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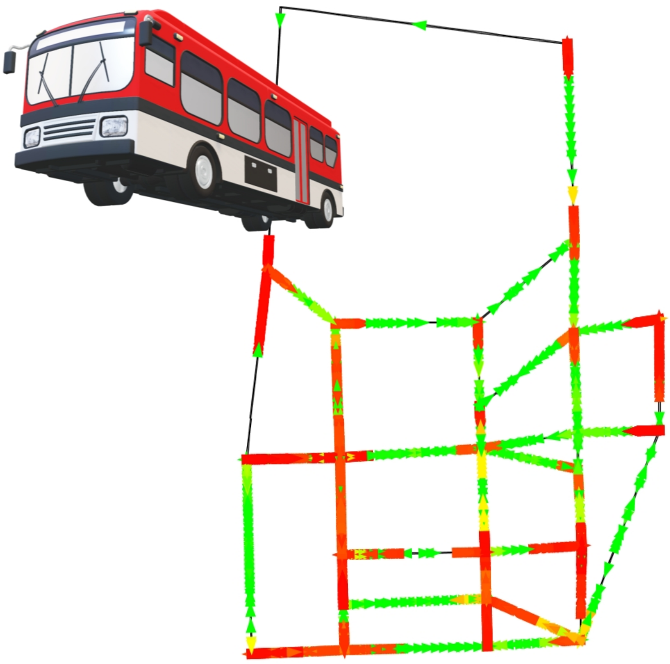

# Evaluating the Impacts of Dedicated Bus Lanes on Urban Traffic with an Agent-Based Model, October 2018

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October 2018

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# Abstract

*Dedicated Bus Lanes* (DBLs) have the potential to improve the performance of bus services while encouraging mode switch from private cars to *Public Transport* (PT), reducing travel times and relieving urban congestion. The primary goal of the thesis is to assess the impact of DBLs on urban road traffic through the *Multi-Agent Transport Simulation* (MATSim) framework.

The DBLs effects are investigated based on the example transportation network of the city of Sioux Falls. Three scenarios are compared: (1) ***No DBLs*** - PT and private cars compete on the same road space; (2) ***Added DBLs*** - new DBL is added to every street link; and (3) ***Converted DBLs*** - one of the lanes on each street link which is exploited by PT is converted into a DBL which in turn, reduces the number of available lanes for cars. Street Links with only one lane are not converted into DBLs. The proposed MATSim-based methodology can be employed for estimating the effect of DBLs in any metropolitan area. The addition of DBLs results in decreasing congestion and reduction of the travelers' travel times, for all modes. For the current population of Sioux Falls, the reduction in travel time is, on average 4%. With an increase in the Sioux Falls population, these effects are disproportionally stronger reaching 14% and 26% when the population is duplicated and tripled, respectively.

The sub-goal of the thesis is to evaluate MATSim's downscaling rules and estimating the minimal population fraction that guarantees adequate representation of the full population dynamics. The likely results of the thesis demonstrate that the model dynamics for the full population and the downscaled population remain similar when the population fraction is higher than 10%. For a population fraction lower than 10%, the discrepancy between the 100% and the downscaled dynamics increases non-linearly. Thus, a population fraction of 10% is suggested as the bottom limit for MATSim downscaling.

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| | |
|---|---|
| ABM | Agent-Based Modeling |
| AI | Artificial Intelligence |
| ATD | Average Trip Duration |
| CPU | Central Processing Unit |
| DBLs | Dedicated Bus Lanes |
| DTA | Dynamic Traffic Assignment |
| FIFO | First in First Out |
| FWHM | Full-Width Half Maximum |
| GMA | Genetic Modification Algorithms |
| GP | General Purpose |
| MATSim | Multi-Agent Transport Simulation |
| MNL | Multi-Nominal Logit |
| MOBSim | Mobility Simulation |
| MRD | Mean Relative Deviation |
| PCE | Passenger Car Equivalent |
| PHD | Peak Hour Duration |
| PT | Public Transport |
| Qsim | Queue-based simulation |
| RR | Representation Ratio |
| SUMU | Simulation of Urban Mobility |
| STDEV | Standard Deviation |
| T2T | Terminal-to-Terminal |
| TLVM | Tel-Aviv Metropolitan |

# 1 Introduction

In a mixed traffic flow where buses and cars compete on the same road space, buses would hardly become an attractive mode of choice for urban travelers. Mixing between *Public Transport* (PT) and private vehicles results in additional congestion for both PT and private cars which produces bus delays, decreases travel speeds, and increases dwell times for PT passengers, resulting in the poor performance of the bus service.

Bus prioritizations schemes, such as bus priority signals, transit malls, bus gates, etc. have been widely investigated in the literature (Eichler & Daganzo, 2006; Janos & Furth, 2002; Koryagin, 2015; Levinson & St. Jacques, 1998; Oakes, ThellMann, & Kelly, 1994; Roberts & Buchanan, 1993; Viegas & Lu, 2004; Wu & Hounsell, 1998). These schemes are essential for sustainable and efficient urban transportation, mitigating air pollution and reducing PT operational costs (Shu & Yong, 2009).

*Dedicates Bus lanes* (DBLs) are broadly considered as a useful bus prioritizing scheme. DBLs can decrease passengers' travel time thus encouraging a modal shift toward PT and reducing traffic congestion for private cars. DBLs can be constructed for a whole transit network, single transit line or a part of it (Kim, 2003). They can be added to a transport infrastructure or converted from the existing *General Purpose* (GP) lanes. Converting GP lanes into DBLs may, however, generate more congestion (Shu & Yong, 2009). Surprisingly in some cases, it has been reported that the addition of DBLs did not increase the overall usage of buses, while in several developing countries DBLs did enforce higher bus usage (Garrett, 2014).

This thesis focuses on a large-scale agent-based simulation of DBLs establishment with an emphasis on the travelers' mode choice. The results of this thesis show that DBLs do encourage modal shift to PT in Sioux Falls by reducing the average trip duration of the PT passengers and, indirectly, trip time of the private car users. These positive effects are particularly strong during the peak-hours and will be essentially and non-linearly stronger in the future when the Sioux Falls population size will be doubled and tripled.

The rest of this thesis is organized as follows: Chapter 2 presents the literature review. Chapter 3 presents background information on the MATSim simulation framework and in particular regarding DBLs. Chapter 4 describes the Sioux Falls case study scenario. The applied methodologies are outlined In Chapter 5. Chapter 6 reports the study's simulation results that are summarized and discussed in Chapter 7. Finally, the future outlook and conclusions are presented in Chapter 8.

## 1.1 Objectives of the research

The primary goal of this thesis is to investigate the qualitative effects of DBLs on the urban road traffic and the associated human travel behavior using the *Multi-Agent Transport Simulation* (MATSim) framework (Horni, Nagel, & Axhausen, 2016) and its PT extension (Rieser, 2010). Most of the previous studies investigated performance of DBLs focusing on the micro-level of a single DBL established along an artificial road or a small synthetic network and applying a simplified view of mode choice (See Chapter 2). MATSim is capable of high-resolution representation of a population and a transportation network and is highly customizable, modular and a flexible simulation environment. The sub-goal of the thesis is to assess the abilities of MATSim to produce similar and viable outputs across different downscaled scenarios, an important issue that was not systematically investigated before.

A case study of the city of Sioux Falls, South Dakota (Chakirov & Fourie, 2014) is chosen to achieve the goals of the thesis. Sioux Falls is a well-documented test network for investigating transportation problems where agent-travelers adapt to changes in the transportation network.

# 2 Dedicated Bus Lanes, a literature review

Multimodal cities tend to focus on investment in rail-based transit, which is costly and requires decades to fully mature. The alternative is to focus on bus transit improvements such as DBLs. A DBL network supported by other transit-friendly policies can make PT travel speeds competitive with the private car, providing travelers motivations to choose PT. Bus transit improvements create a positive feedback loop of improved PT services, more diverse transit ridership, more political support for pro-transit policies, and more transit-oriented development (Litman, 2015). The main benefits of DBLs are described in Table 1.

Table 1. Benefits of Dedicated Bus Lanes by [Litman, 2015]

| **Improved Transit Service**<br>*Service Quality (speed, comfort, etc.)* | **Increased Transit Travel**<br>*Transit trips or mode share)* | **Reduced Car Travel**<br>*Automobile Travel Reductions* |
|---|---|---|
| o Improved transit operating efficiency<br>o Improved bus passenger travel speed and reliability<br>o Value of having options that may sometime be useful)<br>o Equity benefits (since existing users tend to be disadvantaged) | o Direct benefits to new users<br>o Increased fare revenue<br>o Increased public fitness and health (by stimulating more walking or cycling trips) | o Reduced traffic and parking congestion<br>o Consumer savings<br>o Reduced chauffeuring burdens<br>o Increased traffic safety<br>o Energy conservation<br>o Air and noise pollution reductions |

DBLs are broadly investigated in the literature. In the following sections two categories of DBLs studies are distinguished - modeling studies and field studies.

## 2.1 DBLs evaluation in the field

Field studies were conducted by analyzing observed data instead of generating new artificial data using simulations. A study of the DBL effect on a single inter-regional road in Seoul, South Korea compared data before and after the introduction of a single DBL. The researchers found that the addition of the DBL resulted in a mode shift from cars to buses of more than 12% of travelers and improved their bus travel times (Choi & Choi, 1995). In 2003, another study on DBLs performed in Seoul, South Korea, compared empirical data inside the entire metropolitan area before and after the introduction of DBLs. The researchers found that increasing the DBLs from 52 Km (in 1993) to 218 Km (in 2001) improved the average travel speed of buses and made them the predominate travel mode in Seoul (Kim, 2003). However, other studies report contradictory results. The introduction of bus lanes did not increase the overall usage of buses in Runcorn, England and in Houston, Texas the addition of DBLs even reduced transit use by 10% (Garrett, 2014).

In Los Angeles, California a one-mile DBL segment was initiated as a pilot from 2004-2007 on Wilshire Boulevard. The Los Angeles County Metropolitan Transportation Authority found that during the worst periods of traffic congestion on Wilshire Boulevard it took roughly 30 minutes to drive a 1.5 miles ride on the mixed traffic lanes. On the contrary buses on the adjacent DBL traveled the same distance in about 2.5 minutes (Agrawal, Goldman, & Hannaford, 2012). Table 3, depicts the DBL-related travel time savings documented across the United States of America.

Table 2. Examples of travel time savings documented on urban dedicated bus lanes

| **City** | **Street** | **Time Savings** |
|---|---|---|
| Los Angeles | Wilshire Boulevard | 0.1-0.2 [min/mile] (a.m.)<br>0.5-0.8 [min/mile (p.m.) |
| Dallas | Harry Hines Boulevard | 1 [min/mile] |
| Dallas | Ft. Worth Boulevard | 1.5 [min/mile] |
| New York | Madison Avenue (dual bus lanes) | 43% express bus<br>34% local bus |
| San Francisco | 1st Street | 39% local bus |

(According to [KFH Group, 2013])

As empirical literature points out, travel time savings are a crucial benefit of DBLs. Increasing transit travel speed and reliability tend to increase PT ridership and reduces private car traffic (Handy, Tal, & Boarnet, 2010). These findings were further expanded in a study conducted in 2012. The study compared 21 different PT priority schemes around the world and their associated travel time saving effects on modal shifts. The analysis was done only for single roads, before and after the introduction of the transit priority scheme (Currie & Sarvi, 2012). The study found that travel time savings for PT can increase the transit ridership while reducing private car travel times.

Figure 1, displays the PT ridership gains associated with the travel time saving obtained by PT according to the aforementioned study. Each point in the figure represents one of the 21 different transit priority schemes. The elasticity of bus trips concerning travel time is estimated to be 0.4 to 0.6 (Paulley et al., 2006), so a 10% travel time saving for PT typically increases the ridership by 4-6%. The elasticity mentioned above suggests that a DBL that reduces total transit travel times by 5-15% will increase the PT ridership by 2-9% (Litman, 2015).

