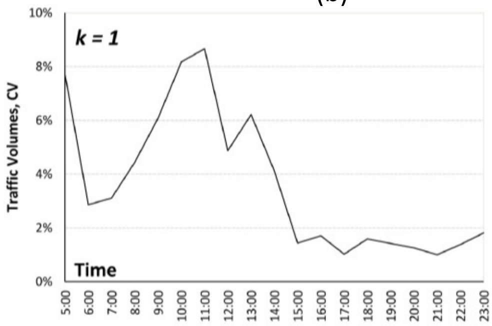
(a)



(b)



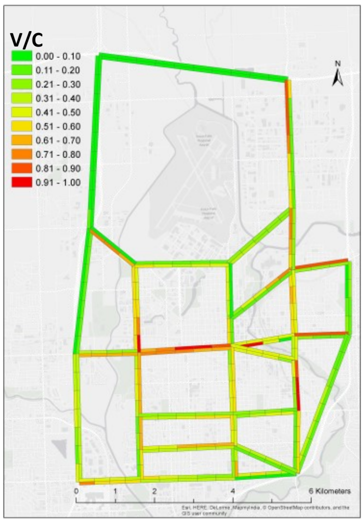
(c)

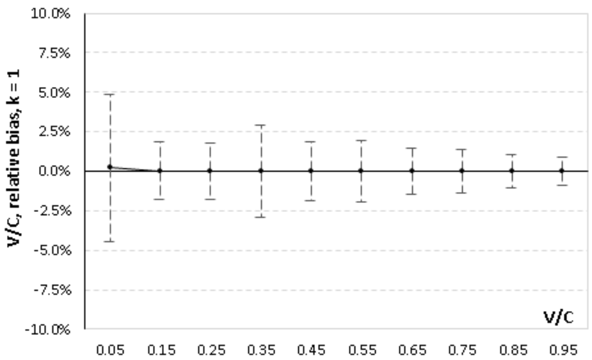


(d)

Figure 6.4. (a) mean and STD (error bars) a number of departures; (b) mean and STD (error bars) of 5-minute traffic volumes; (c) CV of the number of departures; (d) CV of traffic volumes.

The spatial patterns of traffic congestion were evaluated using the volume-to-capacity ratio (V/C), where $V/C \geq 1$ indicates extreme levels of congestion and the existence of bottlenecks (Highway Capacity Manual, 2016). Figure 6.5 presents a map of the average hourly value of V/C during the morning peak, 6:30 – 11:00, and relative bias b_i^1 that remains below 2% for all most levels of V/C. This variation of V/C is similar to that reported by (Paulsen et al., 2018) for Santiago, Chile.





(a) (b)

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Figure 6.5. V/C patterns by road links for k = 1: (a) Average V/C; (b) Average and STD (error bars) of relative bias of the V/C by links

6.8.2. Results of downscaled models aggregate vs disaggregate statistics.

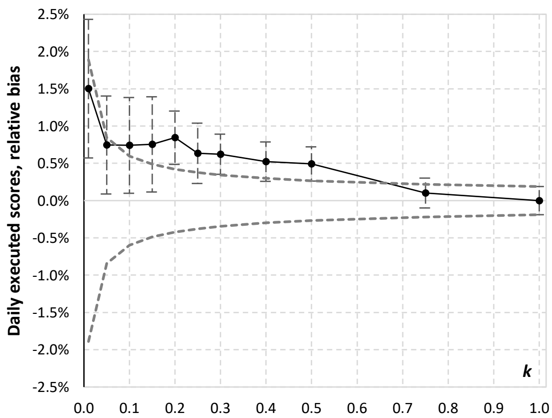
The effects of downscaling on the statistics of different outputs vary. Some of the statistics for k = 1 are closely repeated in every downscaled runs down, even at very low values of k, whereas some needed to be averaged to be closer to the statistics of the full-scaled models, while some deviated even for relatively high values of k. I present the results first for aggregate statistics, followed by disaggregate ones.

Aggregate Statistics

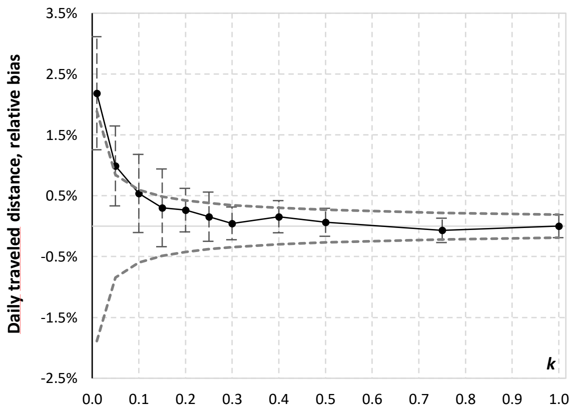
First, I present the results for three non-scalable statistics (executed scores, travel distance and trip duration) followed by two scalable statistics (car departures and traffic volumes).

Non-scalable statistics

Figure 6.6 shows two non-scalable statistics for which the relative bias remained below 1% even for low values of k. One is the average daily executed scores, and the other is the daily traveled distance. The relative bias of both statistics was systematically positive but very low, and remained below 1% up to k = 0.05. The STD of the bias remained below $CV_c^1/\sqrt{k}$. I thus can assert that a few downscaled runs (aimed at ruling out the existence of outliers), are sufficient for obtaining reliable estimates of these statistics, possibly with a slightly positive bias.



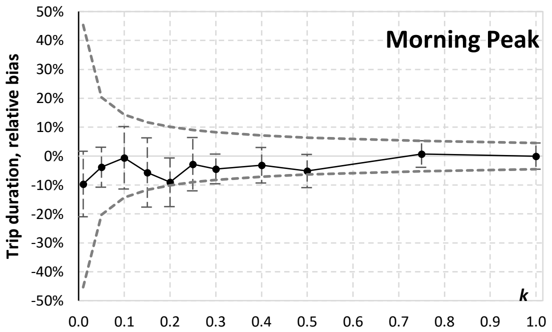
(a)



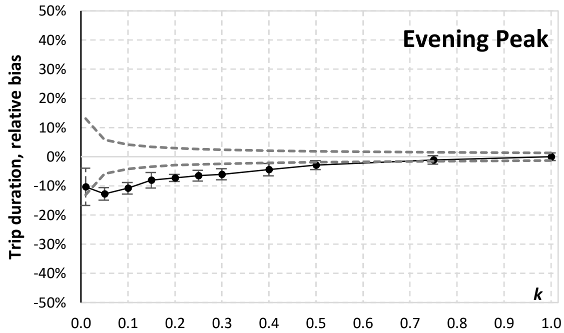
(b)

Figure 6.6. The dependency of the average relative bias m_b^k and its standard deviation s_b^k (error bars) on the downscaling fraction k for (a) the average daily executed scores and (b) the traveled distance. Dashed continuous lines denote $\pm CV_c^1/\sqrt{k}$ boundaries.

In contrast, the hourly average trip duration was more biased than the previous two statistics, and its dependence on k changed by day periods (Figure 6.7). To simplify, I averaged the results over the morning, evening, and off-peak hours. For each of these three periods, the relative bias and its STD were low up to k ~ 0.30-0.25, but below these values, the relative bias steadily decreased for the evening peak, steadily increased for the off-peak period, and kept fluctuating for the morning peak. Applying a t-test, for each $k < 0.4$, the bias for the evening peak and the off-peak periods significantly and systematically deviated from zero ($p < 0.01$). In order for the bias of the average trip duration to remain within the safe boundary for all hours of the day, the value of k must exceed 0.20. Note that for $k \leq 0.20$, the STD of the average trip duration for the morning peak and off-peak periods was at least 5%, and the statistics of one downscaled run, even if not identified as an outlier, can deviate from the full-scale statistics by 20% or more. Averaging over 10 repetitions reduced this bias to ~10% (Figure 6.7).

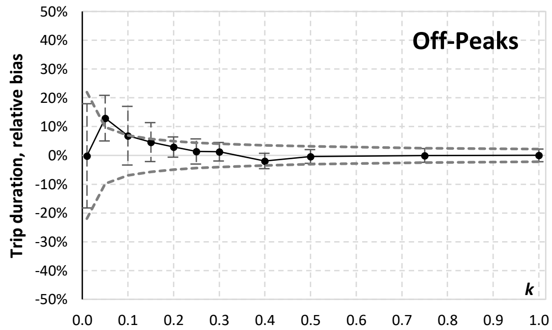


(a)



(b)

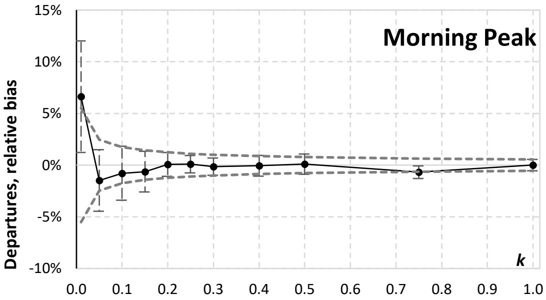
Figure 6.7. The average relative bias and its STD (error bars) for the average trip duration for (a) Morning peak; (b) Evening peak (c) Off-peaks period. Dashed continuous lines denote $\pm CV_c^1/\sqrt{k}$ boundaries



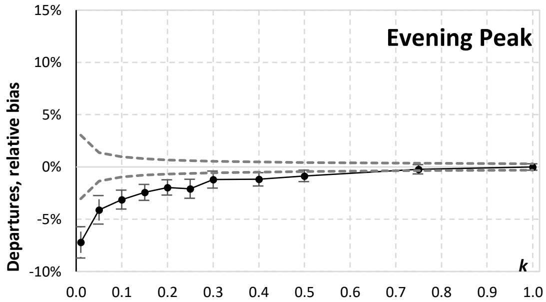
(c)

Scalable Statistics

Figure 6.8 presents the average relative bias and its STD for the number of daily car departures. As observed, the average bias remained below 5% for all tested k. The STD proportionally increased with the decrease of k for the morning peak period but remained below 5% up to $k = 0.1$. For the evening and off-peak periods, STD remained low for all k. I thus conclude that, as above, a few downscaled runs, necessary to rule out the existence of outliers, are sufficient for obtaining reliable estimates. The estimates' bias is close to 0 for the morning peak period; negative but low for the evening peak, and positive but low for the off-peak hours.



(a)



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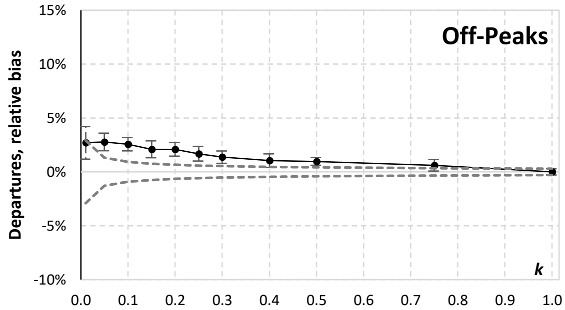
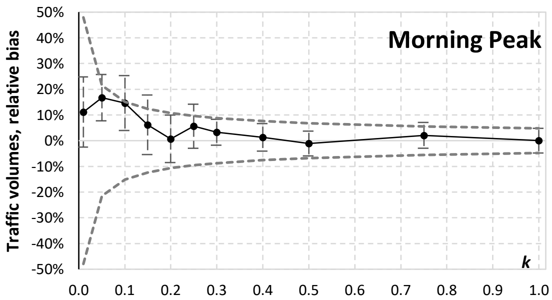


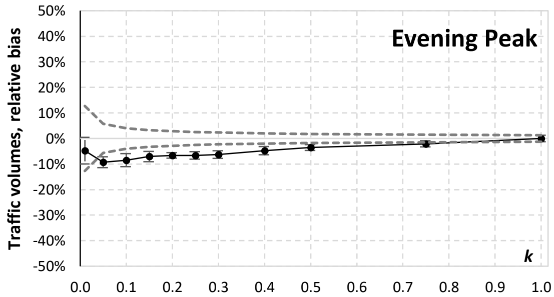
(c)

Figure 6.8. Average relative bias and STD (error bars) of the number of daily car departures - (a) Morning peak; (b) Evening peak (c) Off-peaks period. Dashed continuous lines denote $\pm CV_c^1/\sqrt{k}$ boundaries.

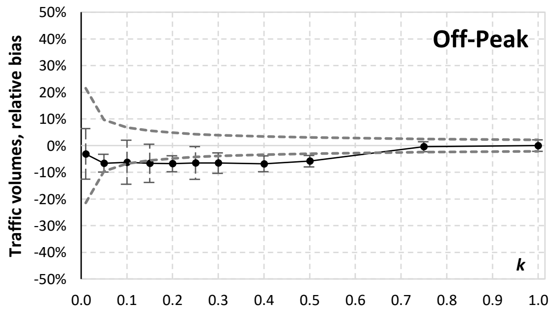
Figure 6.9 shows the average relative bias and its STD for –the average traffic volumes. The average bias for these statistics was higher than for the number of daily departures, varied for the morning peak hours. It systematically negatively increased with the decrease in k for the evening and off-peak hours. The bias STD was very low for the evening peak hours, while starting from *k* = 0.20, reaching 10% for the morning peak hours. Overall, I conclude that both scalable statistics are properly represented for *k* > 0.2.



(a)



(b)



(c)

Figure 6.9. Average relative bias and STD (error bars) of the traffic volume for (a) Morning peak, (b) Evening Peak and (c) off-peak hours. Dashed continuous lines denote $\pm CV_c^1/\sqrt{k}$ boundaries

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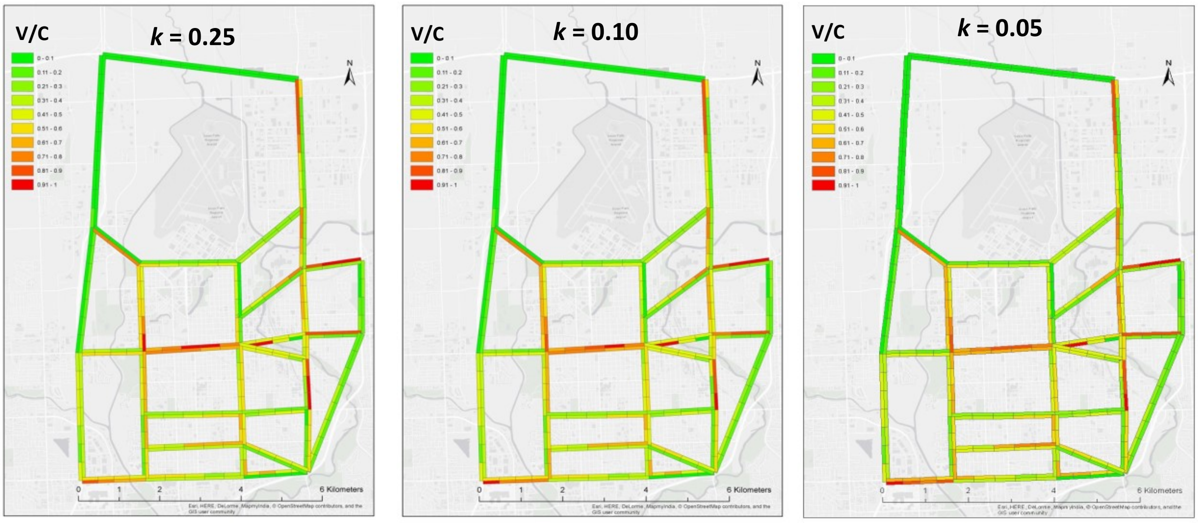
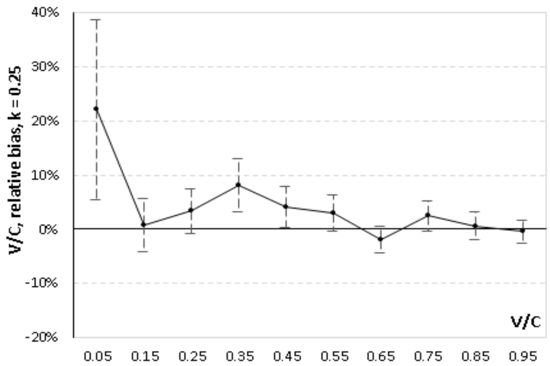
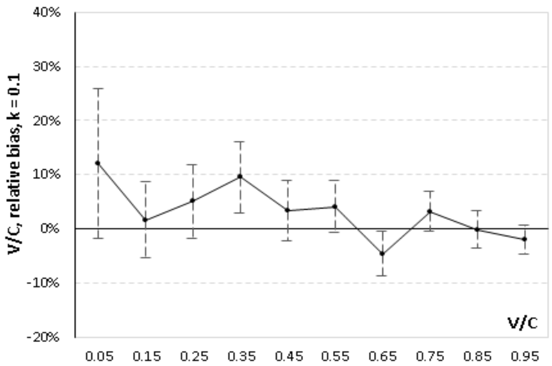
Disaggregate statistics

The only disaggregate (and non-scalable) statistic I consider is the volume-to-capacity ratio (V/C). Figure 6.10 presents maps - for three specific values of *k* - 0.25, 0.1, and 0.05 - of the average hourly V/C during the morning peak (06:30-11:00). All appear visually similar to the map of *k* = 1 (Figure 6.5), including the average relative bias (by links) as dependent on the V/C value for each link.