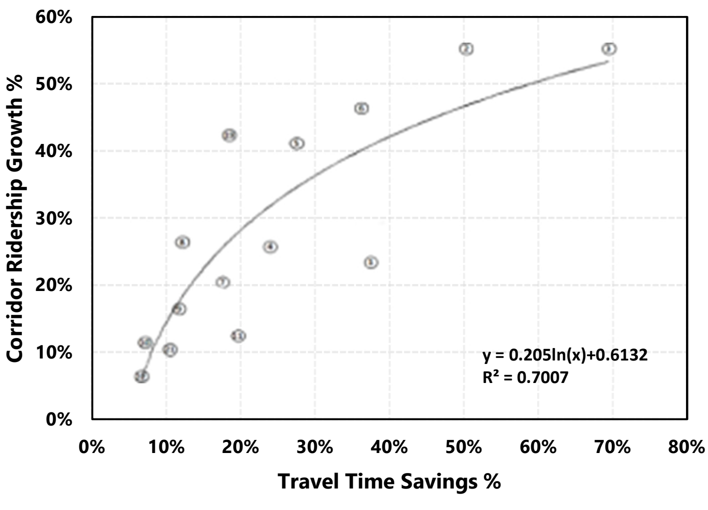


Figure 1. Transit Ridership Gains from Transit Travel Time Savings (from [Currie & Sarvi, 2012]).

## 2.2 **Model-based DBLs studies**

Model-based DBLs studies use modeling and simulation tools to analyze the effects of DBLs. A study of the impacts of a DBL on a single road in Toronto, Canada using the TRANSYT-7F simulation tool (mostly used for signal timing design and optimization of traffic flow) demonstrated that a single DBL reduced the travel times of buses when compared to the same road without a DBL (Shalaby, 1999). Another study of adding a DBL on a single road in Chennai, India with a traffic flow simulation showed that a single DBL improved the average travel times of buses (Arasan & Vedagiri, 2010) and similar results were found in another simulation study (Zhou & Peng, 2013). Examining traffic flow on a single road using a cellular automata traffic flow model (Zhu, 2010) demonstrated that adding a DBL is the most effective when demand is close to the road capacity bottleneck or exceeds it. Hence, there is no justification for a DBL when the traffic flow density is low. The traffic flow comparison is made for a case of single DBL, where one of the two lanes in the road is converted to a DBL. In the case of a mixed traffic road with two lanes also demonstrated that DBLs are useful in close to congestion states (Zhu, 2010). Figure 2, compares both cases mentioned above of a mixed traffic state and a single DBL (the bus-to-car vehicle ratio is 0.1). With the addition of a DBL, buses keep the same speed velocity even when adding more buses. In the mixed traffic case, buses keep their speed velocity until the vehicle density on the link exceeds 0.17.

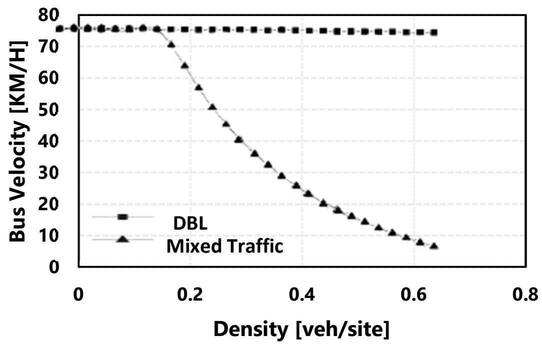


Figure 2. Bus velocity–density (According to [Zhu, 2010]).

A study with the *Simulation of Urban Mobility* (SUMU) software found that for low bus volume density, a DBL did not improve bus travel times (Witheridge, Passow, & Shell, 2014) thus strengthening the results of (Zhu, 2010).

A study of urban congestion management policies such as congestion pricing, transit subsidies, and DBLs, through numerical analysis of a simple model also demonstrated that the positive effects of DBLs on traffic congestion are the strongest among all investigated mechanisms (Basso, Guevara, Gschwender, & Fuster, 2011).

Another study investigated DBLs effects on the efficiency of congested networks comparing user equilibrium, travel costs, demand and road resources before and after the addition of DBLs (Yi & Dalin, 2014). They suggested that the best way to improve the network efficiency is by attracting more PT users. A combinatorial optimization approach for a bus-lane infrastructure layout was applied to a sample network derived from the Haidian district in Beijing (Yu, Kong, Sun, Yao, & Gao, 2015). The study demonstrated that the removal of DBLs caused the longest average travel time for the bus passengers. Adding DBLs to all links of the network reduced average travel time for bus users. Average travel times of other modes on the non-DBL link were 20% higher than for the buses.

A multi-modal *Dynamic Traffic Assignment* (DTA) model was applied to analyze the impacts of DBLs on small transport network with and without DBLs for the different size of travelers' population (Shu & Yong, 2009). For the small population of 2000 travelers, there was no justification for adding DBLs. DBLs were justified only when the population size was higher than 5000 persons when the total travel time in the DBL scenario became lower than in the no-DBL one.

To conclude, most of the modeling efforts, take the positive effect of DBLs for granted (Shalaby, 1999), or focus on the algorithms of their establishment (Basso et al., 2011; Shalaby, 1999; Shu & Yong, 2009; Thamizh Arasan & Vedagiri, 2010;

Witheridge et al., 2014; Yi & Dalin, 2014; Yu et al., 2015; Zhou & Peng, 2013). These algorithms are based on a simplified view of the travelers' mode choice and applied to a small portion of the urban road network. The MATSim framework is a step ahead, assuming that each of the model agents individually explores all of the available modes and chooses a particular one based on the mode utility. MATSim is inherently closer to urban reality, where travelers compare between the available modes in regards to their specific origins, destinations, and the schedule of daily activities.

# 3 The MATSim simulation Framework

MATSim is a JAVA agent-based simulation environment that mimics the human view of traveling choice (Horni, Nagel, & Axhausen, 2016) including learning, reasoning, and self-correction (McCarthy, 1987). MATSim development started more than two decades ago and combined perspectives of a physical view of complex systems and transportation engineering. The MATSim software is employed worldwide - in Indonesia, Brazil, South Africa, Switzerland, Germany, South Korea, Poland, Israel, Singapore, Austria and other countries (Horni, Nagel, & Axhausen, 2016).

## 3.1 What is an Agent-Based Model?

MATSim is an *Agent-Based Modeling* (ABM) environment. It considers shared dynamic environment where autonomous agents coexist, and their actions and reactions affect one another. A single agent is a discrete, autonomous entity with its own goals and behaviors and can adapt and modify its own behaviors. The goal of ABM is to evaluate the insights arising from agents' emerging behavior of heterogeneous agents' society. Numerous ABM simulations are applied in biological, economic, social, business, technological studies and more. A study which compared 83 different ABM simulations in different fields claims that MATSim was one of the most complex

ABM. Regarding the number of agents which an ABM can handle, MATSim was placed at the highest level (“extreme-scale”) due to its ability to simulate a population of millions of agents over vast urban networks (Abar, Theodoropoulos, Lemarinier, & O’Hare, 2017).

The MATSim simulation environment and its components used in this research are presented in depth in sections 3.2-3.6 below.

## 3.2 The “MATSim Loop”

A Typical MATSim simulation is continued until converging to an equilibrium in which agents cannot further improve their daily plans' utilities.

The “heart” of MATSim resides inside the “MATSim Loop” (Figure 3) that represents a single day. A typical “MATSim loop” starts with the “Initial Demand” step (Section 3.3) when the population of agents and the transportation network are established. Next step of “MATSim loop” is the simulation of the agents’ activities, including travels (Section 3.4), which is done using the *MOBility Simulation* (MOBSim). After the daily activities are performed, agents are scored based on their performance. This stage of the “MATSim loop” is called “Scoring” (Section 3.5) and agents’ scores (i.e., utilities) are calculated using economic utility functions. In the next “Replanning” stage (Section 3.6), MATSim uses Co-Evolutionary Algorithms to improve the agent's daily plans. A “MATSim Loop” ends with an analysis of the events (Section 0) recorded during a daily simulation run.

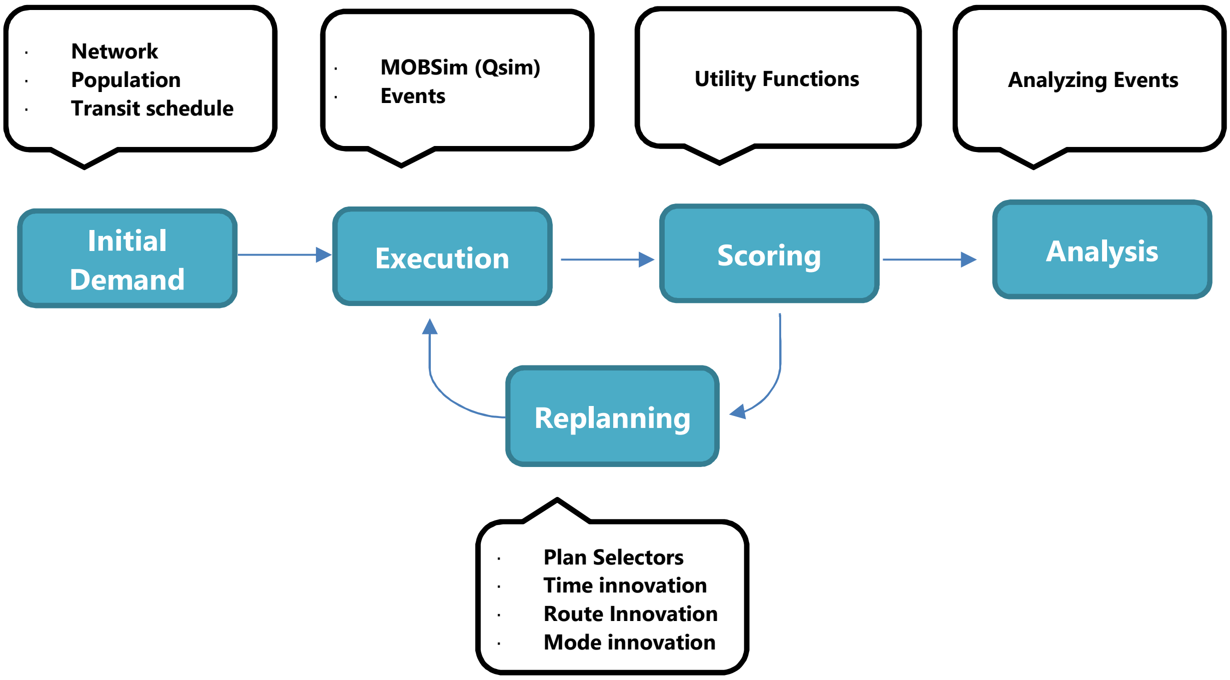


Figure 3. Flowchart of the "MATSim loop".

## 3.3 Initial Demand

The "MATSim loop" (Figure 3) starts with the "Initial demand" stage when all the input files are loaded, which includes the transportation network (Section 3.3.1) and a population of agents (Section 3.3.2), whereas a "Transit Schedule" that is necessary to simulate PT traffic (Section 3.3.3) is not mandatory.

### 3.3.1 Transportation Network

A MATSim transportation network consists of nodes and connecting links. Each link in the network is characterized by its length, allowed modes, maximum allowed free-flow speed and maximum per hour vehicle capacity a link can hold. Figure 4, displays a schematic example of the MATSim network.

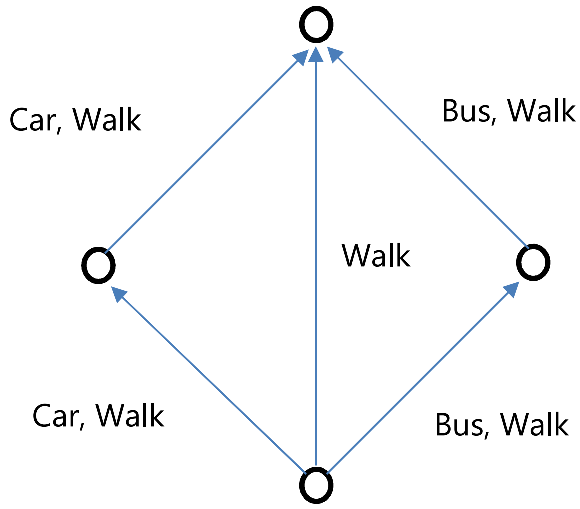


Figure 4. Example of MATSim network, multi-modal links connects between the nodes (black circles).

### 3.3.2 **Population and plans**

In addition to the transportation network, MATSim demands population of agents. Each agent has its own properties and spatially located activities combined into agent's plans. Initially, an agent possesses one plan consisting of "Activities" and "Legs."

- **Activities** of an agent, e.g., home, work, shopping, etc., are defined by the desired start and end times and are explicitly located in regards to the network.
- **Legs** are the modes of transportation an agent uses to reach its activities (e.g., "Walk", "Car", "Bus", "Rail").

The actual route of each leg is generated based on the Dijkstra shortest path algorithm (Dijkstra, 1959). "Car", "Bus" and "Rail" legs are simulated in the Qsim block of the "MATSim Loop" (3.4.1). 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) teleported modes do not influence the network's capacity (Horni, Nagel, & Axhausen, 2016).

Figure 5, presents an example of a daily plan chain. An agent starts its first activity at "Home" and departs at 7:00 with a "Car" leg to "Work". The agent intends to arrive at 10:00 to "Work," continues to "Lunch" by foot, returns to "Work" by walking and travels by car back to "Home" trying to reach it towards 19:00.

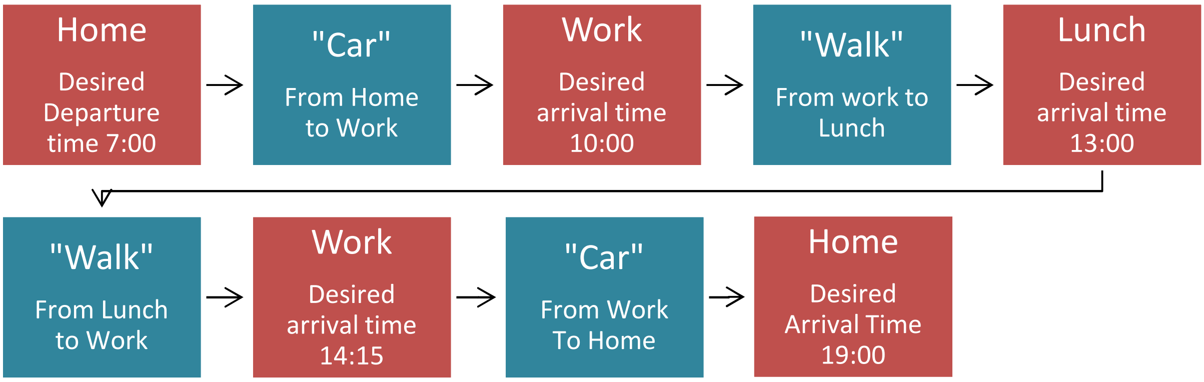


Figure 5. Abstract example of an agent's daily plans: activities (Red) legs (Blue).

### 3.3.3 **Transit Schedule**

By default, MATSim supports a very detailed public transport (transit or PT below) implementation (Rieser, 2010). PT in MATSim is represented by transit vehicles (i.e., buses, trains, trams) which traverse along a fixed route. A transit vehicle in MATSim is characterized by its daily schedule. A transit vehicle picks up and drops-off agents at stops. Each transit vehicle is a unique entity with its maximum travel speed, size, and a maximal number of passengers (capacity). Agents in MATSim are proactive - when a PT leg is defined agents can explore the variety of PT options available for arriving at their desired activity.

## 3.4 Execution (MOBility Simulation)

The MATSim's MOBSim starts with the initial demand (Section 3.3), loads vehicles into the transportation network and performs a *Queue-based simulation* (Qsim component) to generate traffic flows (Horni, Nagel, & Axhausen, 2016).

### 3.4.1 Qsim

QSim advances vehicles (Legs) along the network links until arriving at agent's activities. Qsim employs a *First-In-First-Ou*t (FIFO) approach for moving a vehicle along links: the first vehicle that enters a link is also the first one that leaves it (Figure 6). When a car enters "Link 1" at an intersection, it is added to the tail of the waiting queue. The car remains in the queue of "Link 1" until arriving at the head of the queue, and until the time for traversing the link with free flow, traffic flow has passed. Then, if "Link 2" permits entrance, the car proceeds along the Link 2. Other, non-FIFO traffic flow models are computationally more demanding (Horni, Nagel, & Axhausen, 2016).

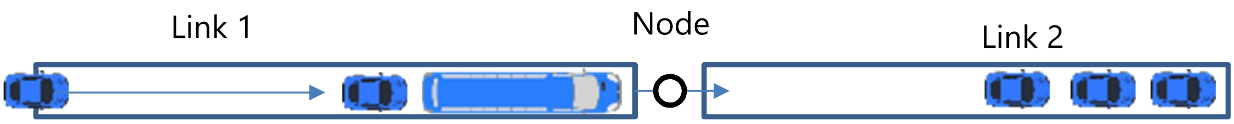


Figure 6. Example of the Qsim's FIFO-based advance along the network.

Numerous MATSim agents pursue their goals at the same desired time, thus competing for the limited network capacity, which results in emerging traffic congestions. The FIFO approach of the MATSim's Qsim enables an efficient computation for millions of agents. The Qsim approach is the main reason why MATSim is considered as an "Extreme Level" ABM (Abar, Theodoropoulos, Lemarinier, & O'Hare, 2017). The main disadvantages of the Qsim approach are that the lanes of the links are not represented, and vehicular positions on the links are not simulated either.

Qsim accounts for two link attributes *flow_capacity* (1) and *storage_capacity* (2).

*Flow capacity* specifies how many vehicles can leave the respective link per a time step:

$$flow\_capacity = \left(\frac{capacity\_value\_of\_link}{capacity\_period\_of\_network}\right) \times flow\_capacity\_factor \tag{1}$$

*Storage capacity* defines the number of vehicles that fill into a network's link:

$$storage\_capacity = \left(\frac{length\_of\_link \times number\_of\_lanes\_of\_link}{effective\_cell\_size}\right) \times storage\_capacity\_factor \tag{2}$$

Where *flow_capacity_factor* and *storage_capacity_factor* multipliers are used for adjustment of the flow and storage capacities in case of the downscaling that is, running MATSim simulations with some fraction of agents' population instead of running it with the entire population of travelers (see section 5.2)

### 3.4.2 MATSim's Events

MATSim is implemented as an event-driven software. The main idea of this type of software design is that a computer program is waiting to receive signals from its components - agents. When the signal (event) is detected, the software reacts to it.

In MATSim, events represent agents' actions such as a PT vehicle unloading passengers or a when an agent reaches a leg of its daily plan. As the MOBSim simulates agents' mobility (section 3.4), it records all agent's actions and timestamps (usually at a temporal resolution of a second). The output stream of events includes millions of records that describe all of the agents' actions during a single day. This stream of events is the source of data for analyzing agents' mode choice, trip duration, comparing simulation counts to real traffic counts and more. The events stream is usually analyzed in the last phase of the "MATSim Loop" (Figure 3).

An example of a typical sequence of MATSim events for one agent is presented in Figure 7 below.

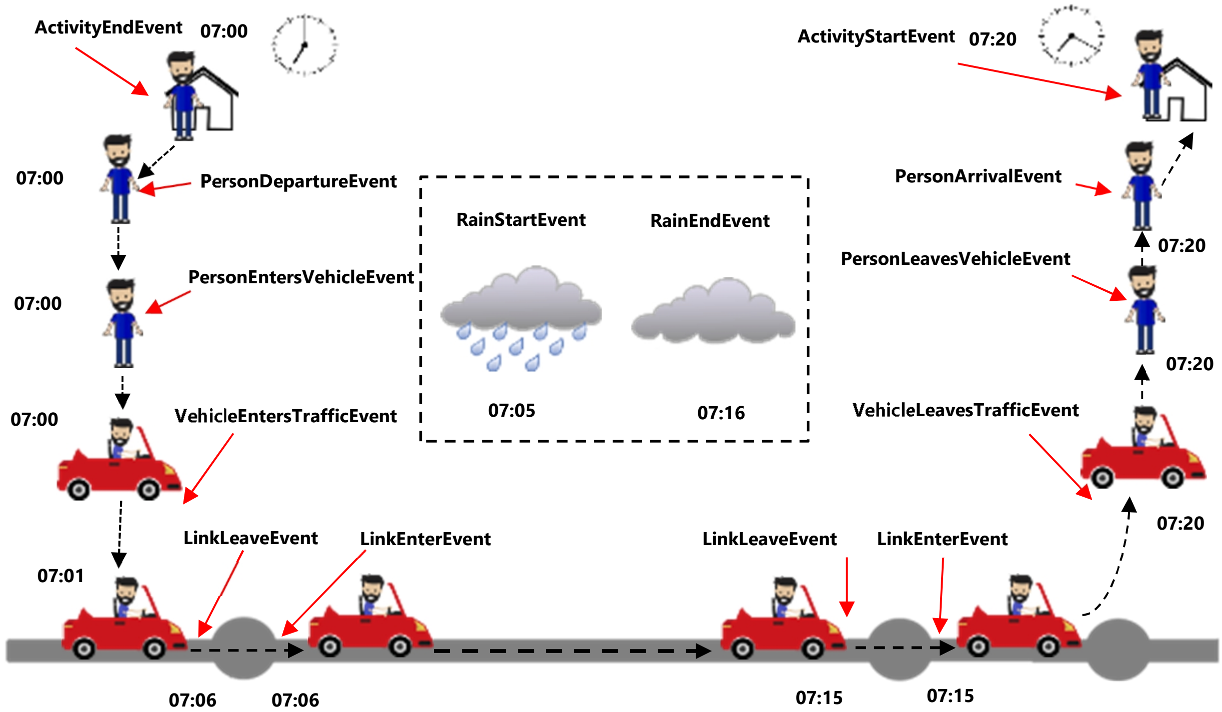


Figure 7. MATSim's example of "rain" events.

The sequence of events in Figure 7:

- **ActivityEndEvent** is recorded when an agent finishes her activity.
- **PersonDepartureEvent** is recorded when an agent starts her trip.
- **LinkEnterEevent** is recorded when a vehicle enters a road link.
- **LinkLeaveEvent** is recorded when a vehicle leaves a road link.
- **PersonArrivalEvent** is recorded when an agent arrives at her planned location.
- **ActivityStartEvent** is recorded when an agent starts her activity.

MATSim allows for customizing existing events and creating new ones, like rain or road frost. When a "Rain" event occurs (Figure 7), it can change the links' free-speeds and vehicular capacities. New events such as "RainStartEvent" and "RainEndEvent" specify when and where the rain in the simulation will start and end. Looking at Figure 7 "RainStartEvent" triggered the reduction of links capacity at 07:05 and "RainEndEvent" cancels this reduction at 07:16.

## 3.5 **Scoring and Utilities**

Scoring is the next step of the "MATSim Loop" which comes right after the "Execution" phase (Section 3.43.4). MATSims' agents are evaluated at each iteration based on the performance of their daily plans. Agents are scored according to the time they spend in their activities and time spent traveling to/from their legs.

MATSim simulation is performed until the average population scores stabilize and the system reaches the "Relaxed State". Figure 8 displays a typical MATSim evolution of scoring. The simulation in Figure 8 stabilized at the ~1250$^{th}$ iteration. Basically, it is not possible to foresee when the scores will stabilize.

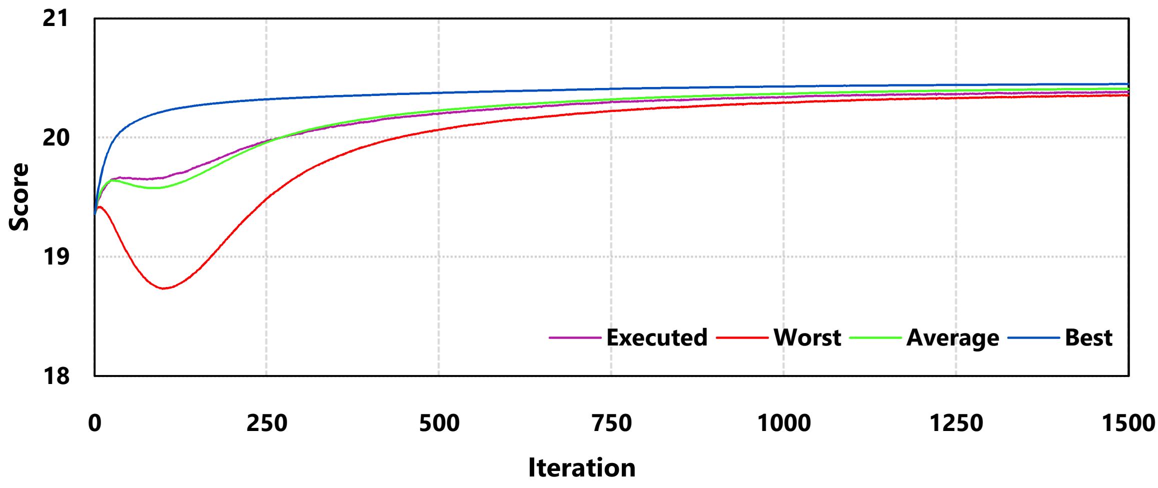


Figure 8. Typical evolution of MATSim's average population scores obtained for the Sioux Falls scenario in (Chakirov & Fourie, 2014). "Executed" is the average score for all executed agents plans, "Worst", "Average" and "Best" are the average scores for the corresponding sets of agents' plans.