(a) (b) (c)





(d) (e)

Figure 6.10. Average hourly V/C during the morning peak for (a) *k* = 0.25; (b) *k* = 0.1; (c) *k* = 0.05 and the average relative bias of V/C (by link) and STD (error bars) in downscaled scenarios, for *k* = 0.25 (d) *k* = 0.1 (e), *k* = 0.05 (f)

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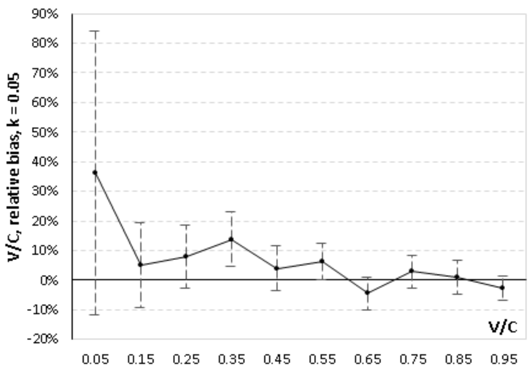
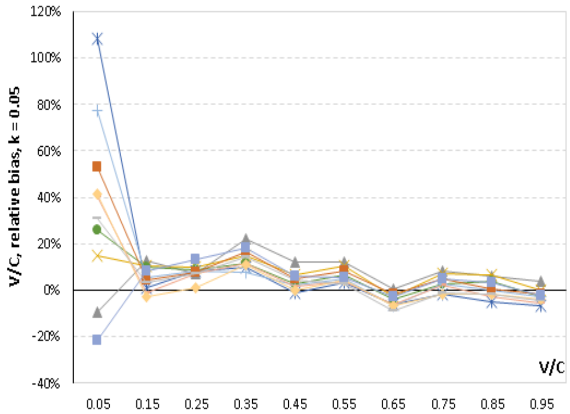


(f)

A quantitative comparison (Figure 6.10 d-f) suggests that the downscaled scenarios properly reflect the link values of V/C for V/C > 0.1. The STD of the relative bias of V/C remained for these links at around 5% and below while reaching ~15% for links with V/C ≤ 0.1. The latter represents links with very low volumes. As can be seen, the STD of the relative bias decreased with the increase of V/C, i.e., proper recognition of the congested links demands fewer repetitions of the downscaled simulations compared to the estimates of flows where the link is very low.

Figure 6.11 presents traffic flows as dependent on V/C for each of 10 simulation runs performed for *k* = 0.05 with different downscaling random seeds. As can be seen, the value of the traffic flow for the road links with V/C ≥ 0.15 is very similar in all runs. This synchronization terminates for V/C = 0.05.

Figure 6.11. The relative bias of V/C for each of 10 repetitions of the downscaled scenario *k* = 0.05



6.8.3. Results of downscaled models aggregate vs disaggregate statistics.

I estimated the model runtime as dependent on *k*, with the parallel version of QSim (Dobler, 2010) and one simulation run for each value of *k*. All simulations were performed on the same workstation with 7820x Intel® Core™ X-series Processor, 8 physical and 16 logical cores, and the CPU was manually overclocked to 4.5ghz. The workstation had 32GB of Corsair® RAM, overclocked to 3000mhz.

The simulation parameters (besides the value of *k*) remained the same in all simulations. In my experiments, I tested that the runs' time, which differs in the random seeds only, was the same and, thus, each simulation was run only once for each number of cores and *k.*

The lion's share - 76% - 92% - of the runtime in each iteration was taken by the QSIM mobility module. The next processes were scoring, iteration startup, plan innovations, and disk writing. The dependency of the runtime per iteration on *k*, for a different number of cores is presented in Figure 6.12. The performance was similar for the number of cores between 2 and 11; in all these cases, the performance was higher than in the 1 and 12 cores.

`

The estimates fluctuated for k < 10%, while for higher k fractions, the performance with 2-11 cores was 15-20% higher than with 1 or 12 cores. This phenomenon was initially mentioned by (Dobler, 2010), who assumed that the lack of improvements might be related to the growing synchronization time.

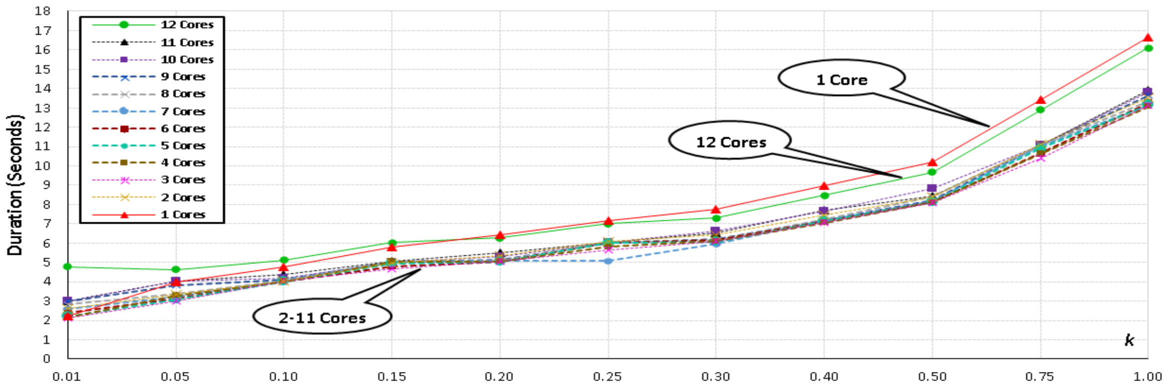


Figure 6.12. Average daily iteration runtime as dependent on *k*, for different numbers of cores.

It is worth noting that the decline in the performance with the increase in k is quite low. For example, in the case of 2-11 cores, the computation time improvements, per iteration time for k = 1 is, roughly three times longer than for k = 0.1. Even for an output statistic with a low variance, e.g., averaged daily scores or traveled distance, one could achieve better estimates by running simulations with the highest possible k compared to repeating runs with lower k several times. Evidently, if the full-scale simulation is too heavy for the available hardware and running the same downscaled simulation several times is the only possible solution to contend with this limitation, the overall run time may well exceed that of the full-scale one. Naturally, a stronger machine could well be a better solution, though.

6.9. Discussion

With the standard hardware of the year 2023, the number of agent-travelers that can be practically managed in a large-scale MATSim scenario lies between 200K and 500K. With this number of agents, depending on the computer memory and other hardware components, a single model run will take a few hours. The number of travelers in a typical metropolitan region is often higher, and practically MATSim cannot manage full-scale metropolitan simulations. How can modelers be certain that randomly selected fractions - say 10% of the travelers - generate the dynamics that correctly replicate a full-scale simulation?

The One-Represents-Several (ORS) downscaling concept, as implemented in MATSim, is simple and effective. My major conclusion is that downscaling up to the level of 20% is always qualitatively safe. This result is based on the quantitative robustness of the congestion patterns generated in the model's downscaled version, i.e., the level of congestion over the links, as reflected by the V/C ratio remained constant on all links with V/C > 0.1 up to the values of k = 0.05. This local robustness entails sufficient stability of the other output statistics that I investigated. Their average bias for the values of k between 1 down to 0.20-0.25 always remained below 10%. Downscaling to 10-15%, commonly applied in MATSim, can result in a larger but still acceptable bias. Downscaling below 10% can be risky. These results are in good agreement with the literature. I thus assert that downscaled runs should be repeated as many times as necessary to recognize possible outliers and reduce the variance of the relevant statistic averaged over the downscaled runs to the level expected for the full-scale model. The more repetitions of a downscaled scenario are performed, the lower the variance of the parameters' estimates, but, practically, 10 repetitions are enough. My estimates provide a benchmark for modelers in planning the number of experiments.

Studying MATSim's parallel version performance by repeating the same simulation with the number of cores varying between 1 and 12, similar to (Dobler, 2010), I have demonstrated that several processors accelerate calculations, but only by 15-20%. Moreover, the performance of the parallel version of MATSim with 12 cores was, again, lower than with 2-11 cores and similar to the model performance with 1 core.

Several issues demand further investigation, including the trustworthiness of downscaled results transferred from one network to another. Here, no clear answer exists. A downscaled study that is based on one network is evidently insufficient for far-reaching conclusions. The topology of the street network and demand patterns may likely also affect the performance of downscaling. In this respect, it is important to note that the average number of agents traversing a network link daily in the full-scale SF simulation is about 500. This value is quite similar to the reviewed simulation studies presented in Table 6.1 - varying between 100 and 1,000. I thus assert that in this respect, the SF car traffic patterns are roughly similar to the rest of the scenarios simulated with MATSim.

The current study's limitations are that all calculations were considered with only one transportation mode, i.e., cars. As explained MATSim capacity adjustments (3) – (4) are insufficient in mixed traffic simulations, where cars and PT interact on the same road space. Future studies should also stress downscaling with other Agent-based transportation models. Especially with the inclusion of SAV, where even more computational power will be needed for the SAV dispatching algorithms, downscaled simulations will likely become necessary. Out-of-the-box downscaling with SAV may not work as the number of SAV vehicles must be reduced proportionally to equations (3) – (4) alongside the population. This could raise new questions, such as how the SAV passenger occupancy in an ORS-downscaled scenario could be reflected in the full-scale one.

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CHAPTER 7 - Study 2: Road traffic and mode choice sensitivities to congestion and parking charges

The second study of the thesis focuses on the mesoscopic simulation of mitigating traffic congestion through road and parking pricing. The chapter starts with a background, establishes the tested scenario (JMT), and concludes with the results.

7.1 Background

7.1.1. Mitigating congestion as the major goal of transport Agent-Based Modeling for policymaking

Historically, Transportation Demand Management (TDM) policies have attempted to mitigate traffic congestion by discouraging car travel (Shiftan & Golani 2005). TDM policy can be hard and soft. Hard policies are based on negative economic incentives, such as congestion charges or pricing parking (Vickrey, 1969; Rouwendal & Verhoef, 2006; Shoup, 2006). The hard policy implementations in Singapore, Stockholm, and London (see an overview in Section 3.3.1) indicate that they must be sufficiently strong to be effective (May et al., 2010; Timms, 2013), while avoiding political and social controversiality (Eriksson et al., 2006; Viegas, 2001). Soft policies enforce positive incentives to prefer public transportation over private car (Bamberg & Schmidt, 2003). However, these policies mainly lead to temporal car-use shifts (e.g., driving at off-peak times), have high opportunity costs, and subsidize drivers unfairly (Ben-Elia & Ettema, 2011; Tillema et al., 2013).

The provision of travel information via Advanced Traveler Information Systems (Hegyi et al., 2005) and real-time navigation mobile apps (Mokhtarian & Tal, 2013) has become increasingly popular (Davies, 2012; Chorus et al., 2006). This information gives individuals an illusionary sense of control over ambiguous conditions (Kemel & Paraschiv, 2013), even when its reliability is limited (Ben-Elia et al., 2008, 2013; Ben-Elia & Shiftan, 2010). The attempts to encourage car drivers to use PT by providing relevant information have failed mainly since car drivers mostly ignore PT information (Farag & Lyons, 2012).

Due to soft policies' ephemeral nature, hard policy measures, like congestion charges, remain viable and popular instruments amongst policymakers to deal effectively with traffic congestion (Baghestani et al., 2020; Gu et al., 2018; Small & Yan, 2001; Van Den Berg & Verhoef, 2011; Yang & Huang, 2004). Suggested as a type of market failure correction tax (Pigou, 1920;, Salant & Seegert, 2018), congestion pricing is mostly fixed/time-based distance tolls for driving particular roads or cordon pricing, which implies applying fees for drivers crossing an imaginary boundary of a specific area (Abu Libdeh, 2017).

Notwithstanding, the impact of congestion charges on individual travel behavior and consequently on the collective system dynamics and network performance, as well as their coevolution, remains insufficiently addressed in the literature.

Another hard congestion management policy measure is parking pricing. Drivers cruising for parking in demanded areas constitute a significant traffic congestion generator. Hampshire and Shoup (2018) consider that 15% of the traffic flow were car drivers cruising for parking, while Dowling et al. (2020) assert that cruising drivers can comprise up to 50% of the traffic. Cruising for parking also contributes to fuel waste and increased air pollution. At the same time, parking lot construction has high facility costs, negative impacts on urban environments, and opportunity costs due to the loss of real-estate development potential (Geva et al., 2022). Pricing of curbside parking can reduce the demand for parking very effectively (Vickrey, 1954; Shoup, 2006). This assertion has been verified in various economic models (Arnott & Inci, 2006; Anderson & de Palma, 2004; Inci & Lindsey, 2015; Inci, 2015). The critical issue is to keep parking prices high enough to deter excessive cruising but not too high to affect economic activity negatively. Several cities have initiated parking pricing programs to maintain average occupancy rates (Pierce & Shoup, 2013).

To date, neither congestion charging nor pricing parking policies have comprehensively addressed the underlying issue of demand management. Modeling the combined impacts of congestion charges and parking prices on traffic and travel behavior can provide policymakers more freedom to plan and fine-tune demand management policies (Kaddoura et al., 2020a). A major drawback of this delay was the lack of proper evaluation tools that can capture the co-evolution of drivers' behavior and the consequent system dynamics. I apply for this purpose the MATSim ABM, which can simulate travelers' behavioral responses to changing traffic conditions brought about by implementing various policy instruments.

7.1.1.1 Congestion charge schemes

Many cities considered congestion pricing, yet only five have successfully implemented it operationally: Singapore, London, Stockholm, Milan, and Gothenburg. The rest failed due to solid public opposition (Gu et al., 2018). These cities applied a cordon scheme that charges car drivers either inbound (Milan, Gothenburg) or both inbound and outbound (Singapore, Stockholm), except for the travel within the bounded area whenever they pass the border of the charged zone. London is an exception, as there is also a Zonal charge for traveling inside the boundaries of a charged zone (AbuLibdeh, 2017). Singapore was the first to apply congestion charges in 1975 to alleviate the congestion of the central business district (≈17 km^2) during morning peak hours (Phang & Toh, 2004). Its Area Licensing Scheme (ALS) The ALS was a cordon-based scheme with a time-dependent charge applied between 7:30 – 9:30 with a charge of SGD 3.00, about €1.3 back in 1975 when the average monthly income was

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around 400€ (Rao and Bhanoji, 1980) and growing since then to €4500 (Singapore Ministry of Manpower, 2023). the ALS charge reduced congestion by 44% until it was discontinued in 1997 (Phang & Toh, 1997). In 1998, the ALS was replaced by Electronic Road Pricing (ERP)—a fully automatic system based on The ERP scheme is a fully automated system detecting in-vehicle electronic smart cards. The ERP reduced overall trips by 15% (Santos, 2005). The charges vary from 0 to about 5€ by the time of day, vehicle types, and location of control points on specific highways; the ERP system works weekdays from 7:00 am to 7 pm.

London's Central Charge (LCC) was introduced in 2003, initially set at [put in in pounds], or 5.75€ that time, for entering the charge zone, which area is 21km^2. Nowadays, the fee for visitors is 17.7€ (each time they enter the zone), compared to Londoners' average monthly income of 5,250€ (GLA 2022), and zone residents pay 10% of it only. As of today, car entries to the charge zone decreased by 33% from 2003 to 2008. The two overall significant congestion charge goals are to lower congestion and increase PT usage; the revenues from the LCC were put back into London's PT system infrastructure (Santos & Shaffer, 2004; Leape, 2006). Recent Ride-hailing services in London, which are exempted from charge, brought an increase in congestion and lower speeds compared to when there were no ride-hailing services (Lehe, 2019; Tang, 2021).

In Milan, a general congestion charge was introduced in 2012, costing 5€ per day for entering the city center, 8km^2, between 7.30 AM and 7.30 PM. City center residents were exempted from the first 40 entries per year into the zone when the congestion charge was first initiated, but today they pay a reduced fee of 2€ per entry (European Union, 2013). The average monthly income in Milan is around 4,220€ (Duvnjak, 2018).

In Stockholm, a cordon-based toll around the central city (30 km^2), established in 2007, reduced traffic by 22% in 2008 (Eliasson et al., 2009). Half of the trips shifted to PT, and traffic remained at the level of 2008 until 2011 (Börjesson et al., 2012). The congestion charge in Stockholm is set on weekdays during the daytime. The cost of passing is € 2 during peak hours (7:30–8:30, 16:00–17:30). The charge is imposed in both directions; thus, a return trip during peak hours costs € 4. The maximum total amount per day is € 6. The average monthly income in Stockholm is around 4,690€ (Stockholm Salary Explorer,2022). Motorcycles/disabled users/emergency vehicles driving to the city center region are exempted, as are all weekend drivers (Börjesson et al., 2012).

In Gothenburg, the second-largest city in Sweden, a cordon toll was introduced in 2013, varying between 9 SEK (~1€) to a total daily of 60 SEK (~6€); the charge varies during peak hours 07:00-08:00 and 15:00-17:00) for a max amount of 22 SEK (~21€) during those periods (Börjesson et al., 2012). The charge reduced car traffic in the area by 12% the year after being introduced, with most car users switching to PT (Börjesson and Kristoffersson, 2015).
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Unlike other cities, revenues were entirely devoted to new road construction, not PT (Borjesson et al., 2015), which seems counter-effective in the long run. The monthly income in Gothenburg is around 4,310€ (Gothenburg Salary explorer, 2022).

Table 7.1 describes the implemented congestion charge schemes, their effects, and the parking prices in the congestion charge area.