### 3.5.1 How does an agent obtain its score?

Scoring is a crucial element of MATSim, and it is used to evaluate whether an agent's plan is "good" or "bad". In real life there are cases where a person does not always choose the "best" trips, some travelers may prefer a trip under congested conditions, others might always prefer PT trips for social reasons, and even some might prefer to stay at home when it rains. The way to bridge this gap is by using utility functions which are taken from the field of economics. In economics, a utility function measures the satisfaction of a consumer as a function of the consumption of real goods - such as food, travel mode, etc. Utility functions rely on the consumption of real goods rather than nominal goods (such as money which is measured in nominal terms). Utility functions are usually obtained from surveys where people state their preferences for choosing a specific good over another set of goods (Ben-Akiva & Lerman, 1985). For example, one can always choose to travel by car and not by bus, in this case, the utility of choosing a car will be 1.

In MATSim the term utility and score are interchangeable. MATSim uses the default "Charypar-Nagel" scoring function to evaluate an agent's daily score (Horni et al., 2016):

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \tag{3}$$

The daily score of an agent is comprised of its marginal utilities of performing N activities ($S_{act,q}$) and the agents' marginal (dis)utilities of performing all the legs between these daily activities $\mathrm{S}_{\mathrm{trav,mode(q)}}$.

The sum of all the marginal utilities of activities is usually a positive value defined as:

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{late.ar,q} + S_{early.dp,q} + S_{short.dur,q} \tag{4}$$

- **Performing an activity** ($S_{dur,q}$) is the utility of performing activity *q* where opening times of activity locations are considered.
- **Waiting** ($S_{wait,q}$) refers to the waiting time spent at a closed activity. For example, arriving early to a closed store.
- **Late arrival** ($S_{late.ar,q}$) is the penalty for arriving late to an activity. For example, getting late to work.
- **Early Departure** ($S_{early.dp,q}$) implies to the early departure from an activity. For example, leaving work early to take the kid from school.
- **Activity duration too short** ($S_{short.dur,q}$) is the penalty for defining a "too short" activity in the simulation (usually this parameter is zero).

Traveling is considered a (dis)utility since usually, an agent obtains a negative score for performing legs. It is calculated as:

$$S_{trav,q} = C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,q} + \beta_m \cdot \triangle m_q + \left(\beta_{d,mode(q)} + \beta_m + \gamma_{d,mode(q)}\right) \cdot d_{trav,q} + \beta_{transfer} + X_{transfer,q} \tag{5}$$

- **Mode-Specific constant** ($C_{mode(q)}$) is a constant (dis)utility for favoring a certain mode over another mode.
- **Time spent traveling by a mode** ($\beta_{\mathrm{travel,mode(q)}}$) refers to the marginal utility of time spent by traveling by a particular mode. For example, in real life, if a traveler can work during a train ride - his marginal utility of time will be higher than a traveler who is traveling by car which can't work while driving.
- **Travel Time** ($t_{trav,q}$) is the travel time between two activities (*q* and *q+1*).
- **Utility per monetary unit** ($\beta_{\mathrm{m}}$) is the marginal utility of money (positive value).
- **Fares and tolls** $\triangle \mathrm{m_q}$ is the factor in the change of a monetary value caused by fares or tolls for the whole leg.
- **Distance** ($\beta_{\mathrm{d,mode(q)}}$) is the marginal utility of the travel distance.

- **Mode Distance** ($\gamma_{\mathrm{d,m\ ode(q)}}$) is the mode-specific monetary distance rate.
- **Travel Distance** ($t_{trav,q}$) is the travel distance between two activities (*q* and *q+1*).
- **Transfers** ($\beta_{transfer}$) are the PT transfer penalties.
- **Check Transfers** ($\mathrm{x}_{transfer,q}$) is a binary parameter which signals if a transfer occurred between the prior and the current leg.

An example of the above "Charypar-Nagel" scoring function of an agent is presented in Figure 9. In this example, an agent starts its first trip from a "Home" activity. The trip is made via a "Car" leg to" Workplace" activity. Its last trip is from the "Workplace" to "Lunch" which is performed by a "Walk" leg:

- **Activity scores** the agent fares a positive value for performing an activity (red lines) the purple dots specify the end/start time of an activity. The dashed blue lines specify the marginal utility of performing an activity (meaning that there is a limit to the score an agent can accumulate when it is performing an activity). In this example, when the agent arrives early to the "Workplace", he gains a score of zero until the "Workplace" allows entering ("Workplace opening time" in Figure 9).
- **Legs scores** usually provide a negative score to an agent. In the example below, when performing a leg by "Car", an agent receives an immediate negative penalty (This penalty may be derived from the mode-specific constant $C_{mode(q)}$). In contrast, when an agent chooses a "Walk" leg it does not, receive a penalty, since there are no expenses for walking. Nevertheless, using a "Walk" leg results in a much steeper negative slope when compared to the slope of the "Car" leg. The steeper slope of the "Walk" leg is due to the longer travel times by foot when compared to the "Car" leg.

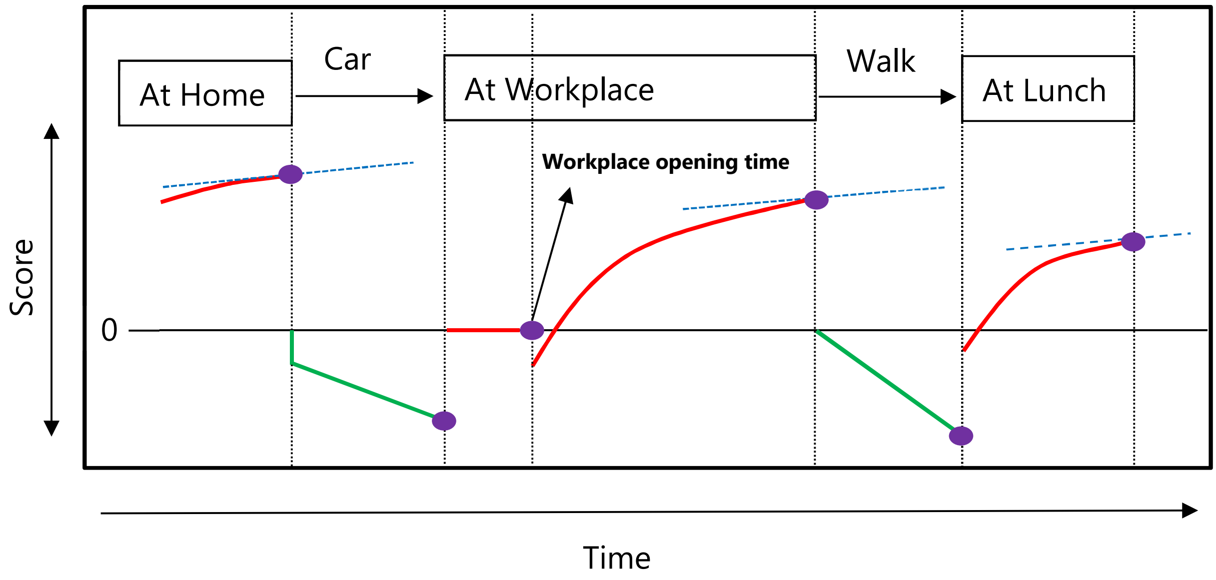


Figure 9. Example of the "Charypar-Nagel" agent's scoring function change during a single day. Scoring of agent's activities is shown in Red and of the legs in Green. Purple dots denote the end/start time of activities; blue lines denote the marginal utility of each activity.

## 3.6 **Co-Evolutionary Replanning**

The last step inside the "MATSim Loop" (Figure 3) is the co-evolutionary "Replanning" phase. In this phase, agents can "shuffle" their daily plans through a reinforced learning process that optimizes their daily score. The "Replanning" stage of MATSim is adopted from *Genetic Modification Algorithms* (GMA), which are usually used in the biology fields. In Biology, the GMA mimics the evolutionary process of natural selection by using fitness functions. During the GMA iteration, some of the population will produce new offspring, and some of the population will die. Conversely, from the GMA, agents in MATSim cannot die, and they will not produce offspring. Instead, MATSim agents will compete together on limited road space, day-by-day through a co-evolutionary process; the agents will learn and adapt until none of them can further improve their daily plans. The MATSim co-evolutionary "Replanning" process consists of three steps:

1. **Plan Removal (Choice set reduction)** where each agent has a configurable number of plans which he stores in its memory. In real life an experienced traveler in the urban city might be aware of several routes and modes which he can choose from to get from point A to B. By default, an agent can remember up to five different plans. A maximal number of memorized plans is five. If the number of plans in agent's memory is higher than five, then the least scored plans are removed from the agent's memory.
2. **Innovation** (**Choice set extension)** Figure 10, presents a basic MATSim simulation, which starts with an "Initial population" that contains agents who possess only one plan in their memory, to begin with. Each plan is executed by the MATSim MOBSim (as mentioned in section 3.4). After the "Execution" stage, the plans get scored based on the utility functions, described in section 3.5.1. Following the "Scoring" step, in the "Replanning" phase, a configurable portion of the population is eligible to be selected from a random draw. If the agents are chosen in the draw, their plans are cloned and modified (the modified plans are selected to be executed by the MOBSim in the next iteration). In MATSim the cloning and modification process of the plans is referred to as innovation or mutation. Such innovations found in MATSim are:
    - **Time innovation** allows agents to modify the start and end times of their activities.
    - **Mode innovation** allows agents to switch mode for certain legs.
    - **Route innovation** allows the agents to re-route by finding less congested paths.

- **Location Choice innovation** allows agents to change their initial activity location (this module is not a part of the default MATSim framework).

Eventually, in the later iterations, agents will not be able to improve their daily scores by mutating their time, mode choice and route. The system and the population will reach a state of equilibrium ("Relaxed State") where the scores of the agents converge (See Figure 8).

3. **Plans selection (Choice)** after completing the innovation phase; some agents can possess more than one plan in their memory, due to the copying and the modifications to the agent's plans. Therefore, before the next iteration starts (the "Execution" stage in Figure 10) - the simulation must choose one plan precisely to execute on the network. Choosing between the different plans of each agent is done using a *Multinomial Logit* (MNL) model (which considers the previously executed plan scores). The plan selection procedure only affects all the agents who were not drawn for mutation and innovation. The mutated plans are automatically selected for execution at the next iteration.

Three "Replanning" steps are connected: At the "Removal" step "Bad" plans are removed, at the "Innovation" step new and potentially good plans are generated, and at the "Selection" step "Good" plans are selected. "Good" / "Bad" here refer to plans' scores.

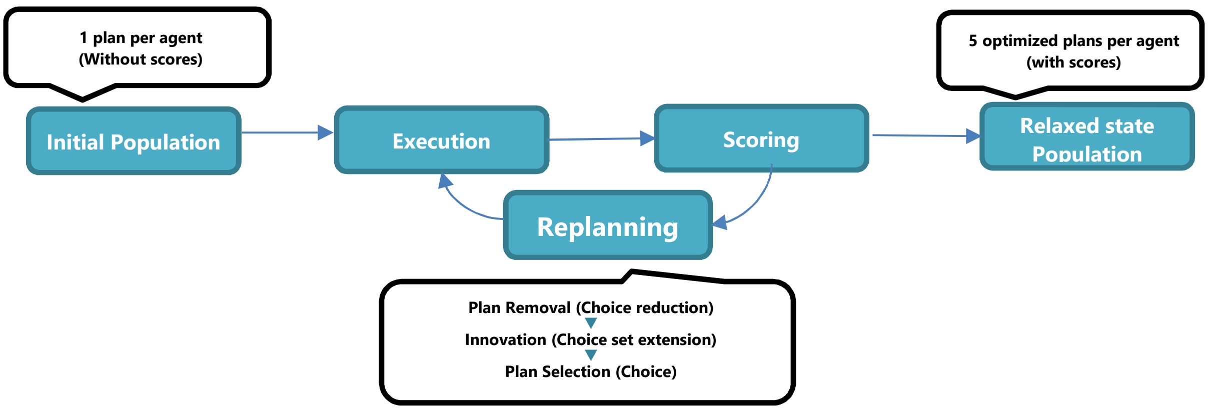


Figure 10. Schematic example of the MATSim Co-Evolutionary algorithm

# 4 The Sioux Falls Scenarios

The road network of the City of Sioux Falls, South Dakota is widely used since 1973 as a test case scenario for transportation planning for examining different network design problems, algorithms, and methodologies. In 2014 the Sioux Falls scenario was adapted as an agent-based scenario in the MATSim framework (Chakirov & Fourie, 2014). This scenario was extended by adding an extensive bus network and a synthetic population which was derived from real micro-census and land-use information. The Sioux Falls 2014 network uses the traditional Sioux Falls network introduced four decades earlier. This scenario consists of arterial roads:

- **Urban Road** consisting of two lanes with a vehicular capacity of 800-1000 cars per lane per hours
- **Highway** consisting of three lanes with a vehicular capacity of 1700-1900 cars per lane per hour

The adapted network was divided into 334 links and 282 nodes to achieve a link size of 500m. 133 bus stops are spread around the transit network with the above link interval of 500m between each station. The Transit schedule consists of 10 bus lines with a headway of five minutes. In the original Sioux Falls 2014 scenario, there are no DBLs - traffic mixing occurs where buses compete with private cars on the same road space across all links (see Figure 11a below).