Table 7.1. Congestion Pricing Schemes and Impact

Characteristic	Singapore	London	Stockholm	Milan	Gothenburg
Year Introduced	1975	2003	2007	2012	2013
Charged Zone	18 km^2	21 km^2	30 km^2	8 km^2	13 km^2
Hours of the day, weekdays	07:00-19:00	07:00-18:00	06:30-18:30	07:30-19:30	06:00-18:30
Charge rate and type	5€ Cordon + highways	17.7€ Cordon	3€-12€ Cordon	≈5€ Cordon	1€-6€ Cordon + highways
Who pays in full	Non-residents	Non-residents	Non-residents	Non-residents	Non-residents
City residents monthly income	€4,500	5,234€	4,220€	4,687€	4,306€
Entry trips reduction (%), (year of the report)	15%(2005)	33%(2008)	22%(2012)	33%(2018)	12%(2015)
Other effects	Increased traffic speed 18-22 → 24-28 MPH, 15% higher PT ridership	30% decrease in PT delays, 38% increase in PT ridership	30-50% decrease in PT delays, 4-5% increase in PT use	4% increase in traffic speed	Minor travel time savings

7.1.1.2. Priced Parking Schemes

Parking fees are another transport-related Pigouvian tax (IHT, 2005) that can effectively reduce transportation demand and arrivals to a congested area (Shoup, 2006; Fulman & Benenson, 2021). Different pricing schemes can be applied: fixed fees, dynamic fees by time of day, hourly prices, and, recently, demand-responsive ones. Parking prices can influence car arrivals in the short run, including drivers' shifts to other modes (Litman, 2016), and in the long run, parking pricing can reduce private car ownership, reinforcing the use of PT. As the parking pricing mechanism is commonly implemented by local government, it has several advantages, including ease of implementation and low management cost, given that municipalities are already well-rehearsed in collecting fees. In addition, it's possible to have specific pricing policies by location (e.g., neighborhoods) or by customer profile (e.g., disability discount) (Glazer & Niskanen, 1992). Nowadays, parking fee administration and collection can be managed digitally via mobile apps (Lin et al., 2017). Parking fee revenues often go to the local municipality budget. At the same time, congestion charges have vague beneficiaries (such as a public-private franchise), and understanding where the revenues end up is more complicated (Calthrop et al., 2000).

In Singapore, a parking coupon was introduced in 1980, noting drivers' time and duration of parking. In 2000 electronic parking was introduced. During rush hours, the hourly rate is 2.20€/h between 07:00-17:00 in central Singapore and is capped at 19€ for the whole day (History of parking Singapore, GOVTECH Singapore, 2021). The UK Road Traffic Act 1991 decriminalized parking enforcement, allowing councils to apply for the power to enforce some of the restrictions themselves – and to encourage them to do so, keeping the revenue. London's hourly on-street parking policy is 7.72€/h for petrol or diesel cars and 5.60€/h for electric or hybrid vehicles. For permit-holding residents, there are dedicated lots with varying weekly prices of 5€-59€, depending on the area. (On-street Parking, the City of London, 2022). Milan's parking rate is 2€/h for the first two hours, 3€/h for any additional hour between 08:00-19:00, and 2€/h for any extra hour between 19:00-24:00. Parking for residents on the yellow curbside roads is free in Milano (Croci, 2016). In Stockholm, on-street parking costs between 9€/h and 12€/h on weekdays with a daily fee of around 38€ (Stockholm parking, 2022). In Guttenberg, permit-holding residents do not pay, while non-residents pay €4.80/h for the first two hours, an extra €0.80 per hour afterward, and a fixed €44 per day (Parking permits, City of Guttenberg, 2020).

7.1.2. Modeling the effects of congestion charges and priced parking

7.1.2.1. Modeling Congestion charges

Models often accompany the study of congestion charge impacts. Initially, these were analytical economic models based on the rational traveler's normative behavior (Vickrey, 1969, Arnott et al., 1993; Ben-Akiva et al., 1986, Arnott et al., 1993, Anderson and De Palma et al., 2004). However, for practical applications and policy assessment, models should consider drivers' travel behavior as dependent on the local spatial and temporal circumstances. GIS databases allow for an explicit representation of the spatially heterogeneous transportation infrastructure, thus establishing the background for spatially explicit ABM.

Zheng et al. (2012) investigated dynamic cordon congestion pricing in Zurich using MATSim. They demonstrated that travel time savings outweigh charging costs. The charges eased traffic congestion inside the cordon area, and no extra congestion was generated outside the cordon. Agarwal and Kickhöfer (2015) investigated with MATSim the impact of a dynamic congestion charge in Munich, applying the scheme of charging proportionally to the

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accumulated traveled distance instead of crossing the cordon. They found that a congestion price of 38 cents/km introduced at peak hours reduced the average car trip time by 8 minutes. Kaddoura & Nagel (2019) applied MATSim to establish a dynamic congestion charge in Berlin by adjusting toll levels to the congestion level. However, even with a dynamically optimal congestion charge, only a small share of trips was switched from car to bicycle (5%) and PT (3%). The optimal charge presented in the paper computes delays because of an agent based on the queuing dynamics at the bottleneck link. A toll depends on the agent's position in the queue link, the number of following travelers (in the same queue), and their Vehicle travel time savings. He et al. (2021) tested a congestion charge policy in NYC using MATSim and found that a 14$ cordon pricing reduced car arrivals to the center by 127K (the share of the changes was not reported). Overall, spatially explicit ABM reproduced quantitative realistic spatially explicit effects of the congestion charges in every city in the models implemented.

7.1.2.2. Moedling priced parking

Various modeling approaches have been applied to investigate the effects of parking price on cruising time (Brooke et al., 2014). Polak and Vythoulkas (2014) identify (1) Discrete choice models, where parking prices and availability are treated as factors that affect individual travel choices based on revealed or stated preference surveys; (2) Parking as one of the components of general traffic models, including explicit simulation of cruising for parking in traffic ABM. In this review, I limit myself to the ABMs of parking, that is, to the high-resolution models that simulate cruising for parking in the heterogeneous urban environment.

One of the first models of this kind was PARKIT (Waterson et al., 2001), where a traffic simulator was used to study parking search behavior. Coppola (2002) studied the interaction between parking supply and demand on parking choice by categorizing parking places by type and location using a hierarchical logit model. Bonsall and Palmer (2004) exploited PARKIT to study drivers' parking, route choice, access, and egress time. Chou et al. (2008) investigated parking demands using an intelligent agent-based system that optimized parking selection for each driver and provided a route to a chosen parking facility. Benenson et al. (2008) developed the PARKAGENT ABM model of driver parking behavior in a spatially explicit environment and exploited real-life parking scenarios. To establish optimal parking prices in urban parking spaces of the inherently heterogeneous demand and supply, Levy and Benenson (2015) suggested a PARKFIT algorithm. This algorithm was recently extended to include an arbitrary regime of car arrivals and departures and verified with the spatially explicit ABM of parking search (Fulman and Benenson, 2020). Bischoff & Nagel (2017) incorporated parking search into the MATSim agent-based traffic simulation environment

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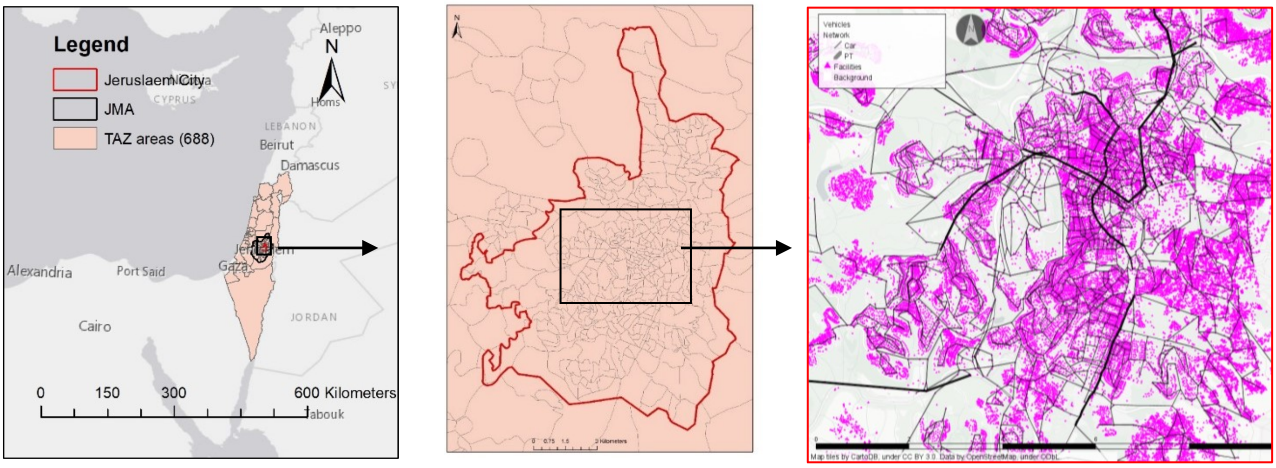
that I will employ in this research yet ignoring possible pricing effects. Similarly, Gu et al. (2021) developed a microscopic parking simulation model and used it to calibrate and validate a macroscopic traffic model.

The models above did not investigate the combined effects of the two major policy alternatives—parking prices and congestion charges—for reducing car arrivals in congested areas. I investigate this combination using MATSim, in a case study of Jerusalem which also includes a city-wide DRT introduction.

7.2 Jerusalem scenario data

In this study, I focus on the MATSim Jerusalem scenario (JMATSim) which was calibrated and validated based on data on infrastructure, traveling population, and activities as of 2017-2020, supplied by the Jerusalem Transportation Master Plan Team (JTMPT). The layer of roads contains the data on links' capacities, while the layer of buildings/facilities the data on the land use and construction height (Figure 7.1). Agents' daily activities are constructed based on the travel behavior survey at the resolution of 688 Traffic Analysis Zones (TAZ) in Jerusalem, provided by the JTMPT.



(a) (b) (c)

Figure 7.1. (a) Jerusalem Metropolitan Area (JMA); (b) Zoom to TAZ coverage within the Jerusalem city boundaries, and (c) JMA building layer + Network + PT lines

Jerusalem roads are represented in the JMATSim by 9K links. The JMA PT network is represented by 336 transit lines, with 2,637 stops, and 15,145 daily bus departures.

7.2.1 Establishing daily travel plans for Jerusalem agents

The JMATSim traveler population consists of internal travelers whose origin (O) and destination (D) are within the JMA, and external travelers whose origin or destination is outside the JMA. Initially, agents' origin and destination are established at the resolution of

TAZ, both inside and outside the JMA area. Then, these data were disaggregated from the resolution of TAZ to buildings.

Disaggregation of the population and OD data: The origins of households residing in each TAZ were distributed among residential buildings in this TAZ in proportion to the buildings' floor area, estimated based on the building's foundation area and height. In the same way, the TAZ-based destinations were distributed among the buildings identified in the database as facilities suitable for the destination's activity, i.e., work, school, leisure, and others, matching the facility buildings' use and floor area. For external travelers whose origin or destination is outside JMA, the external location is set at the centroids of outer TAZ. In contrast, the destinations of the travelers who arrive at the JMA are set, as above, at the TAZ facilities.

Jerusalem is a multiethnic city, and to reflect group-level differences in travel plans, JMATSim internal travelers were split into its three main subpopulations[6]: "Secular Jews," "Ultra-Orthodox Jews," and "Palestinian Arabs." These subpopulations differ in their residential patterns Figure 7.2, income, can ownership, and, consequently, OD matrices. The households are recorded in the Jerusalem census data and was accounted for when establishing the structure of the TAZ population. Note, trips are reflected by the OD matrices that the JTMPT supplied for each subpopulation.

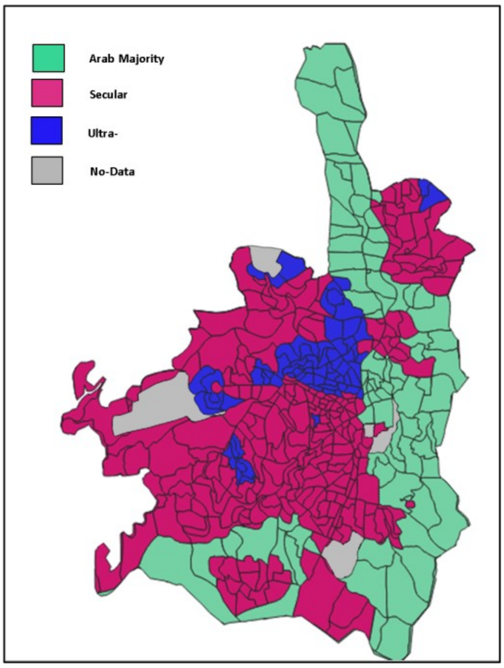


Figure 7.2. Jerusalem City map by population

[6] The trips of the West Bank Palestinians are not included into the JMATSim model due to insufficent data and geopolitical barriers and constraints.
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In total, 106,173 facilities were identified for performing activities (Figure 7.3), and the period of activities was set according to five typical time slots determined by the JTMPT, like working hours of governmental offices between 8:00 – 17:00 or shops between 10:00 – 20:00. The model was investigated with 450K agents representing 30% of the JMA population (as shown in Study 1 30% is good enough to generate adequate output parameters). That is, the downscaling factor is $k = 0.3$.

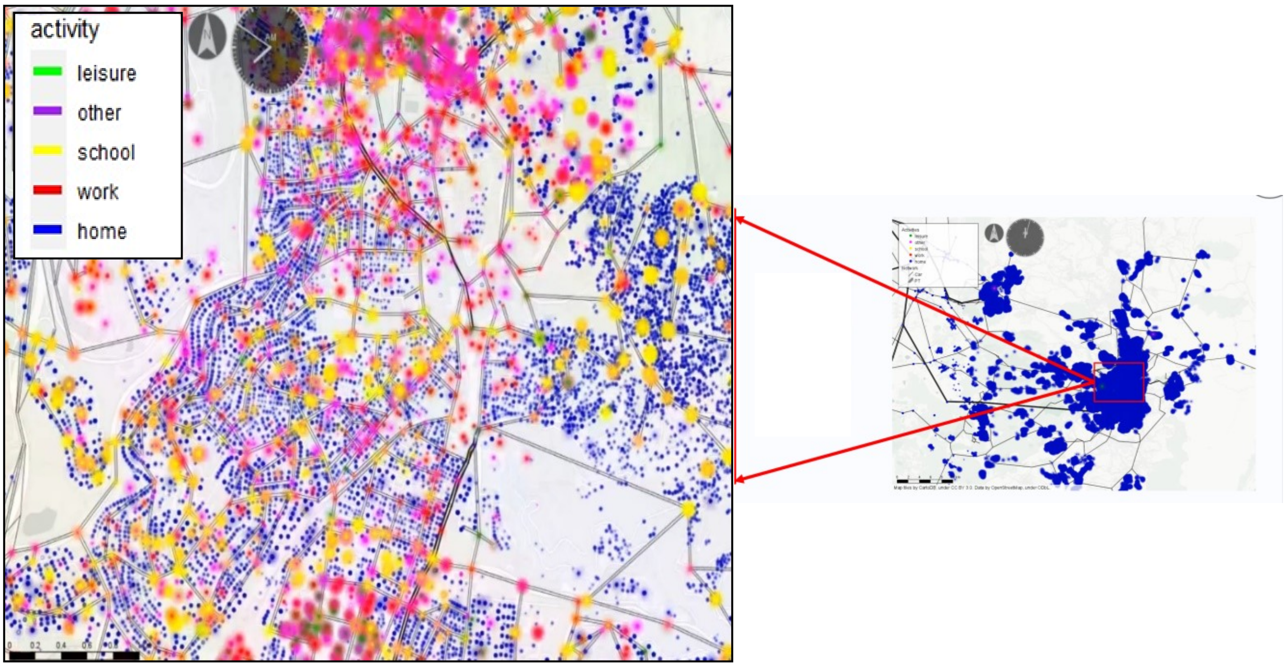

Figure 7.3. JMA Buildings and activity locations at 08:00.

7.2.2 Establishing agents' utilities

Parameters of the JMATSim agent utility functions (2) and (3) were set by modifying the parameter vector B, with the corresponding index, of the most recent open MATSim Berlin scenario. The latter is based on open data, does not exploit travel behavioral surveys, and is built as a background for spatially transferable agent-based transport simulation scenarios (Ziemke et al., 2019). To establish a Jerusalem scenario, we assume that the cost of car use in Berlin and Jerusalem is similar, as well as a willingness to pay for public transport. The modified coefficients of utility functions, denoted by index J, are presented below:

- Marginal utility of performing an activity per hour: $B_p = 6 \rightarrow J_p = 6.3$
- Per hour salary $B_s = 25€ \rightarrow J_s = 15.69€$, according to salaryexplorer.com
- Marginal utility of money $\beta_m = 0.6 \rightarrow J_m = 0.96$

In addition, some of the mode-specific parameters of the Berlin score function were modified to fit the modal split of the Jerusalem travel surveys: $C_{mode(PT)}$ from -0.3 in Berlin to -3.0 in Jerusalem to reflect essentially lower PT attractiveness there; $C_{mode(car)}$ from -1.0 to -1.7; $C_{mode(bike)}$ from -1.8 in Berlin to -60.0 in Jerusalem to reflect the problems of bike riding in hilly Jerusalem.

7.2.3 Calibration and validation

JMATSim was calibrated based on traffic counts, applying the CADYTS procedure (Flötteröd et al., 2012) that adjusts vehicle paths to match actual traffic counts. The calibration was performed with the modified mode-specific constants $C_{mode(q)}$ and was based on 2,422 traffic counts for 2017 – 2020, collected over the entire JMA, which area is 1,818 km2. Figure 7.4 presents the match between the observed and simulated traffic counts. This match is essentially better for the calibrated JMATSim model, with the R2 increasing from 0.67 to 0.83 after calibration.