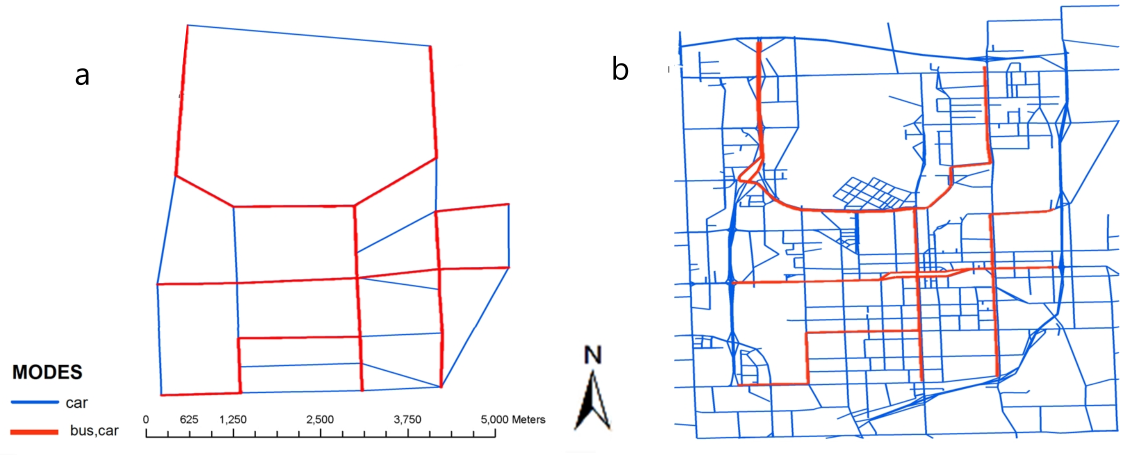


Figure 11. Road and PT networks in Sioux Falls (a) 2014 - 334 links, ten transit lines, 133 bus stops; (b) 2017 - 3705 links, ten transit lines, 150 bus stops.

On the demand side of the Sioux Falls 2014 scenario, the population of travelers consists of 84,110 agents based on social-economic factors such as age, gender, and car ownership. The initial modal split of the population is 78% car use vs. 22% PT users. Each agent has its daily plans consisting of home, work, and secondary activities.

Another MATSim Sioux Falls scenario was considered for this thesis (Hörl, 2017). The Sioux Falls 2017 scenario was created to assess the effects of autonomous taxis in a mixed traffic scenario and includes ten times more links then the Sioux Falls 2014 network Figure 11b. This thesis is built on the well-documented, relatively small-scale and near-realistic Sioux Falls 2014 set-up which was chosen to examine different DBLs scenarios and to measure downscaling in MATSim.

# 5 Methodology

In this chapter, two methodologies are presented. The first is the methodology for assessing the impacts of DBLs (Section 5.1). The second methodology aims at evaluating the MATSim capabilities to produce similar outputs in downscaled scenarios (Section 5.2). Section 5.3 presents the aggregate measures that are used for comparison between the different scenarios. All simulations below were performed on the same workstation computer with 7820x Intel® Core™ X-series Processor with 8 physical and 16 logical cores with the CPU manually overclocked[1] to 4.5ghz. The workstation has 32GB of Corsair® RAM, overclocked to 3000mhz.

## 5.1 Methodology for the DBLs scenarios

The effects of three DBLs scenarios for the Sioux Falls 2014 road / PT networks were examined (See Figure 12):

- ***No DBLs*** scenario of a fully mixed traffic flow which is basically the original Sioux Falls 2014 scenario.
- ***Added DBLs*** scenario, in which an additional DBLs are added to each link exploited by a bus.
- ***Converted DBLs*** scenario, where one lane of each link that is exploited by a PT is converted into a DBL (all Sioux Falls links of this kind contain two or more lanes). The Converted DBLs scenario is introduced, as the Added DBLs scenario might not always be possible to be applied (due to land-use restrictions).


Figure 12. Three DBLs scenarios for the Sioux Falls 2014 road / PT networks, (a) No DBLs; (b) Added; (c) Converted DBLs.

[1] Overclocking is configuration of computer hardware components to operate faster than certified by the original manufacturer.

### 5.1.1 **Assessing the effect of population size**

The effects of the DBLs were explored for the Sioux Falls road network as dependent on the size of travelers' population. In what follows, the size of travelers' population is considered as $k * P_0$, where $P_0$ is a Sioux Falls population in 2014 (84,110 agents) and $k$ is a *representation ratio* (RR) that varies within the interval of [0.2, 3].

To accelerate the simulations runs, MATSim proposes to perform them for some fraction of the real population of the city, i.e., to use $k < 1$. To adjust the model for representing the entire population of the city, MATSim proposes to set the values of *flow_capacity_factor* and *storage_capacity_factor* in equations (1 and (2 (section 3.4.1) equal to $\frac{1}{k}$ (Horni, Nagel, & Axhausen, 2016). This approach was tested for $k > 1$ and it also works. Namely, the model outputs for $k = 2$ was compared with the simulation outcomes obtained for a duplicated population of 84,110 * 2 = 168,220 agents. The daily dynamics of the number of the PT passengers and car departures (Figure 13) were compared and were similar in both cases.

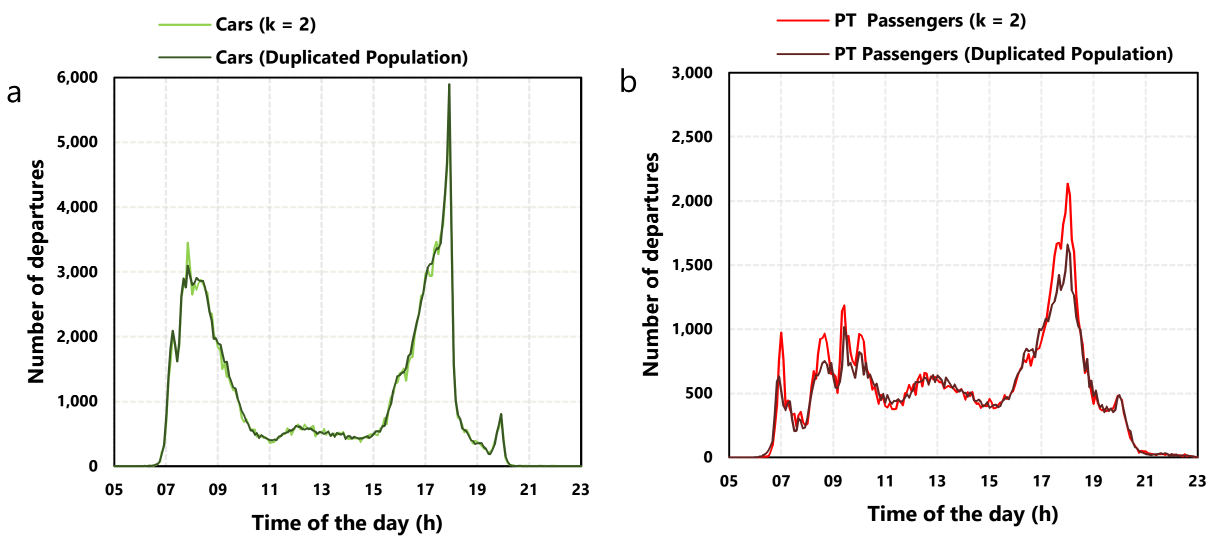


Figure 13. Model dynamics of Car and PT passengers departures for (a) $k = 2$ and Sioux Falls 2014 population of 84,110 agents; (b) versus the same variables estimated in simulations with $k = 1$ and duplicated population of 168,220 agents.

### 5.1.2 Consistency of the MATSim aggregate outputs

MATSim outcomes for the same set of parameters may also differ due to the stochastic nature of the model processes. However, the variation in aggregate model outcomes is very low. To illustrate, Figure 14 presents several model outcomes for several values of $k$ for two model runs that were performed on two different computers. The relative difference between the corresponding outcomes was calculated as $100\% * (1 - \left|\frac{Parameter\_Comp1(k)}{Parameter\_Comp2(k)}\right|)$.

As can be seen, the relative differences between the aggregate parameters are, usually, below 1% and reach 2.23% in one case only – walk share for $k$ = 0.1.

Different from the aggregate outputs, random variation of the models' spatial patterns may be substantial. In this thesis, MATSim's spatial patterns are not investigated and will be examined in depth in future research (see Section 8).

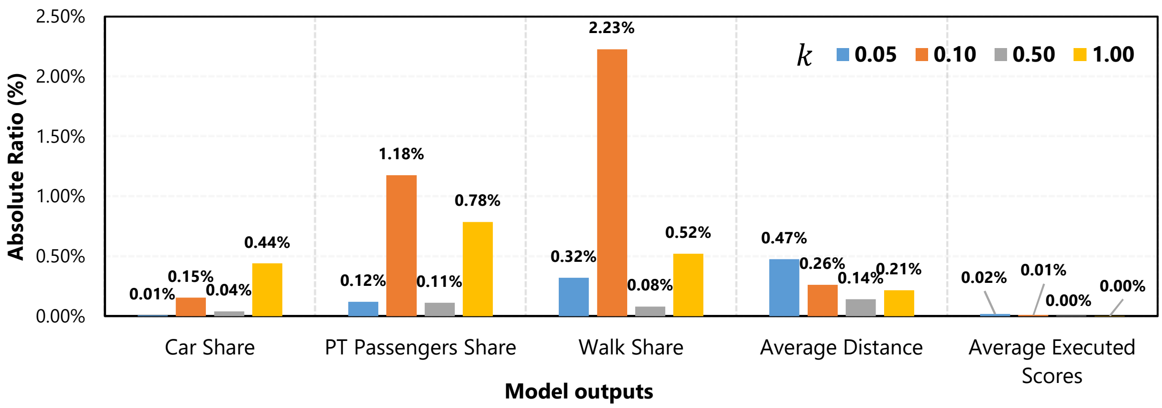


Figure 14. Comparison between aggregate model outputs obtained in two model runs, for four values of $k$.

### 5.1.3 Simulations Setups

All the DBLs scenarios start with the same setup: score functions of the original Sioux Falls 2014 scenario (see Table A1 in Appendix A). Each agent can remember up to five plans, and in each iteration, the worst plan is removed. The simulations ran for 3000 iterations until a "Relaxed State". Innovations (sub-section 3.6) are introduced until the 2700$^{th}$ iteration. Each iteration Re-route, Time and Mode choice innovation are applied randomly for 1% of the agents.

To simulate agent's mode choice the Sub-Tour MATSim module (Ciari, Balmer, & Axhausen, 2008) is applied. The Sub-Tour module enables mode shift from the current agent's mode to one of three: Car, PT or Walk. It is important to note that the Sub-Tour approach limits the mode shift of the car users. Namely, if an agent starts its first leg (usually from a "home" activity) with a car, the car must be used to return to the first activity (home). Sub-Tour does allow that in the course of activities between these two, an agent can leave the car and use other modes (walking or taking a PT to the restaurant during the afternoon break). Figure 5 above presents an example of agent's daily activity with a "Walk" leg in the mid of the working day, and a "Car" legs in the morning and in the evening (back home).

Critical for the PT-related simulations is the *Passenger Car Equivalent* (PCE) specifying the physical size of a vehicle relative to a private car (Nagel, 2016). In what follows, the value of PCE is always 3, meaning that a bus takes three times more road space than a private car.

## 5.2 **Assessing MATSim's downscaling**

Model downscaling is any procedure that infers high-resolution information from low-resolution variables (Wilby & Wigley, 1997). As MATSim simulations are highly computational demanding (Abar et al., 2017), a vital sub-goal of the thesis is to evaluate MATSim's downscaling performance that has not yet been systematically investigated.