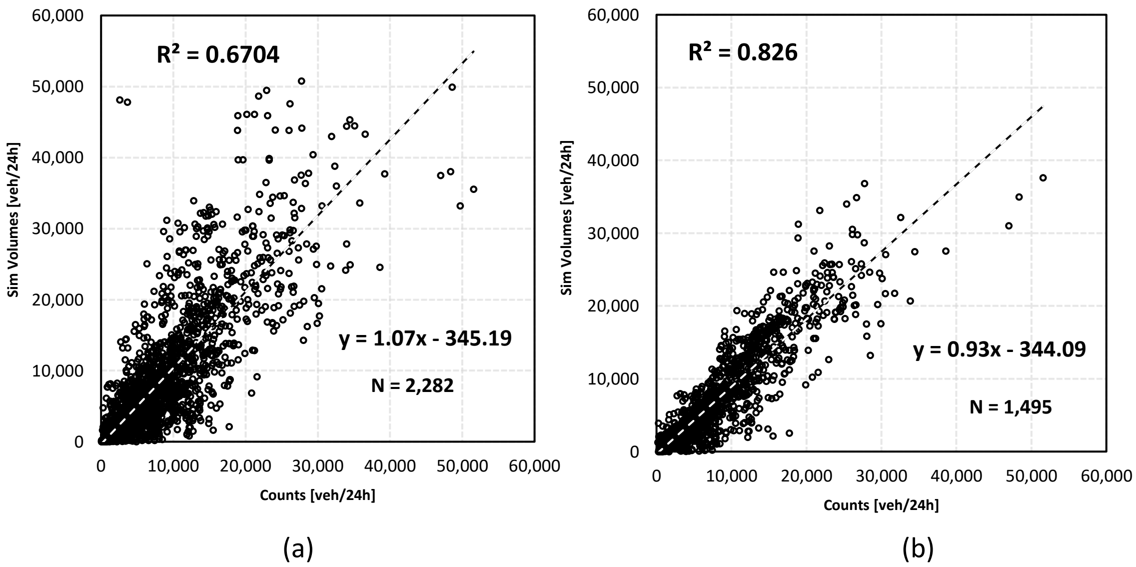

Figure 7.4. The simulated vs. observed road counts; (a) non-calibrated; (b) calibrated model

Count-based calibration was performed based on the modified mode-specific constants $C_{mode(q)}$ in section 4.1.3.

The calibration resulted in a good fit between the field observations and JMATSim outputs. Figure 7.5a presents hourly averages and STDs of the relative deviation between the simulated and observed traffic volumes, calculated as:

$$\frac{(JMATSim\ counts) - (Real\ counts)}{(Real\ counts)} \tag{11}$$

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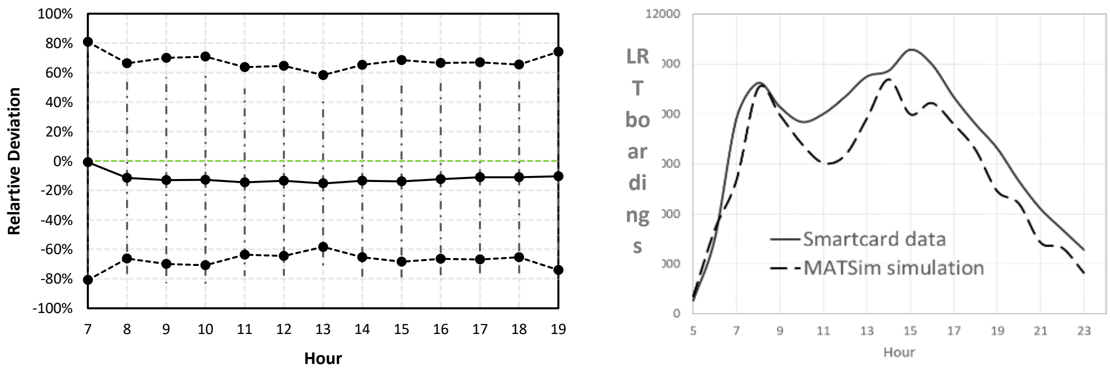
The average deviation remains below 18%, and the STD of the deviations remains at the level of 60-70%. Such a fit is at the level of the best MATSim approximations of the real multi-modal traffic dynamics (Ziemke et al., 2019). The chosen set of parameters best fits the JMATSim number of boardings to the light rail train to the smartcard-based data on boardings (Figure 7.5b). The latter was not exploited in the calibration procedures.



(a) (b)

Figure 7.5. The match between the field observation and the outputs of the calibrated MATSim model: (a) The average and STD of relative deviation of hourly traffic volume; (b) LRT boardings based on the smartcard use records versus the simulated ones.

The use of modified mode-specific constants $C_{mode(q)}$ resulted in adequate reproduction of the Jerusalem modal split by the calibrated JMATSim model (Table 7.2). Note that ~8% of JMA trips ("Ride" column) was done by car passengers. These trips cannot be included in a calibration process and were fixed JMATSim before the calibration.

Table 7.2. JMA actual and simulated modal split

Mode	PT	Car	Walk	Bike	Ride
Travel behavior survey	21.2%	32.4%	37.7%	0.6%	8%
JMATSim	21.9%	33%	35.8%	1.0%	8%

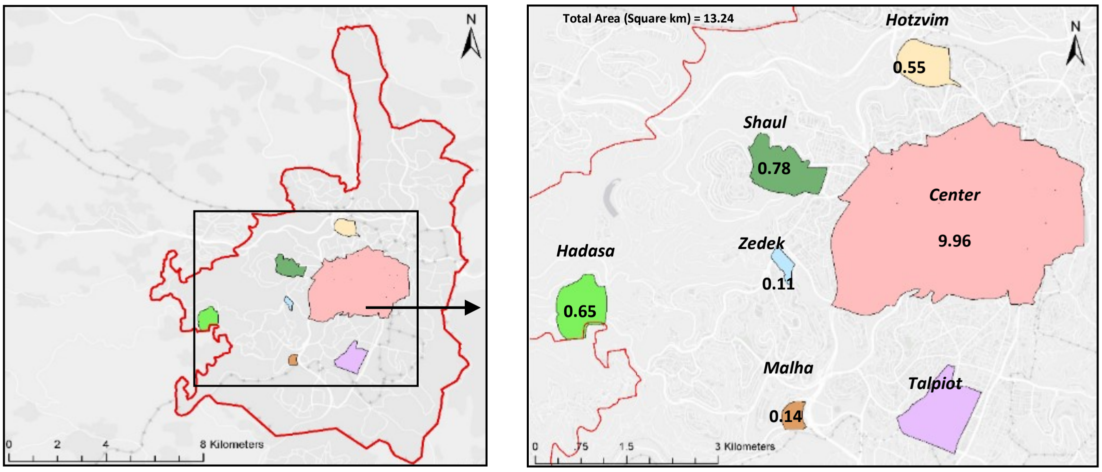
7.2.4 The measure of congestion

To characterize the congestion along the trip route we employ the ratio between the actual agent's travel time t_{OD}^{actual} and the travel time along the same route for free flow $t_{OD}^{free\ flow}$: $r_{OD} = \frac{t_{OD}^{actual}}{t_{OD}^{free\ flow}}$. We employ r_{OD}, averaged over a group of travelers as an index of congestion experienced by the members of this group.

7.3 Investigating congestion mitigation policies in Jerusalem

7.3.1 The policy scenarios

In what follows, I focus on Jerusalem's High-Demand Area (JHDA), which consists of the city center and seven nearby employment areas of a total area of 13 km^2 and comprises about 10% of the city of Jerusalem within its official municipal boundaries (124 km^2) (Figure 7.6)



(a) (b)

Figure 7.6. Jerusalem city (a), and JHDA (b), the latter with the area of each part in km^2.

7.3.1.1 The baseline scenario

Generally, all scenarios below consider cordon congestion charges when crossing the JHDA border (entry charge) and parking fees when parked within the JHDA. Residents of the JHDA are not charged when entering the area but pay when parking for any activity which is not a "home" activity.

The model scenarios differ in the level of entry charges and parking prices. We compare model outputs for the entry charge C varying between $0€ - 20€$ per entrance and the hourly parking price P varying between $0€ - 20€$ per hour, both by 5€ steps. We limit ourselves to the scenarios that are realistic for Israel nowadays and assume that $C + P \leq 20€$. To estimate a parking payment, we record the agent's parking time t_d for each activity inside the JHDA and, if the activity is not "home," calculate the overall payment for parking as $t_d \cdot P$. Congestion and parking prices are included in agent scores using the monetary term $\beta_m \cdot m_q$ of the travel utility function (3).

The runtime of each scenario was 2 hours with an Intel-based system (Core i7-10700 - 8 4.80 GHz cores and 128Gb DDR4 RAM). The number of model agents defines the MATSim performance, which does not depend on the scenario's parameters.

In each scenario, the number of cars arriving at the JHDA, the congestion index r_{OD}, the average parking time in JHDA, and collected revenues were estimated. The scenarios' outputs to the baseline scenario in which congestion charges and parking prices are not imposed were then compared.

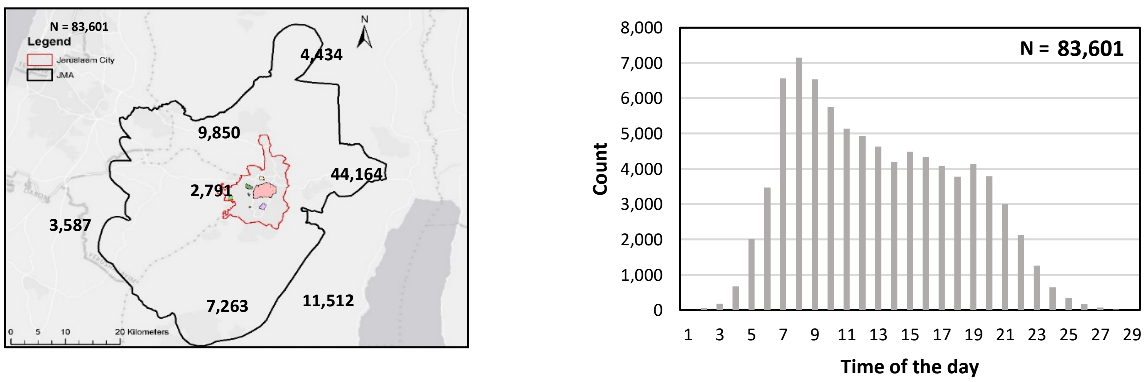
The baseline scenario's characteristics

Table 7.3 presents the major characteristics of the JMA baseline scenario where origin and destination are entirely inside the JMA area.

Table 7.3. Aggregate statistics of the JMA baseline scenario (whole population)

Mode	Average trip time (hours)	Average traveled distance, km	Average speed km/h	Total trips	Mode choice, %
Private car	00:21:11	11.2	31.6	1,439k	33.1
PT	00:55:50	9.2	9.8	956k	22.0
Walk	00:34:41	1.7	3.0	1,555k	35.8
Ride	00:09:22	5.7	36.6	346k	8.0
Bike	01:04:10	19.3	18.09	47k	1.1

Figure 7.7 presents the daily number of arrivals to each of the JHDA parts, with a total of 83.6K arrivals, and the distribution of arrivals by hours of the day.



(a) (b)

Figure 7.7. The baseline scenario statistics: (a) Daily arrivals to JHDA; (b) Hourly arrivals to JHDA; (c) Distribution of the congestion index r_{OD} for the morning peak trips to JHDA.

Figure 7.8 presents the distribution of the congestion index r_{OD} calculated based on the 30k arrivals during the morning peak 6:00 – 10:00

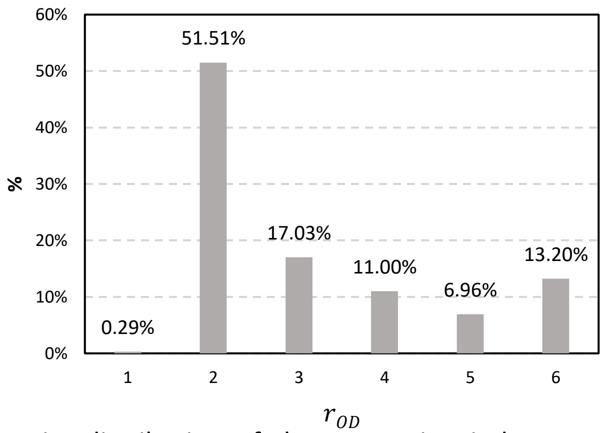
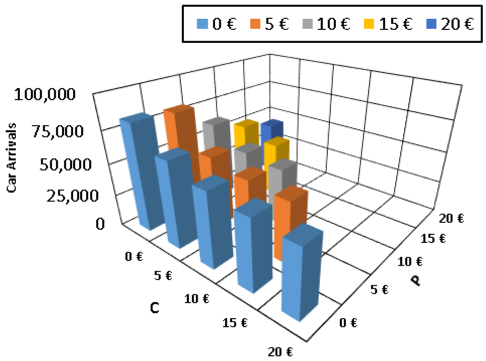


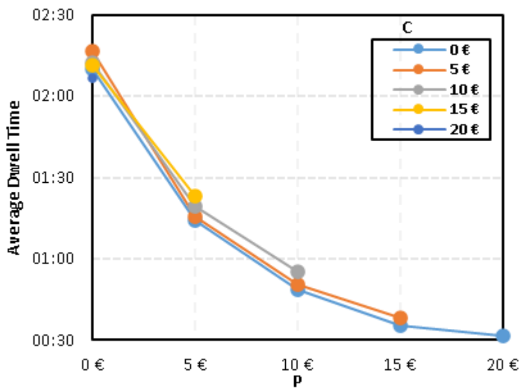
Figure 7.8 The baseline scenario, distribution of the congestion index r_{OD} of the morning peak arrivals to JHDA.

7.3.2 *Entry charge and parking pricing effects*

Figure 7.9 presents the dependences of the basic characteristics of JHDA car traffic on the level of entry charges and parking prices.

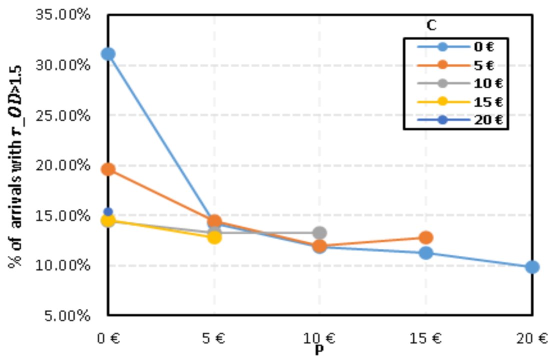


(a)



(b)

Figure 7.9. Effects of the hourly parking price P, for different levels of entry charges on (a) the total number of arrivals to JHDA with a private car; (b) average dwell time; (c) fraction of drivers for whom $r_{OD} > 1.5$.



(c)

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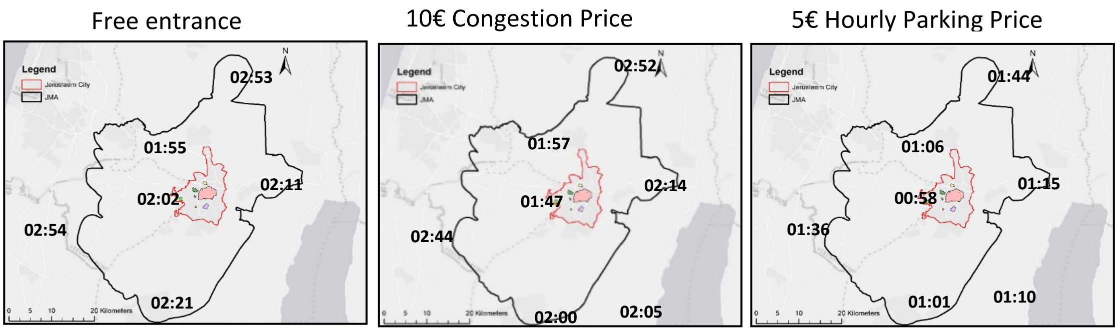
As can be seen, each of the payments decreases the number of drivers arriving at the JHDA with a private car, while the dependence of the number of arrivals on the level of each of the payments is monotonous and non-linear, the same additional payment reduces arrivals less and less (Figure 7.9a). Two phenomena, however, demand special attention: First, as may be expected, the introduction of entry charges without parking prices does not affect the average dwell time in the JHDA (Figure 7.9c, the values for P = 0€), which remains at the level of 2:15 hours as in the baseline scenario. Dwell time is sensitive to the parking price only and the dependence of the dwell time on the price is not linear - the price of 5€/h entails almost a two-fold decrease in dwell time, to 1:15 hours, while the duplication of price to 10€/h reduces the average dwell time to 45-50 minutes.

The second phenomenon is of sensitivity of the congestion index to the payments as far as the parking prices are 5€ or higher (Figure 7.9b). This is because the drivers arriving at the JHDA are only partially influenced by traffic conditions there and the value of r_{OD} is defined by traffic conditions outside the JHDA.

The different effects of the entry charge and parking prices can be illustrated by the parking dwell time related to non-work activities, which, in the basic scenario is 1:27 hour. In the case of the 10€ congestion charges the average dwell time increases to 1:42, while in the case of the 5€ hourly parking price the dwell time decrease to 0:57 hour and, thus, the total payment for arriving at JHDA becomes 5€ only.

Notably, the entry charges decrease car arrivals but do not affect the average dwell time in the JHDA, which remains at the level of 2:15 hours, very close to the baseline scenario. Imposing parking prices entails a two-fold decrease in dwell time to 1:15 hours (Figure 7.10).



(a) (b) (c)

Figure 7.10. The average dwell time of drivers arriving at JHDA (a) baseline; (b) 10€ entry charge, zero parking price; (c) 5€ hourly parking price, zero entry charge

The effect of payments on the dwell time related to two major types of activities – all Non-Work activities excluding "Home," and "Work," for two most realistic scenarios of introducing one of the mechanisms is presented in Table 6.3.

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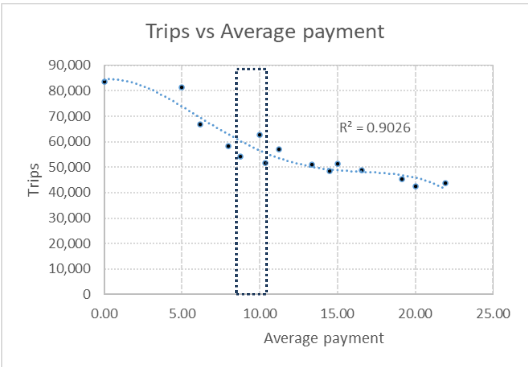
Table 7.4. The average dwell time for JHDA car trips

Activity	No Charges	5€ Hourly Parking Price	10€ Entry Charge
Non-Work excluding Home	01:27	00:57	01:42
Work	05:29	03:26	04:54

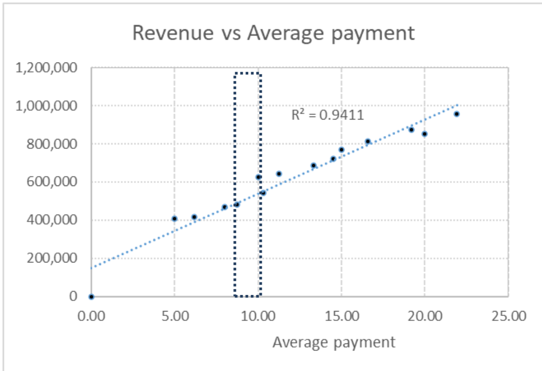
Parking priced at 5€ reduced the average non-work dwell time by half an hour, while the work dwell time was reduced by two hours. The entry charge of 10€ enforced 15 minutes longer non-work stay in the JHDA and reduced the average work dwell time by half an hour only.

7.3.3 pricing Studying combined effects of congestion charges and parking pricing

To assess the combined effects of parking prices and the entry charge for a certain scenario we consider an agent's a payment M_a for arriving and staying in the JHDA for t_a hours, calculated as $M_a = C + t_a \cdot P$. The average, over the agents with the destination in the JHDA, value of agents' payments will be thus $M = C + \bar{t}_a \cdot P$, where $\bar{t}_a$ is the average dwell time over the agents with the destination in the JHDA, as presented in Figure 7.9b. The dependences of the number of trips, total revenue, and level of congestion on M for the investigated scenarios are presented in Figure 7.11.



(a)



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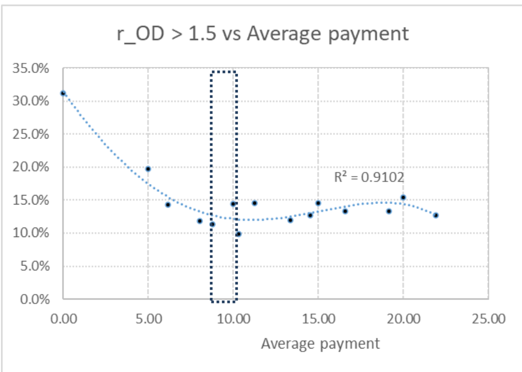

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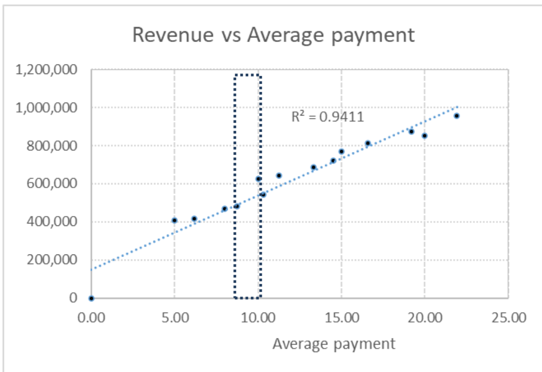

(d)

Figure 7.11. Dependence of the major characteristic of the JHDA's state on the overall payment M: (a) Number of arrivals to JHDA with private cars, (b) Total revenue (c) Effect of congestion on the drivers arriving to the JHDA; (d) Total revenue;

As can be seen in Figure 7.11, up to a value of $M{\sim}8-10€$, the system is strongly affected by M; for the higher values of M, the effect fades out despite a linear increase in the total revenue (Figure 6..10d). Accounting for an average dwell time in JHDA (Figure 6.10d), three policy options that we consider as most realistic are as follows:

(1) Entry charges of $8-10€$, no parking price,
(2) Parking price of $6-7€/hour$, no congestion charges, and
(3) Entry charges of $4-5€$, parking price $4-\ 5€$ per hour

Each of these policies decreases congestion twice and results in 500-600€K daily revenue that is directly proportional to the decrease in congestion. Higher payments increase revenue, but their effect on congestion is disproportionally low. The stakeholders could choose between congestion charges and parking prices or apply both to affecting different categories of drivers.

The decrease in the number of visitors arriving with the car and the increase in the number of PT users is a part of the changes in the modal split among the JHDA visitors. Figure 7.12 presents a modal shift, relative to the baseline scenario, for the scenarios that we consider realistic: entry charge only, 5€ or 10€, parking price (5€) only, and entry charge 5€ and parking price 5€/hour. As can be seen, the increase in congestion charges results, in addition to the PT use, in the increase in the number of visitors coming to the JHDA on foot.

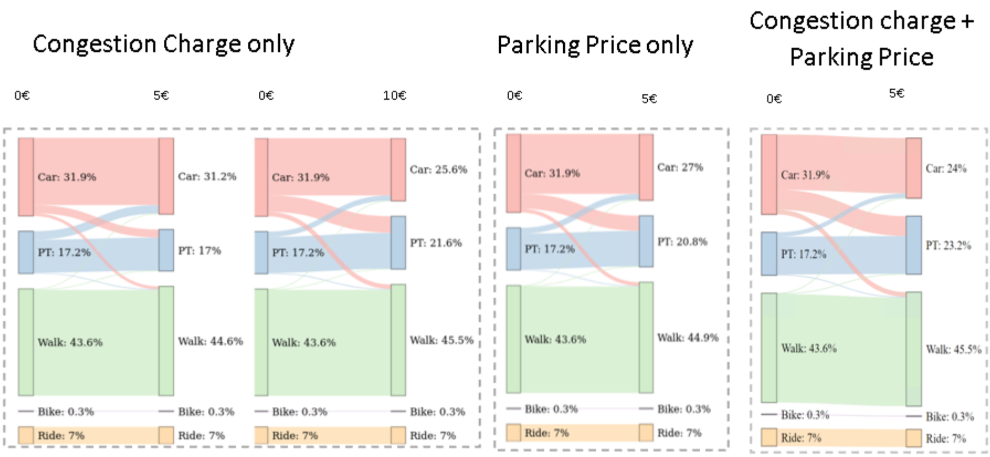

Figure 7.12. The mode choice changes among the travelers arriving at JHDA in response to the entry charge of 5€, 10€ and 20€ (and zero parking price) and parking price of 5€ (and zero entry charge).

7.4 Discussion

Undoubtedly, both parking prices and entry charges are primary policy measures to mitigate traffic congestion. To our best knowledge, however, they have never been evaluated simultaneously with a spatially explicit model of the real city as a holistic congestion mitigation policy. Spatially explicit modeling made it possible to test a policy that applies an

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entry charge and/or parking prices to specifically targeted employment and service centers, i.e., not a universal cordon. For this purpose, we have established, calibrated, and validated the MATSim multimodal traffic simulation model of the Jerusalem Metropolitan Area. The model fits well with the real data on Jerusalem traffic dynamics, including road counts, modal split, and PT boardings.

Investigating model scenarios, we found that the overall payment is a determinant of the system's changes. A ≈10€ (≈40ILS at 2020 prices) combined payment can reduce cars' arrivals to the city center by approximately 25%, minimizing congestion and reducing travel time there. This finding corroborates actual congestion charges imposed in cities such as Singapore, London, Stockholm, Milan, and Gothenburg, where the average charge is ≈9€ (as in Table 7.1), and enforces travelers' modal shift from driving to PT.

The consequences of each payment type are different: entry charges reduce arrivals, while parking prices reduce arrivals and dwell time at the city center. Consequently, establishing parking prices may deter, in the first place, drivers that arrive for long periods, while the congestion charge affects those who arrive for short periods. A policymaker obtains a pair of flexible management tools whose combined effect may allow controlling the congestion with moderate fees, avoiding strong public opposition against the negative economic incentives.

Notwithstanding, we found several limitations worth noting in the application of MATSim for congestion management evaluation. First, the MATSim utility function does not differentiate between activities, which is crucial given that charges influence mandatory and discretionary activities differently (Zheng et al. 2012). One can expect that charging will have a lesser impact on work activities than on non-work ones, and, regarding parking prices, the elasticity of demand should be lower for work than for services or shopping (Kelly et al. 2009). The modeling framework does not reflect all of these. Another limitation is that travelers of the JMATSim are considered to have the same income, i.e., our simulation has no income effects. Wealthier travelers are less sensitive to charges than low-income groups (Barri et al., 2021). MATSim framework does allow the agent-specific income that would affect the agent's utility function (Plessis et al., 2012), but we had no access to the data on between-group and within-group variation of income for the three groups of JMATSim travelers - "Secular Jews," "Ultra-Orthodox Jews" and "Palestinian Arabs."

Future work should allow these flexibilities in the model design. Furthermore, it would be interesting to investigate the impacts of shared modes such as ridesharing and understand the perspectives of ridesharing and the level of charging necessary to bring a substantial modal shift towards it; see the preliminary study for Tel Aviv by Ben-Dor et al. (2019, 2022).

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CHAPTER 8 – Study 3: Automated DRT service introduction impacts on mode choice and traffic

The third study employs the calibrated and validated MATSim model of JMA to examine the effectiveness of automated shared DRT in Jerusalem. The chapter starts with a background followed by a DRT algorithm review and then the experiments.

8.1 Background

8.1.1 Demand Responsive Transit Introduction Modeling

DRT can be considered in three modes of operation (see Table 8.1):

Table 8.1 Major strengths and weaknesses of transportation systems and modes related to DRT (Tyrinopoulos and Antoniou., 2020

	Strength	Weakness
Carsharing	Reduced vehicle ownership, fewer parking requirements, reduced vehicle travel, cost savings	Uncertainty of supply, especially for the return-trip option
Ridesharing	Cost savings for riders, reduced vehicle miles traveled, reduction in fuel consumption, reduction in greenhouse gas emissions	Lack of trust leading to reduced safety and security, reduced transit ridership and active travel, and increased motorized travel. Empty millage
Autonomous vehicles	Significant cost reduction (due to elimination of driver costs), possible reduction in Emissions and increase in capacity; safety improvements	Might lead to extra vehicle miles traveled (VMT), e.g., due to additional trips and cruising instead of parking increased cybersecurity risks.

DRT adoption is widely discussed in the current literature. Factors like pickup and drop-off times are well studied (Narayanan et al., 2020), whereas factors such as route choice or matching efficiency of other passengers are less addressed (Brell and Philipsen et al., 2019). Users have different expectations for an AV user interface, depending on whether the vehicle is owned or shared. This difference suggests that design and development should differ between personal vehicles and DRT (Tyrinopoulos and Antoniou, 2020).

DRT research is based mostly on stated choice surveys or simulations. Menon et al. (2018) designed a stated choice survey (N = 1214). They suggested 50% of the respondents were unlikely to cease using their vehicle, whereas 61% said they prefer ridesharing in an SAV over private autonomous vehicles. Haboucha et al. (2017) suggested that a 100% penetration rate of SAVs may not be achieved even if the service is free. A common observation is that DRT services will mainly attract users of sustainable modes of transport, i.e., PT, walking, and bicycles (Narayanan et al., 2020). Moavenzadeh et al. (2018) conclude that in the inner city, both PT and private car usage will be replaced by DRT, while private cars will mostly be substituted outside the city core. These stated preference studies are conducted to assess user adoption and used as inputs for discrete choice models. Such models are the basis for providing behavioral parameters that form a critical part of a simulation system (Narayanan et al., 2020).

Various simulations of future mobility with DRT fleets have been conducted. In Singapore, (Spieser et al., 2014) conducted a study to examine approaches to justify an economically viable single-rider DRT when they replace all transportation modes. They found that the entire population of Singapore could be served with a DRT fleet a third of the size of the current number of private vehicles. However, their DRT operation included car sharing but excluded ridesharing. Thus, a single DRT served only one person at any given moment.

In a separate study by Childress et al. (2015), simulation models explored potential shifts in mode choice with the introduction of SAVs in a Seattle-based model. They found that when SAV costs were set to be competitive with private vehicle ownership, up to 43% of all trips could shift to SAVs, leading to a dramatic decrease in personal vehicle usage.

Martinez and Errico (2018) found that the implementation of SAVs in Manhattan, New York, could lead to a reduction of around 75% in the number of cars on the roads, alleviating congestion and potentially leading to reductions in travel time.

An agent-based simulation of Lisbon city center examined replacing other modes with shared DRT (shared taxi bot) operating from door-to-door (Martinez et al., 2017). The authors found the door-to-door decrease the distance traveled by 10–25% if more travelers were willing to rideshare. In this case, carbon emissions would be reduced by up to 40%.

The flexibility of the MATSim simulation environment has made it especially attractive to simulate and model DRT scenarios. A MATSim study (Bischoff & Maciejewski, 2016) conducted for Berlin replaced all private vehicles with single occupancy SAV. They found that a fleet of 100K vehicles could serve 1.1 million existing car users in Berlin with an average waiting time during peak demand times of ~5 minutes, while the 95th percentile was ~14 minutes. The same authors conducted another study for Berlin, substituting all traditional taxis with SAV ridesharing (Bischoff et al., 2017; Maciejewski et al., 2017). They found that 5,000 SAVs could serve 27K taxi trips, i.e., one SAV could replace ~5.4 traditional taxi trips if ridesharing is allowed. Another MATSim study examined whether rideshared DRT could be an adequate substitute for PT in Berlin (Leich & Bischoff, 2018). The study was conducted in a small area with 55,000 agents and four bus lines. They found that about 200 vehicles significantly shortened walking times by 8 minutes, waiting time by 2 minutes, and travel times by 7 minutes compared to PT only. A study conducted by Fagnant and Kockelman (2018) simulated the deployment of SAVs in Austin, Texas and found that a single SAV could replace around 9 to 13 privately owned vehicles, significantly reducing the need for parking spaces. They also found that ride wait times averaged less than 5 minutes in their model, suggesting high levels of service quality for SAV users.

8.1.2 DRT dispatching algorithms

Below, I focus on on-demand taxi services with ride-sharing capabilities. Figure 8.1 illustrates the stop-based journey of such a DRT vehicle serving three passengers.

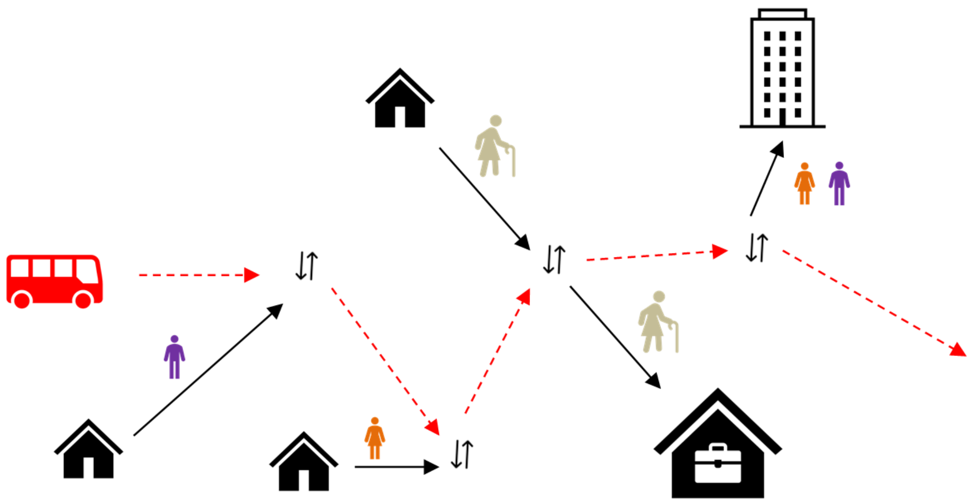

Figure 8.1. Ridesharing DRT trip of a single vehicle that serves three users

The investigated scenarios are an extension to the scenarios in Chapter 7, where I investigated the effects of entrance charges. Here, I continue the inquiry into possible ways to transition from the current transportation system dominated by private vehicles to public and shared transportation.

Conceptually, the DRT service is provided by a fleet that the operator manages in response to the users' trip requests (Figure 8.2). The algorithms of DRT-vehicles dispatching define the effectiveness of the service, i.e., reaction to requests, selecting which will be served and which rejected, and which vehicles will be used for serving those requests. I thus start this chapter with a short review of these algorithms.