Downscaling is investigated with the Sioux Falls 2014 scenario in two setups (Table 3):

- **Car only scenario** considers the case where the whole transit schedule was removed (bus stops, bus vehicles, and the bus network).
- **Mixed traffic scenario** uses the same configurations and scoring functions as no DBLs scenario (section 5.1). Initial population modal split is 78% cars and 22% PT. Buses parameters are modified to reflect the change in the representation ratio $k$ (Table 2, below). Bus capacity and PCE are linearly adjusted for $k \leq 0.5$. In the mixed traffic scenarios where PCE($k$) = $3 \cdot k$ and Bus capacity($k$) = $90 \cdot k$. e.g., in the case of $k$ = 0.5 bus capacity is reduced from 90 to 45 and PCE is reduced from 3 to 1.5.

Sioux Falls congestion effects for the 2014 population (84,100 agents) are relatively weak. Therefore, the population is duplicated, the case of 168,220 agents is considered as a baseline ($k$ = 1) and its outcomes are compared to the outcomes of the downscaled scenarios with $k$ < 1 (Table 3).

Table 3. Sioux Falls population investigated in the model experiments as dependent on $k$

| $k$ | 1.00 | 0.50 | 0.40 | 0.30 | 0.20 | 0.10 | 0.05 | 0.01 |
|---|---|---|---|---|---|---|---|---|
| **Number of agents** | 168,220 | 84,110 | 67,288 | 50,466 | 33,644 | 16,822 | 8,411 | 1,682 |

It is important to note that the study of downscaling effects is not related to the above study of the DBL effects and there is no relation between the results obtained for the same $k$ in these two studies.

## 5.3 Evaluation of the simulations' results

This section presents the performance measures used for evaluating the effects of DBLs (6.1) and MATSim's scaling capabilities (6.2 and 6.3):

- ***Full-Width Half Maximum*** (FWHM) interval (Rollo & Schulz, 1970) is used to specify hours of intensive travel activity. First, the peak hour is defined as the hour of the maximum number $M$ of car departures and then *Peak Hour Duration* (PHD) is defined as a time interval between the moment when the number of departures exceeds $M/2$ and until it declines again to $M/2$ (Figure 15). Morning and evening PHDs are estimated and the rest of the day is considered as Off-Peak hours.

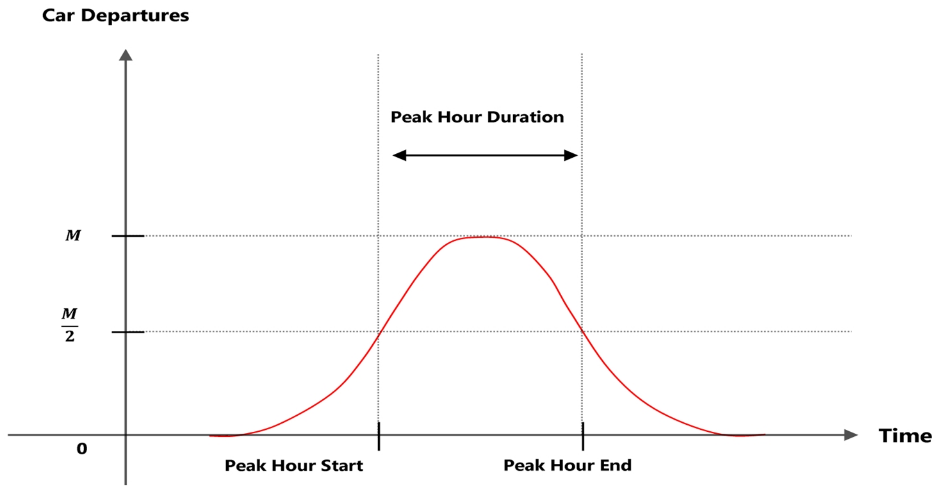


Figure 15. Illustration of Peak Hour Duration (PHD) calculation.

- **Number of agent departures** depend on time and represent the numbers of agents entering traffic between 05:00 and 23:00. Departures are distinguished between private car departures and PT Passenger departures (agents boarding a PT vehicle at a transit station).

- ***Average Trip Duration*** (ATD) is the average agent's trip time by a certain mode such as Car, Walk, PT Passenger and PT Vehicle. To evaluate the performance of the PT vehicles, the Average Trip Duration (*ATD*) of a PT Vehicle is considered which is calculated as the duration of a *Terminal-to-Terminal* (T2T) bus trip – a trip between the starting terminal stop to its last terminal. Note that ATD of the PT Passenger includes waiting times at the bus stops but does not include the duration of the walk from and to bus stops that do not depend on the state of the traffic. The ATDs are calculated over the whole day (05:00-23:00), over the PHDs and over Off-Peak hours.

- **Mode choice** is the modal shares selected by the agents. The modal shares are calculated over the whole day (05:00-23:00), over the PHDs and over Off-Peak hours.
- **Correlation** between the number of departures at a given hour in the downscaled ($0.01 \leq k \leq 0.5$) and the baseline scenarios ($k$ = 1) were used as a mesure of fit of the downscaled scenarios.
- ***Mean Relative Deviation*** (MRD) is employed for comparing between downscaled and the baseline scenario. The MRD is calculated between the number of departures for a certain $k$ < 1 and the number of departures for $k$ = 1 by 5-min intervals of the day and then averaged over the entire day:

$$MRD(k) = \frac{100\%}{N} \sum_{t=1}^{N} \frac{|D(k)_t - D(1)_t|}{D(1)_t} \tag{6}$$

Where N = 216 is the number of 5-min intervals between 05:00 to 23:00, and $D(k)_t$ is the number of departures for a particular $k$ at a time interval $t$.

# 6 Simulations' results

Simulations results below present aggregate characteristics of the output stream of events at the last iteration.

## 6.1 Assessing the effects of Dedicated Bus Lanes

Figure 16 presents the ratios of the model parameters in the Added DBLs and No DBLs scenarios. As can be seen, with the increase of $k$, the ATD decreases in all scenarios. For the PT Vehicle, the ATD ratio is equal to 1 for $k$ = 0.2, and for higher $k$

this ratio monotonously decreases, reaching 0.4 for the tripled population (Figure 16a). The influence of the DBLs on "Car" and "Walk" modes is substantial starting from $k$ ~ 1 and decreases to 0.85 when the population is tripled. In Figure 16b, the fraction of the PT users in the Add DBLs scenario is more than 50% higher for $k = 3$ compared to the no DBLs scenario, while the fraction of the car users for this $k$ decreases by 13% only.

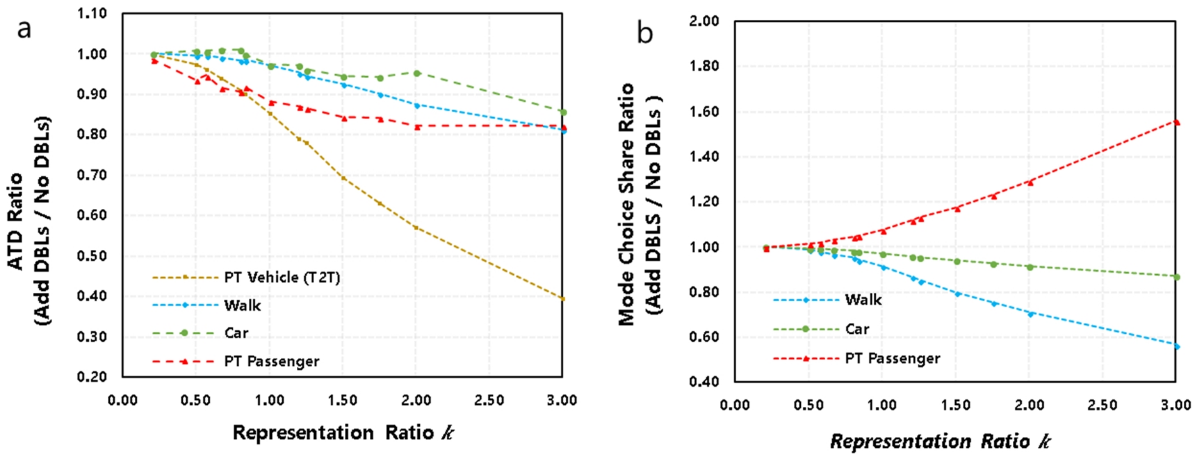


Figure 16. Sioux Falls 2014, Added DBLs and No DBLs scenarios (a) Ratio of Average Trip Duration (ATD), by modes; (b) Mode Choice Shares ratios.

Figure 17 below presents the number of departures between 5 am - 11 pm for three investigated scenarios and 100% population ($k = 1$) while Figure 18 is for the 200% population ($k = 2$). PHD in both figures is the sum of the morning and evening values.

As seen in Figure 17a, and Figure 18a, peak-hour dynamics of the "PT Passengers" in the No DBLs scenario has multiple peaks. These peaks disappear in the Added DBLs and Converted DBLs scenarios (Figure 16b, 17c, 18b, 18c). The duration of the morning and evening PHDs for the 200% population ($k = 2$) is almost doubled compared to the 100% population ($k = 1$). The PT travelers' peaks in the Converted DBLs scenario are higher than in Added DBLs, while car peaks are highest in the no DBL scenarios when "Car" agents do not switch to PT.

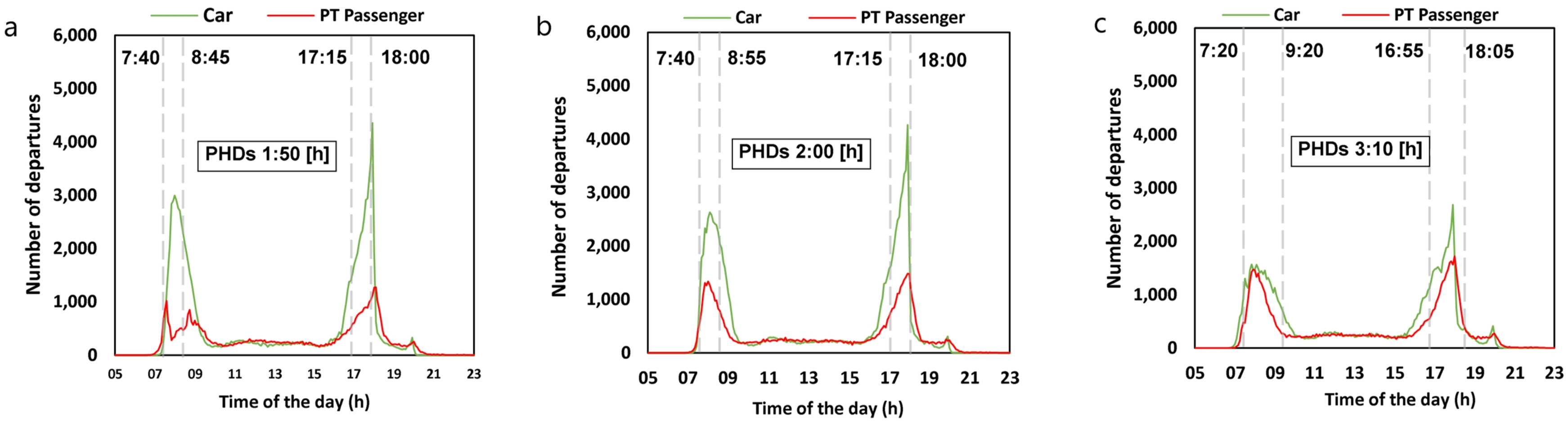


Figure 17. Sioux Falls 2014, $k = 1$, departures (a) No DBLs; (b) Added DBLs; (c) Converted DBLs scenarios.

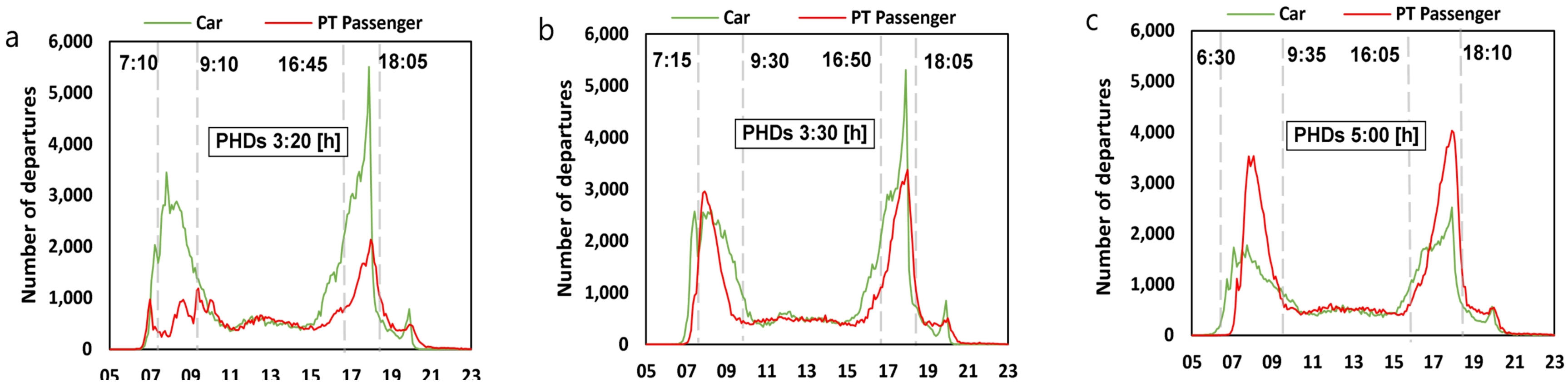


Figure 18. Sioux Falls 2014, $k = 2$, departures (a) No DBLs; (b) Added DBLs; (c) Converted DBLs scenarios

Table 4, presents the ATD values during the Peak and Off-Peak hours for the 100% ($k$ = 1) and 200% ($k$ = 2) populations, while Table 5 presents, by modes, the share of departures.