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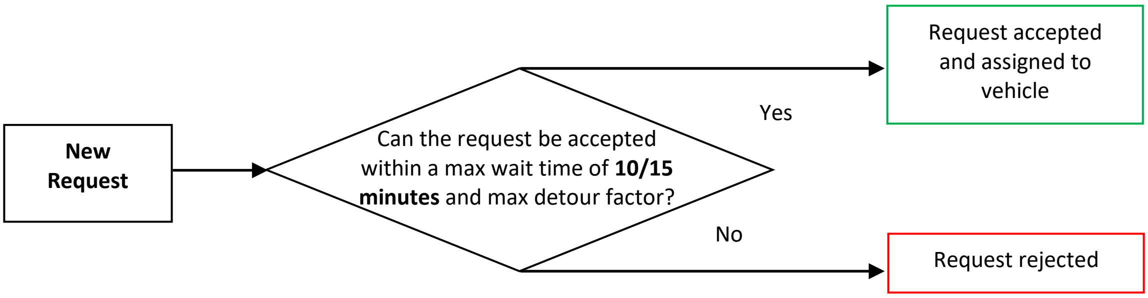

Figure 8.2. The booking process of a typical MATSim DRT algorithm

8.1.1.1 Performance versus Optimization

Algorithms aim to optimize DRT-vehicle scheduling, routing, and re-allocating to minimize operational costs and maximize users' satisfaction. Some notable ride-sharing DRT algorithms are presented below. In all these algorithms, users who need a ride submit a request that includes information on the pick-up location, destination, and desired arrival time. Vehicles instantaneously share their location, occupancy, and planned route (Bischoff et al., 2017).

- **On-demand dispatching algorithm** of Alonso-Mora et al., (2017)

The algorithm considers the DRT system that serves real-time requests for immediate rides establishing the best match between travelers and vehicles, accounting for the travelers' waiting time and vehicles' capacity, and instantaneously re-assessing vehicles in case of changes. It employs mixed integer linear programming to optimize vehicle routing and trip assignments. The algorithm's goal is to minimize the total travelers' time surplus caused by the sharing-induced deviations from the passengers' minimal travel time. The optimality of the service and performance of the algorithm was investigated for Hamburg, Germany.

- **Dynamic Ride-Sharing Service (DRSS)** (Fagnant and Kockelman, 2015):

The algorithm focuses on maximizing the average number of passengers sharing the vehicle and minimizing the total distance traveled by all vehicles. Overall, it estimates the number of autonomous vehicles needed to serve the demand as a function of the travelers' waiting time. The algorithm includes rebalancing - redistributing vehicles within the service area to ensure availability in the areas of highest demand. The major steps of the DRSS process are as follows:

- *Search for the vehicle that can perform the request:* This includes potential handoffs when a seat becomes available after a vehicle drops off its passenger.
- *Conditions for shared rides:*

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- The current passengers' trip duration should not increase by more than a certain percentage due to ridesharing.
- The total trip time for the new passenger should not exceed a certain percentage of the total trip without ridesharing, or 3 minutes.
- The remaining trip time for current passengers should not increase by more than a certain percentage.
- The new passenger must be picked up within a certain waiting time.
- All passengers' total planned trip time should be ≤ to the remaining time of serving the current trips + the time of serving a new trip + 1 minute drop-off time.

- *Evaluating possible pick-ups and drop-offs:* If multiple valid pick-up/drop-off combinations exist for a shared ride, the combination with the earliest final drop-off time is chosen.

T-Share (Ma et al. 2013)

T-Share involves two main parts - dispatching and vehicles scheduling of shared taxis:

- *Dispatching:* The dispatching part involves calculating the shortest path between every vehicle and every customer request and assigning each request to the taxi that can reach it quickly. This process is updated every time a new request comes in or a taxi becomes available.
- *Scheduling:* To optimize the order in which a taxi picks up and drops off passengers, a complex optimization problem accounts for the maximum number of passengers in a vehicle, deadlines for each passenger's trip, and the need to avoid detours that would significantly increase travel time.

T-Share's unique feature is the data structure called a "profitable grid" to find and assign new requests efficiently. This grid divides the service area into smaller squares and keeps track of potential profits that could be made by picking up passengers in each square, essentially accelerating the algorithm. Yet, I am not aware of any study of T-Share's efficiency in real-world conditions.

No practical applications exist (to the best of my knowledge) for the three aforementioned algorithms and several similar ones (Zwick et al., 2020). A common reason for the lack of implementation can be the low performance of these algorithms compared to the BM-DRT algorithm (Bischoff et al., 2017; Maciejewski et al., 2017) described in the next section. For example, Zwick et al. (2020) asserted that the travel and waiting times of Alonso-Mora et al.

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(2017) are larger than those of the BM-DRT algorithm, while its computing speed is five times faster. Therefore, BM-DRT was a natural choice.

8.2 The Bischoff-Maciejewski (BM) DRT dispatching algorithm

The DRT dispatching algorithm of (Bischoff et al., 2017; Maciejewski et al., 2017)—BM-DRT was initially designed for MATSim implementation but can also be employed with any other software. Formally the processing steps of the BM-DRT algorithm are as follows:

Let F be the DRT vehicles fleet. In reaction to the traveler's request R for a trip from A to B starting at t_o, do:

- estimate $t^r_{direct,t,AB}$ – minimal traveler's travel time between A and B if started at t_o.
- loop by the fleet F and find all vehicles $V \in F_{possible}$ satisfying three conditions:
  - V arrives at the pick-up point no later than $t_o + t_{max\ wait}$
  - V has a vacant seat to pick up a traveler,
  - V guarantees an acceptable surplus of travel time to other passengers sharing this ride.

If none of the vehicles $V \in F_{possible}$ satisfy these conditions, the traveler's request is rejected; otherwise, the vehicle from $F_{possible}$, providing a minimal surplus of travel time for all passengers inside the vehicle, is chosen for service.

Formally, the above general rules are implemented as follows:

- loop by $F_{possible}$ and estimate the effectiveness of servicing R by comparing the travel time of the direct travel t^r_{direct} between A and B to the real travel time t^r
- If for $V \in F_{possible}$, $t^r \leq t^r_{max} = \alpha t^r_{direct} + \beta$ (α, β are parameters, typically, $\alpha \sim 1.2 - 1.3$ and $\beta \sim 5 - 10\ min$), include V into $F_{serving}$ for further analysis. This condition is verified for the new passenger and all vehicle passengers.
- If the set $F_{serving}$ is not empty, loop by its vehicles and choose the one that provides the minimal total increase in average travel time for its passengers.

Note that setting $t_{max\ wait} = \infty$ enables serving all requests, with a waiting time that can become very long.

Zwick & Axhausen (2020) compared BM-DRT with the algorithms presented in section 8.1.2. Their study used data from the German ride pooling service from MOIA that operates in Hamburg with 12,427 daily requests of DRT fleet sizes ranging from 50 to 300 vehicles. The DRT service area spans over 200 km² and includes Hamburg's most populated regions. The study demonstrated that the passenger share obtained with the BM-DRT is the highest, and

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its performance is several times higher than all other tested algorithms. For these reasons, I chose BM-DRT for implementation in MATSim.

In my implementation, I also employed BM-DRT-Speed-Up (Kaddoura et al., 2020b). Their idea is to simulate DRT vehicles that do not drive but once in every k (usually, $k = 10$) iteration using the approximate DRT travel times during the remaining $k - 1$ iteration.

It's important to note that BM-DRT can include rebalancing components (Bischoff et al., 2020) which I do not employ. This component estimates relocation costs between the current vehicles' locations and locations of the potential requests and suggests the list of relocations that maximize the gain from serving potential future requests.

8.3 Scenarios of the DRT Services

8.3.1 Application of the DRT dispatching algorithm in JMATSim

To implement BM-DRT in JMATSim I extended it in the following ways:

- Two service configuration options exist: door-to-door and stop-based. The latter improves service efficiency regarding fleet size, rejections, and waiting times (Ben-Dor et al., 2019); hence the analysis below is performed for this scheme.
- Constraining DRT trip origins and destinations (ODs) to designated areas.
- Change of the MATSim DRT iteration loop: MATSim's general approach is that agents with ineffective plans still follow them until mutation happens and a better plan is generated. This approach cannot work for DRT as a "curious" but rejected agent requesting DRT will relapse to an existing plan excluding DRT. A rejected JMATSim agent reverts to the previously used plan without DRT to reflect this drawback.
- Running DRT simulations in MATSim is time-consuming, even with the DRT-Speed-Up module. Therefore, I included the DRT-Speed-Up module in the HERMES extension of JMATSim (see the Methodology section 4.1.1).

8.3.2 DRT service configurations

I compared DRT serving: (1) pick-up and drop-off locations anywhere in the entire city (city-wide); (2) city center core and periphery (core-periphery). Intuitively, the latter approach should be more efficient than the city-wide one, as it is constrained to a high-demand area on one trip end. As the core-periphery setup demands defining the core area, I considered two core definitions: a SMALL center, which includes the core areas of Jerusalem as established in Chapter 7, and a BIG center, which is defined based on the O/D matrix of trips in Jerusalem. As noted, the SMALL center includes the dense historic city center, seven nearby employment zones, and in total, 13 km². The BIG center is established based on the

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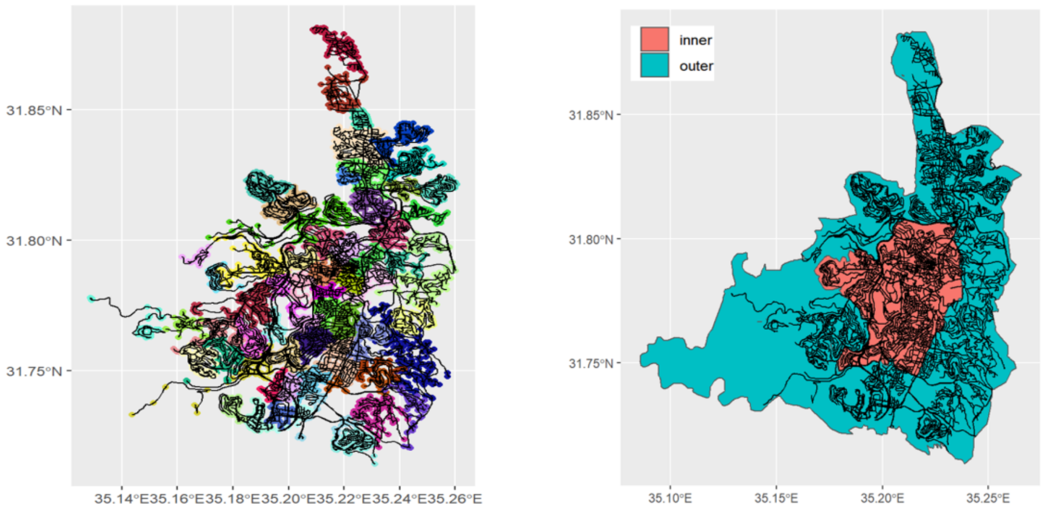
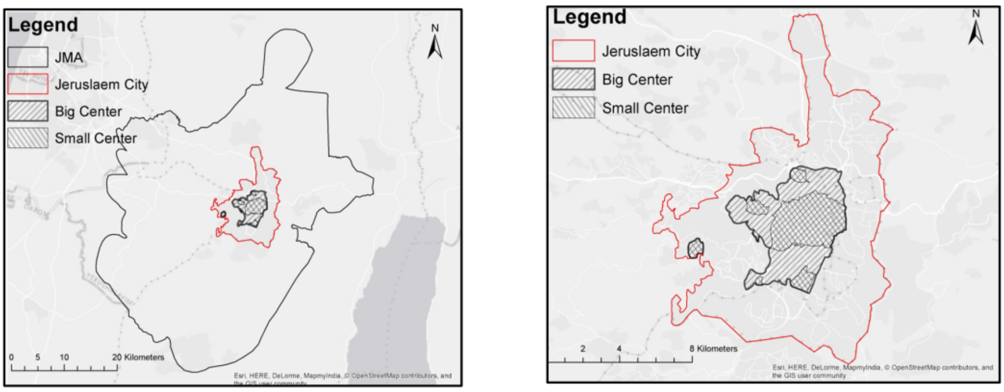
OD matrix using the Louvain algorithm of network community detection (Blondel et al., 2008).

The Louvain algorithm considers each network node as an individual community and partitions the network differently to maximize its modularity. The latter is measured as the ratio of intra-community connections compared to inter-community connections. The algorithm works in iterations changing partitions to increase modularity until it stabilizes. In the case of Jerusalem, 62 communities were revealed (Figure 8.3a). Ultimately, the Louvain algorithm provided an area encompassing all parts of the SMALL center (Figure 7.6a). These areas were merged into the BIG center, encompassing 28 km² (Figure 8.3b). Figure 8.4 presents the SMALL CENTER and the BIG CENTER as described above.



(a) (b)

Figure 8.3. (a) Jerusalem communities obtained with the Louvain algorithm (b) Central and peripheral communities



(a) (b)

Figure 8.4. BIG and SMALL Jerusalem city centers, (a) Zoom to JMA; (b) Zoom to Jerusalem border

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8.3.2.1 *Scenarios parameters*

I analyzed the DRT effectiveness assuming the following conditions:

- City-wide vs. Core-Periphery service.
- Cost-free vs. charged entry and/or parking fees in the city center.

In all investigated scenarios, I employed the following conditions:

- Stop-based DRT service.
- DRT vehicles have ten seats.
- Unrequested DRT vehicles park at the destination end of the previous trip.
- If a DRT request is rejected, an agent performs the plan of the previous iteration.

I employed the following numeric parameters:

- $t_{max\ wait}$ = 15 minutes, $t^r_{max} = 1.5t^r_{direct} + 12\ min$. based on Ben-Dor et al,2019
- For the ***City-wide service***, a fleet size of 5k and 10k DRT vehicles.
- For the ***Core-Periphery*** service, the fleet size is 250 and 1,000 vehicles.

8.4 Results

8.4.1 *City center definition*

Mode choice: In the scenarios with cost-free entrance to the city center, BIG attracts 69% more trips than SMALL, but PT use remains 32-33% regardless (Table 8.2). Entry/parking charges increased the PT use to 51% in the case of the SMALL center. For the BIG center, the entry charges increased PT use to 43%, while parking fees led to 54%. In parking and entry charging scenarios, PT usage rose to 60%.

Table 8.2. Basic trip statistics without DRT, BIG vs SMALL center

Scenario		Trips to the center			Total payment	Trips within the center		
		N	Car	PT		N	Car	PT
SMALL CENTER	Cost-free entrance (0€)	141K	67.5%	32.5%	-	11K	44.5%	55.5%
	Entry charge (10€)	137K	49.1%	50.9%	671K	11K	52.8%	47.2%
	Parking price (5€/hour)	136K	49.4%	50.6%	447K	10K	20.1%	79.9%
	Entry charge (10€) and Parking price (5€/hour)	133K	37.2%	62.8%	813K	10K	21.6%	78.4%
BIG CENTER	Cost-free entrance (0€)	218K	66.3%	33.7%	-	63K	56.2%	43.8%
	Entry charge (10€)	213K	56.8%	43.2%	1213K	63K	61.4%	38.6%
	Parking price (5€/hour)	209K	46.1%	53.9%	587K	59K	25.6%	74.4%
	Entry charge (10€) and Parking price (5€/hour)	206K	39.8%	60.2%	1433K	59K	27.6%	72.4%

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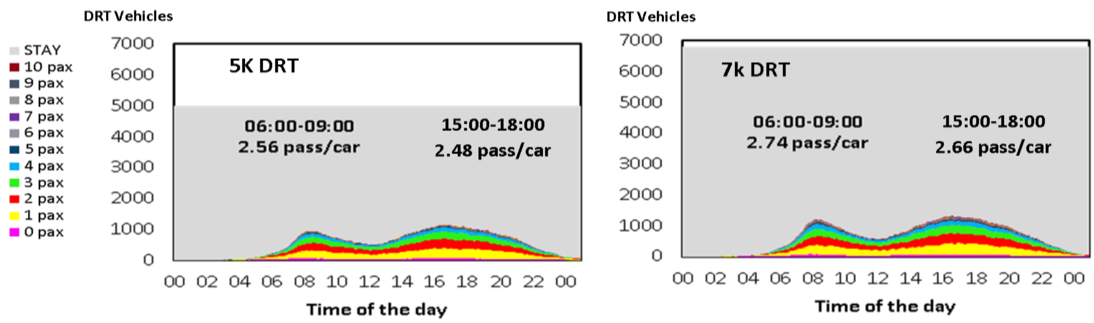
The number of trips: Overall, the BIG center entails six times more internal trips than the SMALL center (Table 8.2). In the cost-free entrance scenario, the car trip share in the BIG center was higher than in the SMALL center, 56% vs. 44%. Charged entrance reduced car arrivals by 4-8K in the case of the SMALL center and 5-12K in the case of the BIG center. Entry charges increased internal car trips ca. ~5% in both cases, while parking fees strongly affected car usage for internal trips—from an initial share of 45-60% to 20-25%. Scenarios combining both measures mirror the scenarios of parking fees only.

8.4.2 *City-Wide DRT service*

The City-Wide scenarios consist of 5K and 7K DRT fleets operating over the entire JMA. Comparing the number of DRT vehicles used in these scenarios (Figure 8.5) shows an excessive fleet size in both cases. The chart shows how many passengers are currently riding in DRT vehicles.



(a) (b)

Figure 8.5. Number of DRT users: (a) 5000 and (b) 7000 fleets—city-wide service

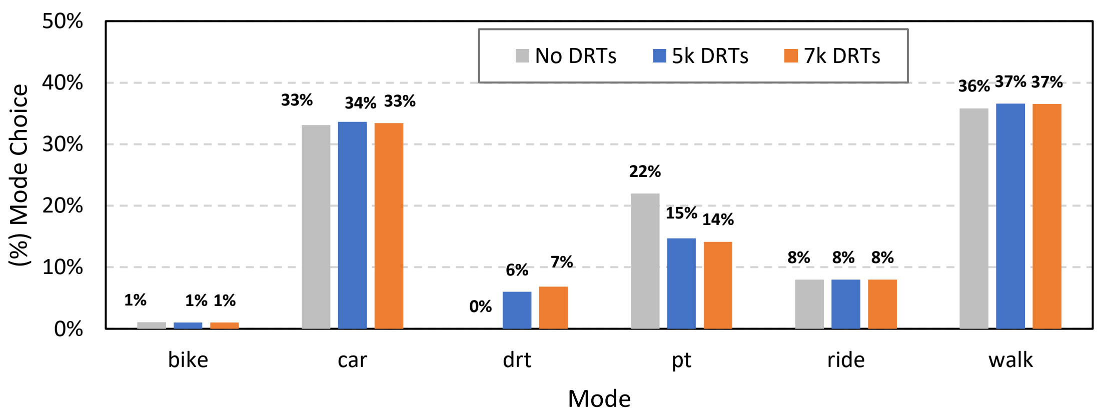


Figure 8.6. JMA mode choice—5k vs. 7k DRT fleet—city-wide service

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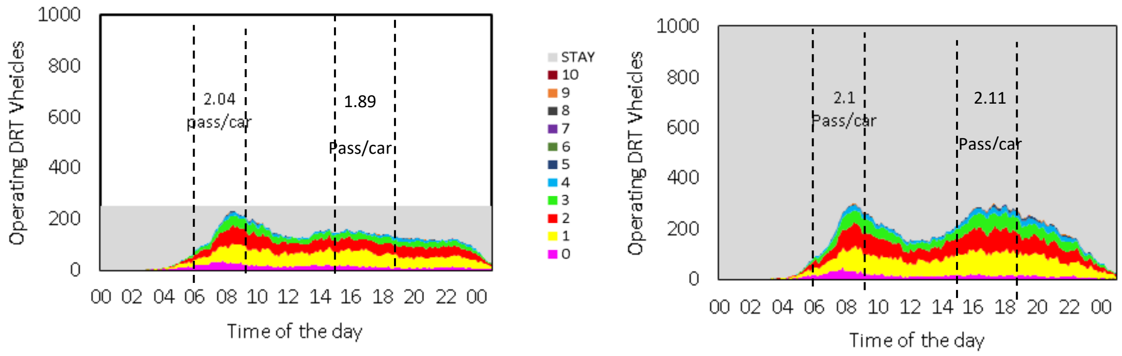
Table 8.3. City-wide DRT service, major statistics (averages)

Fleet size	Waiting Time [mm: ss]	Waiting Time 95 Percentile [mm:ss]	In-Vehicle Travel Time [mm:ss]	Direct Distance [km]	Detour Distance [km]	DRT Rejection rate
5k	07:06	17:02	27:41	10.38	1.57	**1.04%**
7k	06:59	16:52	29:44	11.9	1.69	**0.34%**

The city-wide DRT service scenarios indicate that a fleet of fewer than 1,500 vehicles is sufficient to serve the JMA area. Note that the service attracts ~7% of the PT users and almost no car users.

8.4.3 *Core-periphery DRT service*

For the core-periphery DRT configuration, DRT fleets of 250, 400, 600, 800, and 1,000 vehicles were investigated. Figure 7.7 presents the smallest and largest DRT fleets (250 and 1,000). As expected, a small fleet is exploited more intensively than a large one.



(a) (b)

Figure 8.7. Number of DRT riders: (a) 250-vehicle fleet (b) 1,000-vehicle fleet—core-periphery service

8.4.4 *Core-periphery DRT services with congestion charges*

Following the findings from Chapter 7, I used the scenario of the highest payment for entering the city center, with parking fees (5€) and entry charges (10€) that, intuitively, should maximize DRT demand. I examined the dependence of the request rejection rate and the number of idle vehicles on the necessary fleet size (Figure 8.8). As the fleet grows, rejection rates decrease from 14% for a 250 fleet to 2% for a fleet of 1000. However, in parallel, the number of idle vehicles increases from circa 4% for a 250 DRT fleet to 75% for a 1k DRT fleet. Evidently, these two traits are contradictory (more results for these two scenarios can be seen in tables 8.4 and 8.5).

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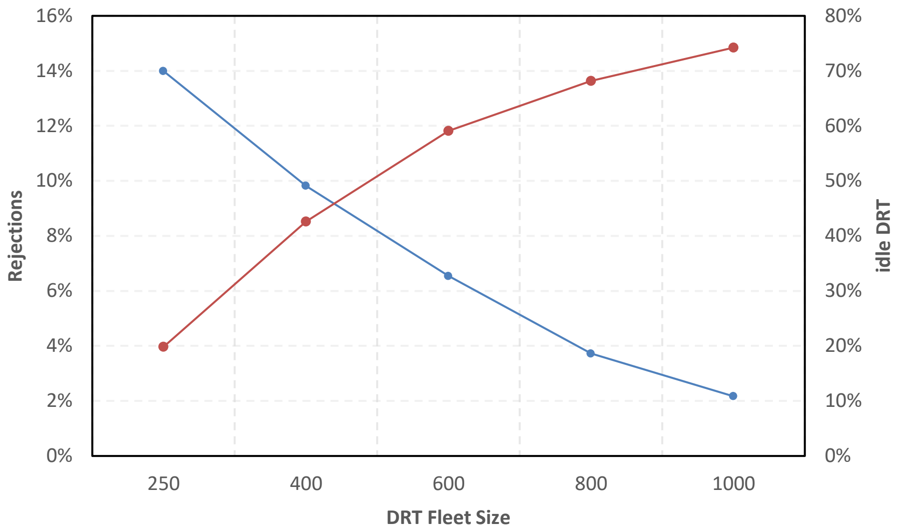

Figure 8.8. Morning peak DRT rejection rates (blue) vs. idle DRT shares (red) with parking and entry charges

To decrease rejection rates, the DRT fleet should be larger, while the fleet should be smaller to increase vehicle use intensity. Based on Figure 8.8, a ~450 fleet seems a good compromise between these two contradicting conditions.

Table 8.4 presents output statistics for the two edge cases of the smallest and largest investigated fleets (250 vs. 1000). A fleet of 1000 vehicles results in almost doubling of DRT trips compared to the smaller fleet—5.5K vs. 8.5K for the SMALL center, and 6.5K vs. 10.5K for the BIG center. Regardless of fleet size, the mode choice remains 52-54%, with two-thirds of DRT users shifting from the PT.

In scenarios of either entry charges or parking prices, total revenues are slightly higher with a fleet of 1000 vehicles. Depending on the center definition, entry charge revenues double for the BIG center compared to the SMALL one. Parking fees, in contrast, yield approximately 420k€ for SMALL and 550k€ for BIG centers. The revenues in scenarios combining entry charges and parking fees are slightly higher than those with entry charges alone. Overall, charged entrance to the city center results in more car users switching to the DRT service, while the number of PT users switching to DRT hardly changed.

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Table 8.4. Output statistics of the core-periphery service, 250 vs. 1,000 vehicles fleet trips to center, total payment and modal split

	Scenario	250 DRT fleet							1000 DRT fleet						
		Trips to the center				Mode switch to DRT		Total payment	Trips to the center				Mode switch to DRT		Total payment
		N	Car	PT	DRT	From Car	From PT		N	Car	PT	DRT	From Car	From PT	
SMALL CENTER	Cost-free entrance (0€)	140K	62.0%	33.7%	4.3%	1.9K	3.7K	-	141K	61.2%	32.3%	6.5%	2.8K	5.7K	-
	Entry charge (10€)	134K	47.5%	45.9%	6.6%	4.4K	4.0K	638K	136K	45.8%	43.8%	10.4%	7.0K	6.4K	620K
	Parking price (5€/hour)	134K	48.3%	45.7%	6.0%	3.4K	4.1K	413K	135K	47.0%	43.8%	9.2%	5.3K	6.3K	426K
	Entry charge 10€ & Parking fee 5€/h	128K	38.8%	54.0%	7.2%	4.6K	4.1K	820K	131K	36.5%	52.0%	11.5%	7.4K	6.7K	779K
BIG CENTER	Cost-free entrance (0€)	216K	61.4%	35.4%	3.2%	2.0K	4.5K	-	217K	60.6%	34.0%	5.3%	3.2K	7.6K	-
	Entry charge (10€)	210K	53.2%	42.7%	4.2%	4.0K	4.3K	1117K	215K	51.2%	40.5%	8.4%	7.3K	7.8K	1098K
	Parking fee (5€/hour)	204K	46.1%	49.9%	4.1%	3.3K	4.7K	547K	205K	44.5%	48.4%	7.1%	5.7K	8.2K	562K
	Entry charge 10€ & Parking fee 5€/h	198K	40.5%	54.9%	4.5%	4.2K	4.4K	1291K	201K	38.8%	52.8%	8.4%	7.8K	8.2K	1262K

Table 8.5. Fleet performance of the core-periphery service, 250 vs. 1000 vehicles fleet

	Scenarios	250 DRTs					1000 DRTs				
		Idle, morning	Idle, evening	Rejection ratio [%]	Total distance [km]	Total empty distance [km]	Idle, morning	Idle, evening	Rejection ratio [%]	Total distance [km]	Total empty distance [km]
SMALL CENTER	Cost-free entrance (0€)	34.40%	40.50%	11.70%	84.9k	7.3k	79.20%	43.60%	2.40%	115.5k	6.8k
	Entry charge (10€)	19.30%	42.70%	12.10%	110.2k	10.2k	74.30%	68.50%	2.60%	160.8 k	12.2k
	Parking price (5€/hour)	24.60%	41.60%	13.90%	98.7k	9.8k	75.80%	70.90%	2.30%	145.2k	10k
	Entry charge 10€ & Parking fee 5€/h	19.80%	44.10%	14.00%	113.3k	13.3k	74.20%	69.20%	2.20%	170.6k	10.8k
BIG CENTER	Cost-free entrance (0€)	23.80%	34.80%	15.50%	101.6k	8k	72.40%	65.50%	2.60%	151.6k	8.9k
	Entry charge (10€)	15.80%	38.00%	18.90%	121.2k	9.9k	66.70%	60.20%	3.90%	197.5k	12.8k
	Parking fee (5€/hour)	19.00%	43.60%	18.50%	110.2k	9.7k	69.00%	63.30%	3.50%	181.1k	12.8k
	Entry charge 10€ & Parking fee 5€/h	15.30%	38.80%	19.40%	121k	9.9k	67.80%	60.50%	3.60%	206.3k	14k

Table 8.5 presents the DRT performance statistics for 250 and 1,000 vehicles:

- For the fleet of 250 DRTs, the rejection rate varies between 11% - 14% in the case of the SMALL center and between 15% - 19% for the BIG center.
- With a fleet of 1,000 vehicles, the rejection rate is meager, ~3% in all cases.
- Waiting and travel times are similar, 7-8 minutes and the same is true for the in-vehicle travel time, 20-21 minutes, and the number of passengers during the morning/evening peak—2.1-2.2 passengers in all scenarios, regardless of the center's definition. During the morning peak, the number is slightly higher for the BIG center.
- The average length of a direct trip is around 8km for the SMALL center and 10km for the BIG center, no matter what the DRT fleet is.
- The average detour distance is ~4km for all scenarios and fleets.
- The idle fraction of DRT vehicles is 15%-34% for the 250 fleet, and in the case of the 1,000 DRT fleet—66%-79%.
- The city center definition influences the number of DRT trips (Table 8.6): 10k in the case of the SMALL center, and almost 60k for the BIG center. This increase is independent of the fleet size.

Combining entry and parking charges yields a comparable reduction in private car trips to parking fees alone: 25% for the SMALL Center and 30% for the BIG CENTER (results are consistent for both fleet sizes).

Table 8.6. Trip statistics within the city center for the 250 vs 1,000 fleets

Scenario		250 DRT fleet			1000 DRT fleet		
		N	Car	PT	N	Car	PT
SMALL CENTER	Cost-free entrance (0€)	10.7K	43.0%	57.0%	10.7K	43.3%	56.7%
	Entry charge (10€)	10.7K	47.5%	52.5%	11.0K	46.9%	53.1%
	Parking fee (5€/hour)	10.9K	25.3%	74.7%	11.1K	25.3%	74.7%
	Entry charge 10€ & Parking fee 5€/h	10K	26.4%	73.6%	10.1K	25.4%	74.6%
BIG CENTER	Cost-free entrance (0€)	62.2K	52.6%	47.4%	62.1k	53.0%	47.0%
	Entry charge (10€)	63K	55.1%	44.9%	62.7k	49.1%	50.9%
	Parking fee (5€/hour)	57.2K	31.1%	68.9%	57.3k	30.0%	70.0%
	Entry charge 10€ & Parking fee 5€/h	56.8K	31.7%	68.3%	57K	31.4%	68.6%

In conclusion, a smaller fleet is cost-efficient for the operator but disadvantageous for the passengers due to longer waiting times and higher rejection rates. A larger fleet improves the level-of-service for passengers but may not be financially advantageous for the operator. The DRT market share will be determined by both the operator's costs and the user's preference. Policy measures, such as congestion and parking charges imposed within the DRT service area, will also play a crucial role in defining the success of the DRT system (Figure 8.9).

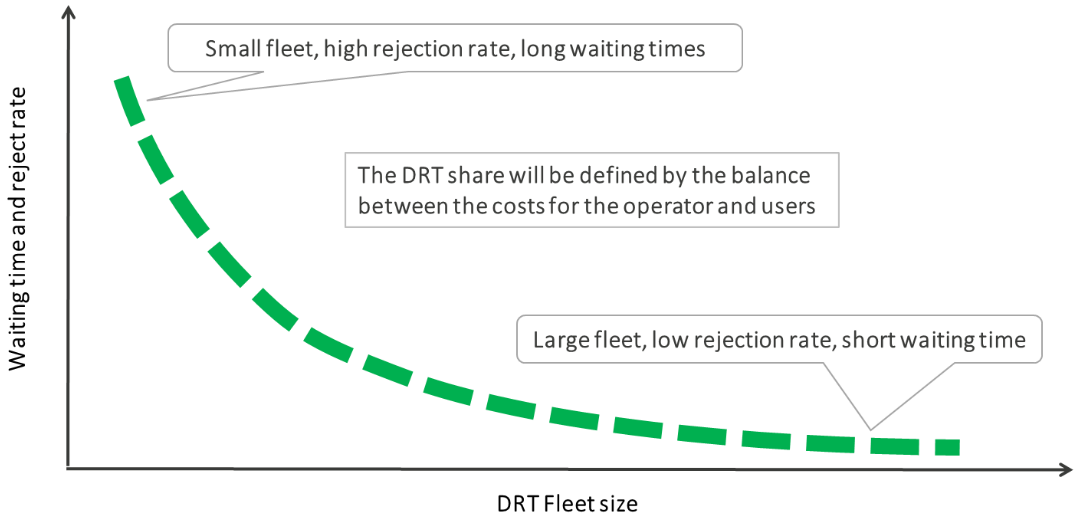

Figure 8.9. The conceptual relationship between the DRT level-of-service and fleet size

8.5 Discussion

The results of the DRT introduction in Jerusalem can be summarized as follows:

When entry to the city center is unrestricted, congestion persists. Introducing DRT services under these circumstances primarily attracts PT-users, with twice as many switching to DRT compared to car users. Consequently, the DRT service itself will not significantly alleviate traffic congestion.

Imposing an entrance charge of approximately €10 reduces the proportion of cars entering the city center by 10-20%, depending on the center's size. Under these conditions, DRT becomes equally appealing to car and PT users. A larger center results in stronger effects.

Parking fees, applied to city center visitors and residents parking at a distance from their homes, substantially influence car usage within the city center. Compared to the entry charges, parking fees prompt more car users to switch to PT and DRT for center-related activities.

Consequently, I assert that parking fees are more effective in reducing congestion than entry charges. Furthermore, the enforcement infrastructure required for parking management is

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simpler to implement using municipal capabilities compared to the technical equipment and special organizational services necessary for managing entry charges in Jerusalem.

In the simulation, the supply, modal distribution, and other attributes of the JMA transportation system are determined by the relative utilities of the available transportation modes and the marginal utilities of travel time and transportation-related costs. By applying the utilities of the JMA, validated using 2020 data, I demonstrate that even an affordable, priced DRT service will have a limited impact on JMA traffic due to the inherent uncertainty associated with the service. Future work could scrutinize this issue further by trying to find the optimal balance between fleet size, service area, and monetary incentives.

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CHAPTER 9 General Discussion, Conclusions and limitations

The following chapter concludes the above thesis with a general discussion, conclusions, limitations, and future outlook.

9.1 Discussion

Urban mobility serves as an essential component in establishing smart cities. It forms the backbone of urban development, influencing various aspects like economic growth, environmental sustainability, social inclusiveness, and overall quality of life (Bettencourt and West, 2010). Understanding urban mobility dynamics is paramount with the increasing focus on creating smart, sustainable, and resilient cities. Importantly, beyond hardware and software considerations, human decisions and not machines control the means and policies for dissipating traffic congestion and alleviating its associated externalities. Hence, the necessity to understand the policy foreground is the essence of the thesis.

The thesis addresses the significant and intricate issue of traffic congestion in urban settings worldwide. Traffic congestion is a multifaceted problem that demands an innovative and comprehensive approach to find effective and sustainable solutions. With the growth of urban populations, traffic congestion has transformed into a complex global problem, a daunting challenge that policymakers and researchers grapple with daily. Given the increasing importance of sustainable urban development and the adverse impacts of traffic congestion on the environment, economy, and public health, addressing this issue has become more critical than ever before (Timilsina & Shrestha, 2009; Raza et al., 2019; OECD-IEA,2016).