As can be anticipated, the highest reduction of the ATDs for all modes and population sizes is achieved in the Added DBLs scenario. During the off-peak hours the traffic in Sioux Falls is almost unaffected, while during the peak hours, the impact of DBLs is substantial: For $k$ = 2, the Added DBLs scenario results in 7% agents leaving their cars in favor of the PT. Together with the 3% of walkers who change their travel mode to PT, this results in 10% increase in the PT modal share compared to the No DBLs scenario (Table 5, $k$ = 1). With the DBLs, T2T bus ATDs remains the same during the peak hours for both $k$ = 1 and $k$ = 2. In the No DBLs scenario, the T2T ATD is two (Table 4, $k$ = 1) and even three times higher (for $k$ = 2) when compared to the Added and Converted DBLs scenarios.

Table 4. Sioux Falls 2014 ATDs* - Off-Peak/Total peak hours

| | No DBLs | Added BLs | Converted DBLs |
|---|---|---|---|
| Off-Peaks ($k$ = 1) | | | |
| Car [min] | 08:06 | 07:50 | 08:48 |
| PT Passenger [min] | 05:08 | 04:41 | 04:47 |
| Bus (T2T) ** [min] | 10:06 | 09:50 | 09:48 |
| Total Peaks ($k$ = 1) | | | |
| Car [min] | 10:21 | 10:01 | 15:26 |
| PT Passenger [min] | 07:11 | 05:25 | 06:17 |
| Bus (T2T) ** [min] | 25:51 | 12:48 | 12:36 |
| Off-Peaks ($k$= 2) | | | |
| Car [min] | 09:45 | 09:00 | 09:18 |
| PT Passenger [min] | 05:40 | 04:46 | 05:00 |
| Bus (T2T) ** [min] | 11:08 | 09:48 | 09:51 |
| Total Peaks ($k$= 2) | | | |
| Car [min] | 18:41 | 17:50 | 24:02 |
| PT Passenger [min] | 08:58 | 06:07 | 06:54 |
| Bus (T2T) ** [min] | 44:57 | 12:27 | 12:29 |

*ATD = Average Trip Duration; **T2T = Terminal to Terminal.

Table 5. Sioux Falls 2014 Mode Shares - Off-Peak/Total pe hours

| | No DBLs | Added DBLs | Converted DBLs |
|---|---|---|---|
| Off-Peaks ($k$ = 1) | | | |
| Car | 49.39% | 50.72% | 50.60% |
| PT Passenger | 45.01% | 43.34% | 44.20% |
| Walk | 5.60% | 5.94% | 5.21% |
| Total Peaks ($k$ = 1) | | | |
| Car | 69.66% | 62.72% | 50.71% |
| PT Passenger | 17.59% | 27.12% | 35.73% |
| Walk | 12.74% | 10.16% | 13.56% |
| Off-Peaks ($k$ = 2) | | | |
| Car | 49.67% | 50.73% | 44.27% |
| PT Passenger | 45.42% | 44.17% | 49.75% |
| Walk | 4.91% | 5.10% | 5.98% |
| Total Peaks ($k$ = 2) | | | |
| Car | 58.35% | 49.17% | 34.86% |
| PT Passenger | 17.96% | 36.46% | 46.79% |
| Walk | 23.69% | 14.37% | 18.35% |

## 6.2 MATSim's scaling in a car only scenario

The car only scenario setup is presented in Table 3. Figure 19a presents the changes to the car ATD as dependent on population size. The Total Peaks include the morning PHD (06:00-07:00) and the evening PHD (17:00-18:00). It is evident that the consistency of the ATD (Figure 19a) remains quite similar across different population sizes, until $k$ = 0.2. This consistency is preserved for the ATDs calculated during the Whole Day, Total Peak and Off-peaks hours.

Figure 19b describes the changes to the average travel distance for the whole day where downscaling below $k$ = 0.1, results in inconsistency in the average travel distance.

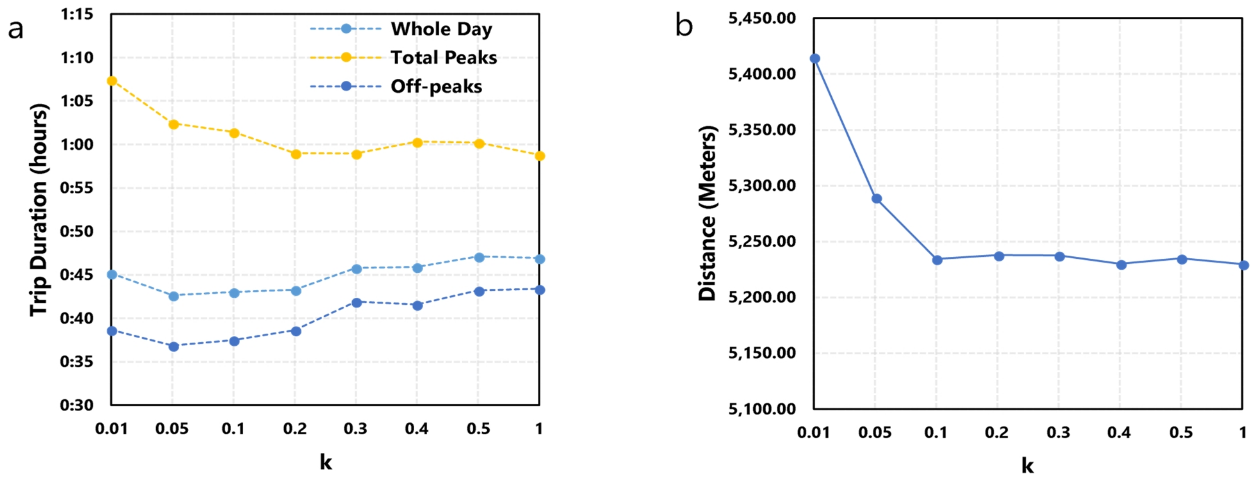


Figure 19. Sioux Falls 2014 downscaling output for the car only scenario, (a) Average Trip Duration during the total Peak Hour Durations (morning + evening), Off-peak and Whole Day (Peak Hour durations + Off-peaks); (b) Average Travel Distance for the whole day.

Figure 20a-h displays departures of agents for the car only scenario. The curves in each Figure 20(b-h) were multiplied by a factor of $\frac{1}{k}$ to make the downscaled scenarios (Figure 20b-h) comparable to the baseline scenario (Figure 20a). For example, the downscaled scenario in Figure 20h ($k$ = 0.01) is based on 1,682 agents.

To compare the scenario's outputs to those of 168,220 agents (Figure 20a), the curve in Figure 20h was multiplied by 100. As can be seen, the curves in Figure 20b-f ($k$ = 0.5 to $k$ = 0.1) are all quite similar and closely resemble the baseline case in Figure 19a. However, the number of departures for $k$ < 0.1 (Figure 20g, h) fluctuates when compared to higher values of $k$.

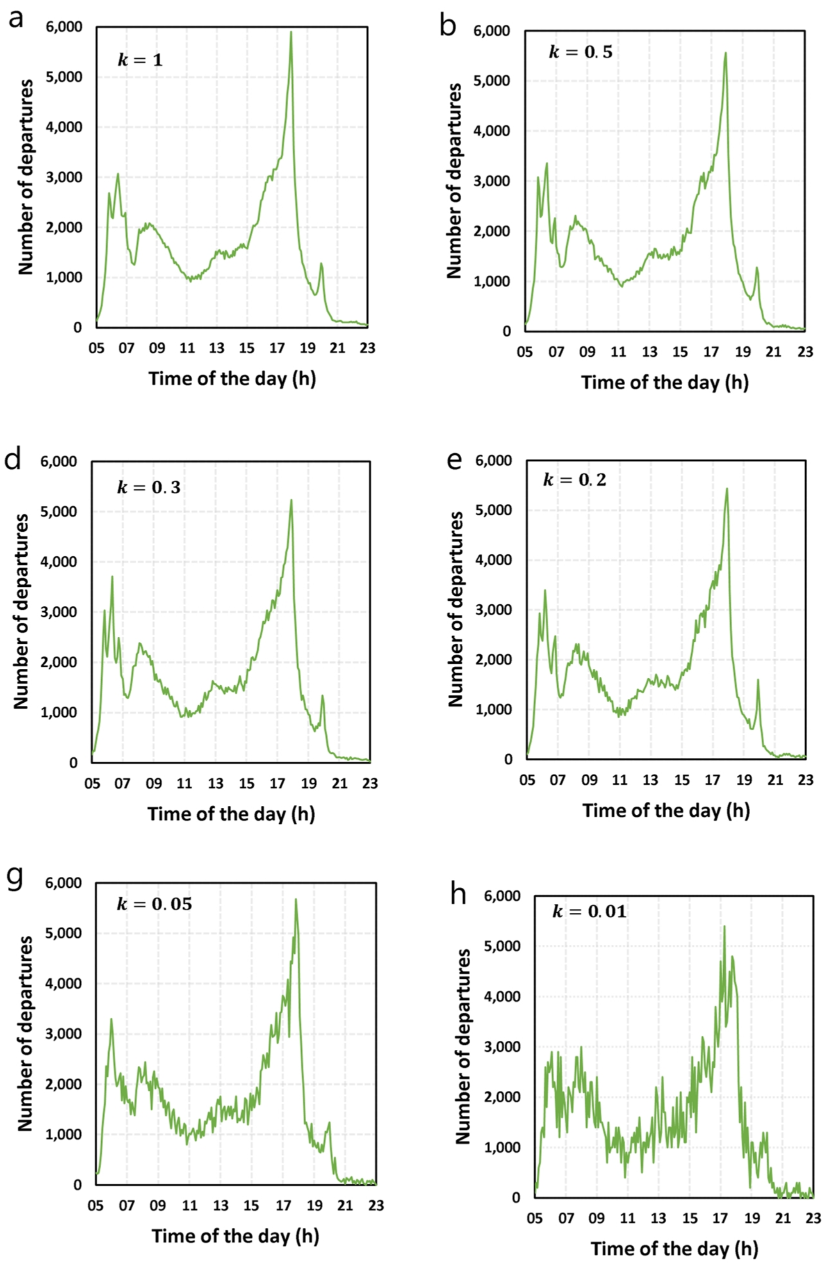


Figure 20. Sioux Falls 2014 downscaling departures for the car only scenario - (a) $k$ = 1; (b) $k$ = 0.5; (c) $k$ = 0.4; (d) $k$ = 0.3; (e) $k$ = 0.2; (f) $k$ = 0.1; (g) $k$ = 0.05; (h) $k$ = 0.01.

A correlation test was done to compare between the results of Figure 20a ($k$ = 1) and the downscaled scenarios (Figure 20b-h). Table 6 displays the values of $R^2$ between the number of departures for 5-minutes intervals (216 observations between 05:00 to 23:00) in the car only scenario for the baseline population ($k$ = 1, Figure 20a) and the same scenario downscaled for $0.01 \leq k \leq 0.5$ (Figure 20b-h). As can be seen $R^2$ decreases slowly up to $k$ = 0.1 and then drops, decreasing to $R^2$ = 0.812 for $k$ = 0.01.

Table 6. Sioux Falls 2014, car only scenario, $R^2$ between the number of car departures for the case of $k$ = 1 and cases of $k$ varying between $0.01 \leq k \leq 0.5$

| $k$ | 1.00 | 0.50 | 0.40 | 0.30 | 0.20 | 0.10 | 0.05 | 0.01 |
|---|---|---|---|---|---|---|---|---|
| $R^2$ | - | 0.989 | 0.984 | 0.973 | 0.959 | 0.958 | 0.933 | 0.812 |

Figure 21 presents MRD($k$) as dependent on $k$ for car departures, in the car only scenario. The MRD($k$) were calculated for the whole day (05:00-23:00) As can be seen, for all $k$ > 0.1 the MRD($k$) is below 15%, but rapidly increases for lower $k$. Meaning that downscaling below $k$ < 0.1 will results in a substantial variation for car departures when compared to the baseline scenario.