The last two decades have witnessed a growing understanding that the impacts of changes to transportation networks demand extensive quantitative modeling. This insight has been crucial for evaluating whether congestion management policies are cost-effective and efficient in achieving their desired objectives. In this respect, data-driven tools have gradually replaced traditional aggregate models. Spatially-explicit MAS has emerged as an effective tool to deal with these challenges, providing detailed and realistic simulations of urban mobility.

MAS and ABMs represent a paradigm shift in transportation modeling. They offer the complexity, dynamics, and individual-level granularity required to accurately capture the nuances of modern urban transportation systems (Abar et al., 2017). The essence of these models lies in their ability to incorporate the heterogeneity and adaptability of individual agents, allowing for a more intricate representation of transportation systems. Unlike conventional approaches, these models capture the dynamic interactions between the individual behavior of travelers and collective system performance, offering a comprehensive projection of real-world transportation systems.

ABMs serve as the core aspect of MAS, focusing on the dynamics of autonomous agents, each characterized by distinct behaviors (McCarthy, 1987). They provide a micro-level view of transportation systems, offering rich insights that substantially elevate transportation planning and policy-making. However, implementing transportation ABMs is not without its challenges. These include issues related to data quality, transparency, validation, reproducibility, and computational cost. While these challenges present hurdles, they also provide the impetus to push the boundaries of transportation modeling further.

MATSim is a leading open-source MAS transportation system capable of large-scale simulations with adaptive behavior. It bridges the gap between macroscopic models, which overlook the intricacies of individual behavior, and microscopic models, which may be computationally intensive and less suitable for large-scale networks. With its dual nature of simulation and optimization, MATSim presents a potent tool for addressing the complexities of urban transportation, providing a robust platform to study and analyze disaggregated transportation dynamics and providing a practical, dynamic, and realistic representation of how individual agents—travelers—interact with each other and their environment, thereby offering a deeper understanding of urban transportation systems. In the thesis, I leveraged the strengths of MATSim to delve into the dynamics of traffic congestion and its potential mitigation strategies.

The literature review elucidates the persistent traffic congestion challenges, underscoring the significant economic and environmental externalities. Congestion not only translates into lost time and increased travel costs but also leads to environmental degradation due to heightened emissions Baghestani et al., 2020; Gu et al., 2018; Small & Yan, 2001; van den Berg & Verhoef, 2011; Yang & Huang, 2005). The standard four-step travel model, widely used for transportation planning, has shown limitations in effectively modeling dynamic traffic conditions. It tends to oversimplify the complexities of human travel behavior, focusing primarily on origin-destination flows rather than the underlying activities that motivate travel. Activity-based models have improved the granularity of travel demand data; however, the application in simulation models remains aggregated

While conventional models are useful for aggregate-level analysis, they fail to capture the intricacies and dynamism of transportation systems (Rafiq and McNally, 2000. While capturing the demand-side link between activities and travel, activity-based models tend to apply travel demand in an aggregated form, thereby missing out on the nuances of individual behaviors. In contrast, MAS can represent urban traffic and transportation problems more explicitly. However, they face challenges balancing the computational

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demands with the need to represent diverse agents in large metropolitan areas. A deep understanding of these issues informs the research design of the thesis, prompting an in-depth exploration of MAS and ABMs in transportation modeling.

Modeling the effects of congestion charges, priced parking, and the potential benefits of introducing DRT can be effectively accomplished using MAS and MATSim (Bischoff et al. 2017) and representing potential policy interventions to manage traffic congestion. Understanding their implications at an individual level and the whole system is crucial for informed decision-making. The application of MAS in evaluating these interventions presents an opportunity to capture the potential effects in a dynamic and detailed manner.

The research is applied in a case study of Jerusalem, modeling the impacts of popular congestion mitigation policies on mode choice and road traffic. Specifically, the study focuses on the systemic impacts of imposing congestion charges—cordon entry and parking fees—as well as introducing ridesharing DRT services. The impacts of these policies on the network's performance are scrutinized through a comprehensive MAS, helping to understand the potential changes to the behavior of individual travelers and overall traffic patterns.

Alongside this study, I presented the state-of-the-art in the field of transportation MAS. I showcased the advancements in the field, the methodological innovations, and the empirical applications that have helped transform our understanding of urban mobility. I also demonstrated the advantages of MATSim as a foundational simulation software system for the research. It points to its operational advantage—the ability to perform very large-scale transportation simulations through the downscaling process. This process involves representing full-scale model scenarios by scenarios with only a fraction of the travelers. Despite its intensive use by MATSim users, downscaling's critical advantage has remained relatively under-investigated. I, therefore, dedicated the first part of the thesis to a detailed investigation of the downscaling robustness in MATSim.

Through a critical examination of an empirical application, Study 1 demonstrated that the dynamics of the full system could be adequately represented by a MATSim simulation based on only 25% of agents. This finding has significant implications for large-scale transportation modeling, suggesting that a comprehensive system representation can be achieved even with a limited set of agents. The study also showcased that several repetitions of the downscaled model run ensure the robustness of the results by revealing potential outliers in space and time. This iterative process serves as a critical validation mechanism, ensuring the reliability of the simulation results.

Further, Study 1 investigated the possible parallelization effects of MATSim simulations. It demonstrates that the performance improvement resulting from parallelization is modest, approximately 15-20%. While this may not seem substantial, it is an important step toward enhancing the computational efficiency of large-scale simulations. The ability to accurately simulate large-scale transport scenarios using only a fraction of agents enhances computational efficiency and increases the tool's accessibility for researchers with limited computational resources. This advancement potentially democratizes the field, allowing for more diverse input and perspectives. The examination of MATSim downscaling and parallelization represents a significant methodological contribution to the transportation modeling field.

Using the knowledge gained from the MATSim downscaling study, I established JMATSim, the MAS traffic simulation for Jerusalem. JMATSim is a data-driven model built on a massive database that includes data on infrastructure, traveling population, and activities as of 2017-2020, encompassing 688 TAZ, a network of 9,000 links, and the JMA public transport network represented by 336 transit lines, with 2,637 stops, and 15,145 daily bus departures. The model includes 450,000 agents, representing 30% of the JMA population, 106,173 facilities, travel behavior surveys, 2,422 road counts, and smartcard data. The development of JMATSim represents an important step towards harnessing big data in transportation science, signaling a shift towards more data-driven, detailed, and robust models.

Using this extensive, real-world data for model estimation and validation increases the reliability and applicability of the findings. It allows for closely imitating the city's existing urban traffic and mode choice. This approach could serve as a blueprint for future studies aiming to predict travel behavior accurately. The development of JMATSim and its application in Jerusalem represent a major achievement of the research.

Based on the validated JMATSim, Study 2 investigated the effects of implementing parking prices and entry charges as policy measures to mitigate traffic congestion in the JMA. It demonstrates that a socially acceptable overall payment of 35-40 ILS (Israeli Shekel) for entering the Jerusalem city center is sufficient to reduce car arrivals by 25%. Such a reduction has the potential to critically alleviate congestion and improve the travel time of all travelers, whether they use public transport or private cars.

The findings offer valuable insights for policymakers, suggesting practical measures to address urban congestion. Policymakers can employ these tools or choose a combination that better mitigates public opposition to negative economic incentives. Overall, the potential effect of parking prices was stronger than the effects of the entry charges of the same level. By quantifying the potential impacts of parking prices and entry charges, the study provides a critical foreground for effective policy design.

Study 3 extended the BM-DRT algorithm (Bischoff et al., 2017) and examined the possible introduction of DRT services to the JMA. I demonstrated two important limitations: first, a
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city-wide DRT service is economically ineffective due to inherently insufficient demand; and second, without significant congestion charges or parking fees, DRT services, even limited to the areas of sufficient demand, will compete with the existing public transport services, primarily attracting its users and not the users of private cars. However, when entrance and parking fees are imposed, a DRT service restricted to core-periphery trips becomes equally appealing to both car and public transport users, significantly reducing congestion.

Again, the study showed that DRT, when introduced with the parking fees, is more effective in managing congestion than DRT with entry charges. The former is also simpler regarding any necessary investment in additional infrastructure. The investigation into the viability and limitations of DRT services contributes significantly to the ongoing discussion about the role of these services in urban transportation (Schaller, 2021; Qian et al., 2020). The findings indicate that DRT services have potential benefits but are not a "one-size-fits-all" solution and should be implemented considering the local context, particularly concerning existing public transport services and potential intermodal competition.

To conclude, the importance of MAS and ABMs in transportation modeling and policy-making has highlighted the significant contributions of MATSim, particularly it's potential for large-scale, detailed, and adaptive simulations. The development and application of JMATSim represented a major advancement in the transport modeling field. The investigation into congestion charges, parking prices, and DRT services provided valuable insights for traffic congestion management policies. Importantly, I showed that the impact of these interventions can be substantial, and their implementation should be carefully considered.

9.2 Limitations

This thesis makes several significant contributions to studying multi-agent transportation simulations, large-scale modeling, and policy evaluation. However, certain limitations must be noted for a holistic understanding of the findings.

1. *Unimodal Downscaling*: The research predominantly focused on unimodal downscaling, involving only simulated car agents. The absence of other modes, including DRT or PT, in the downscaling process may limit the completeness of the simulation models. Including these modes in future studies would likely provide a more comprehensive representation of urban mobility patterns. The downscaling demands of a multimodal simulation may be more conservative compared to one solely based on car traffic.
2. *Static Scenario Assumptions*: The JMA scenario was modeled based on the existing conditions and did not consider potential changes such as future mass transit planned in the city. Therefore, the impacts of prospective changes in infrastructure, technology,

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policy, or population behavior on the transportation network were not considered. DRT can be organized as a feeder network to mass transit stations rather than a main travel mode, thus preserving the natural hierarchy of the transportation system. Increasing the city population would still take a toll on traffic congestion, likely requiring negative incentives to motivate mode choice shifts.

3. *Arbitrary DRT Fleet Size*: In the JMA DRT scenario, the fleet size was selected arbitrarily. While this is a common practice in such studies, it may influence the simulation results, as the availability of DRT vehicles directly affects their potential to replace other modes of transportation. Future work could attempt to develop a continuous function that balances operator efficiency and customer satisfaction so that the fleet is financially viable and yet the level of service is sufficient (Diaz et al., 2016; Alonso-Mora et al., 2017)
4. *Lack of Income Effects and Willingness-to-pay variability*: This thesis did not incorporate income effects or variability in willingness-to-pay into the modal utility functions of the simulation. Both of these factors can significantly impact mode choice and the effectiveness of congestion pricing mechanisms. As such, the current analysis may not fully capture the complexities of real-world traveler behavior. Accounting for income elasticity of demand in the simulation will likely show that higher-income travelers are less likely to shift modes even with high entry and parking fees. In contrast, low-income travelers will be more likely to shift (Small and Verhoef 2007).

These limitations should be seen as opportunities for future research, providing avenues for refining the models and broadening our understanding of urban transportation dynamics and traffic congestion. Despite these limitations, I believe that my thesis presents robust findings and insights valuable to the transportation MAS field, with potential implications for better design and implementation of urban mobility policies.

9.3 Future outlook

Future research could explore several avenues. One direction to explore is the interaction of other policy measures like carpooling incentives or increased investment in public transport infrastructure with congestion charges, parking prices, and DRT services. Other cities with different urban forms, transport infrastructure, and policy contexts could also be examined to validate further and expand the application. Expanding the geographical scope of the research, and applying the same methodology to different cities, would enhance the generalizability of the findings. Factors such as local public transport infrastructure, cultural differences in travel behavior, and regional policy differences could significantly influence the applicability of the findings. Comparative studies involving cities of different sizes, population densities, and levels of development would also be invaluable in furthering our understanding of urban mobility (Ziemke et al., 2019).

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With the continuous advancement of technology and computational resources, there is a need to revisit the downscaling process. Future studies could focus on understanding how newer computational techniques and models can be employed to represent better the complexity and dynamic behavior of urban transport systems – downscaling with mixed traffic of PT and cars and investigating DRT services with downscaling. Computational improvements are always welcome in this field, especially as urban populations continue to grow. Deep learning or other machine learning algorithms could be applied to speed up the simulation or to make more accurate predictions (Chaniotakis & Antoniou, 2020).

As we advance in our understanding of urban mobility, the role of human behavior in shaping transportation dynamics gains increased importance. Moving forward, integrating behavioral insights into MAS and ABM could significantly enhance the reliability of these tools in reflecting reality. This entails diving deeper into individual decision-making processes and their interaction with policy measures and transport system characteristics. Drawing insights from behavioral economics, psychology, and sociology to inform our transport models could yield more nuanced and accurate predictions (Train, 2009).

Moreover, the incorporation of serious gaming elements in transportation simulations promises to bring a new dimension to these studies. Serious gaming, particularly in the transportation domain, can serve as an effective tool for increasing transparency, engagement, and, ultimately, the believability of the models (Szubert & Karwowski, 2020). The interactive nature of gaming simulations can enhance our understanding of individual behaviors and decisions in the context of urban mobility (Chen et al., 2016).

By combining these avenues - enhanced behavioral modeling and game-based simulations - future research can unravel new levels of understanding and intervention in urban transport dynamics. As computational capabilities continue to improve (perhaps quantum computing), the possibilities for more sophisticated, nuanced, and effective transportation studies expand, paving the way for smarter, more sustainable cities.

To wrap up, this research has obtained a comprehensive, data-driven understanding of urban mobility. The thesis's findings offer practical insights for policymakers and urban planners in managing traffic congestion, indicating that a combination of rather simple policy interventions may be the most effective strategy. The use of data-driven, agent-based modeling in this study signals a new era of transportation modeling—more detailed, reliable, and reflective of real-world complexities. The research sets a solid foundation for future research in this area, calling for more detailed, data-driven studies that can contribute to sustainable and resilient urban transportation systems.

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תקציר

עבודת הדוקטורט חוקרת את האתגרים והפתרונות הפוטנציאליים בהדמיות תחבורה בקנה מידה גדול תוך שימוש במודל Multi-Agent Transport Simulation of (MATSim) המחקר מחולק לשלושה חלקים, תוך התמקדות בטכניקות downscaling והערכת מדיניות הפחתת הגודש עם/בלי תחבורה מגיבת לביקוש (תמ"ל).

בחלקו הראשון, המחקר מתייחס למגבלות החומרה ולצורך בטכניקות downscaling ב-MATSim- הממצאים מראים כי הקטנת האוכלוסייה ורשת התחבורה לרמה של 20% היא בטוחה מבחינה איכותית, בהתבסס על דפוסי הגודש. המחקר גם בוחן את הביצועים של גרסא מרובת ליבות של MATSim ומדגיש שיפור צנוע של 15-20% במהירות החישוב. נדונים המגבלות והתחומים למחקר עתידי, לרבות יכולת ההכללה של ממצאי downscaling והצורך בחקירת דרכי תחבורה ומודלים אחרים.

החלק השני של התזה בוחן יישום בו-זמני של מחירי חניה ודמי גודש כאמצעי מדיניות להפחתת עומסי תנועה עירוניים, תוך שימוש במטרופולין ירושלים כמקרה בוחן (שנבנה מאפס). המחקר מוכיח שתשלום משולב של כ-10 אירו יכול להפחית את הגעת המכוניות למרכז העיר ב-25%, ולתמוך במעבר מנהיגה ברכב פרטי לתחבורה ציבורית. מזהים הבדלים מכריעים בין אגרות הגודש למחירי החניה, מה שמצביע על כך שהאחרון יעיל יותר בניהול העומס. המחקר מכיר במגבלות ביישום מודל MATSim להערכת ניהול גודש, ומודגש הצורך במחקר נוסף על מצבים משותפים והשפעות הכנסה.

הפרק השלישי מראה את ההשפעה של שירותי תחבורה מגיבה לביקוש על עומס עירוני ואת האפקטיביות של דמי כניסה וחניה לשיפור המשיכה של תמ"ל. הממצאים חושפים כי גישה בלתי מוגבלת למרכז העיר מובילה לעומס מתמשך, כאשר שירותי תמ"ל מושכים בעיקר משתמשי תחבורה ציבורית. עם זאת, כאשר מוטלים דמי כניסה וחניה , תמ"ל הופך מושך יותר הן למשתמשי הרכב והן לתחבורה ציבורית, וכתוצאה מכך להפחתה משמעותית בעומס. מסקנת המחקר היא שדמי החניה יעילים יותר בניהול עומס מאשר דמי גודש, לאור התשתית הפשוטה יותר ועלויות היישום הנמוכות יותר. מחקר זה מדגיש את הפוטנציאל של צעדי מדיניות משולבים בהפחתת עומסי תנועה עירוניים וקידום חלופות תחבורה בנות קיימא.

בסך הכל, מחקר זה מציע תובנות חשובות לגבי טכניקות downscaling ומדיניות הפחתת גודש במערכות תחבורה עירוניות, תוך מתן מידע לתכנון עירוני ופיתוח מדיניות לתחבורה יעילה ובת קיימא יותר.

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הפקולטה למדעים מדויקים
ע"ש ריימונד ובברלי סאקלר
אוניברסיטת תל אביב

בית הספר לסביבה
ולמדעי כדור הארץ
על שם פורטר

עבודה זו נעשתה במסגרת החוג לגאוגרפיה וסביבת האדם

נלחמים בגודש: הערכת מדיניות תחבורתית רובסטית במודל סימולציה רב-אמצעי מבוסס סוכנים

חיבור לשם קבלת התואר "דוקטור לפילוסופיה" על ידי:

גולן בן-דור

מנחים:

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החוג לגאוגרפיה וסביבת האדם

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המחלקה למדעי הסביבה,

גאואינפורמטיקה ותכנון ערים

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מאי 2023