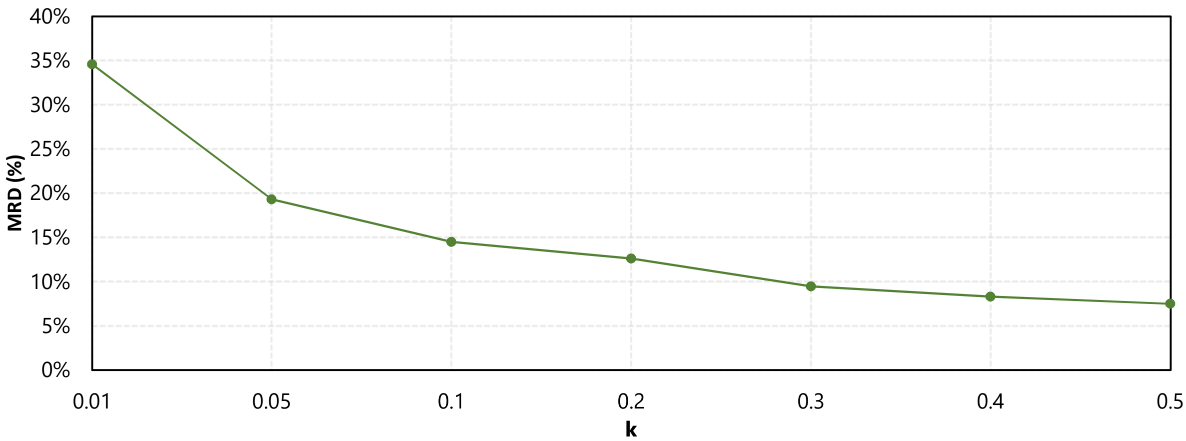


Figure 21. Mean Relative Deviation of the number of departures (equation 6) as dependent on $k$ for $0.01 \leq k \leq 0.5$ for the car only scenario (aggregated for the whole day).

## 6.3 **Scaling of mixed traffic scenarios**

The Mixed traffic downscaled scenario outcomes are based on the setups of Table 3, including bus related parameters.

Figure 22a presents the mode choice outcomes for different downscaled mixed traffic scenarios during the morning PHD (07:00-09:00) and the evening PHD (17:00-18:00), while Figure 22b is the mode choice for the Off-Peak hours, and Figure 21c for the whole Day. The effects of downscaling are stronger for the peak hours (Figure 22a). The differences between the outcomes of different downscaled scenarios are stronger when the scenario size is below $k$ = 0.1. The "PT Passenger" mode share during the Total Peaks (Figure 22a) is 14.14% for $k$ = 1. There is a ~1% change between the different downscaled scenarios and the $k$ = 1 scenario until the $k$ = 0.1 scenario. The change between the downscaled scenario of $k$ = 0.05 to the $k$ = 1 scenario is 12%, which is further lowered by 31% at $k$ = 1.

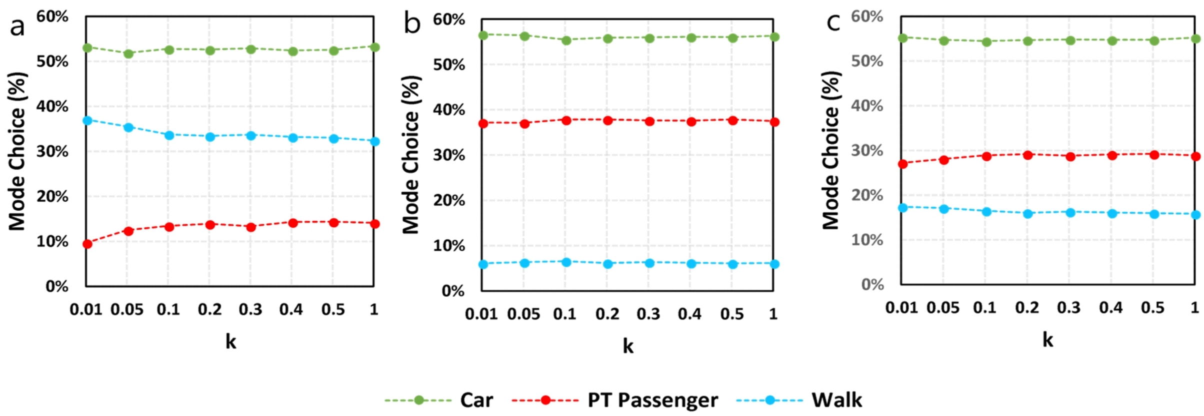


Figure 22. Mode choice of Sioux Falls 2014 downscaling outputs for mixed traffic - Mode Choice calculated during (a) the Total Peak Hour Durations (morning 07:00-09:00 + evening 17:00-18:00), (b) The Off-Peaks hours and (c) for the Whole Day.

The ATDs for the mixed traffic is presented in Figure 23. The effects of the scenario size are stronger during the Total Peaks duration, and ATDs for both the "Cars" (Figure 23a) and "PT Passenger" (Figure 23b) remain similar to the baseline scenario size of $k$ = 1. For $k$ = 0.1, the consistency changes which is also observed in the

"Walk" mode (Figure 23c). The "Walk" ATDs (Figure 23c) show no substantial change compared to the $k$ = 1 scenarios, since "Walk" legs are teleported to their destination.

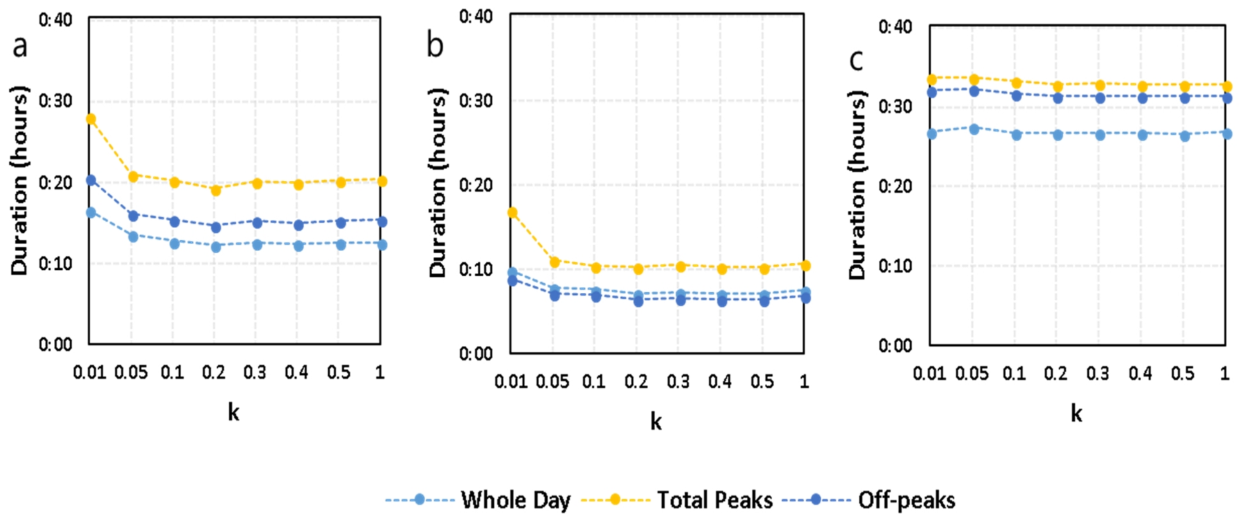


Figure 23. Average Trip Durations of the Sioux Falls 2014 downscaled mixed traffic outputs which are calculated for the Whole Day, Total Peaks and Off-peaks durations and for the modes of (a) Cars, (b) PT Passenger and (c) Walk.

Figure 24a-h displays the departures of "Car" and "PT Passenger" agents in the mixed scenarios. The curves in each Figure 24b-h were multiplied by a factor of $\frac{1}{k}$. The departures of both "Car" and "PT Passengers" remain similar in Figure 24b-f ($k$ sizes of 0.5 to 0.1) and they have close similarities to the baseline scenario of $k$ = 1 (Figure 24a). Scenario sizes below $k$ = 0.1 (Figure 24g, h) results in more fluctuations when compared to larger size scenarios. Similar flows for the size of $k$ = 0.1, were also observed in departures of the car only scenario (Figure 20).

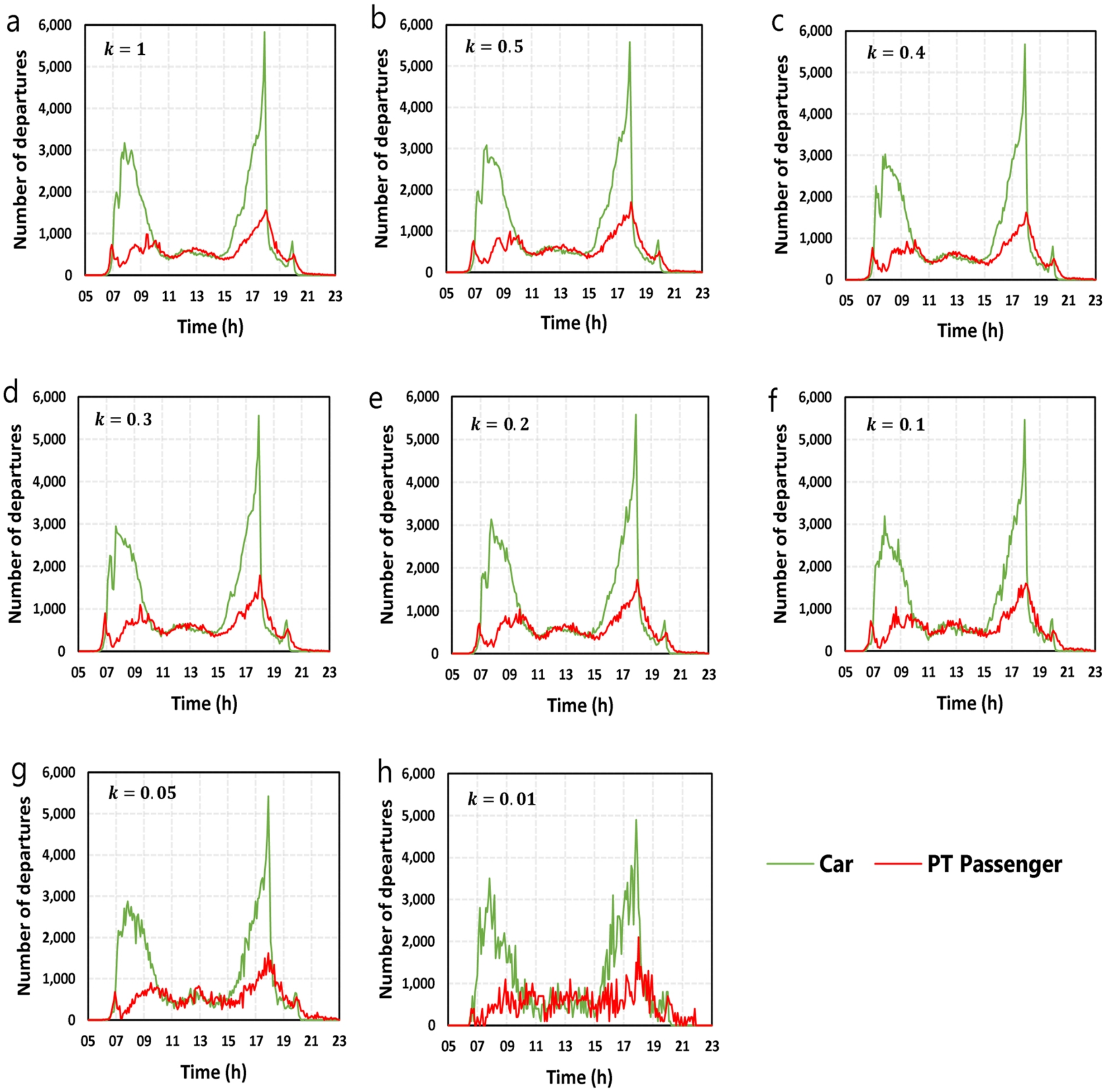


Figure 24. Sioux Falls 2014 mixed traffic scaling departures (Car and PT Passenger) - (a) $k$ = 1; (b) $k$ = 0.5; (c) $k$ = 0.4; (d) $k$ = 0.3; (e) $k$ = 0.2; (f) $k$ = 0.1; (g) $k$ = 0.05; (h) $k$ = 0.01.

Table 7 displays the value of $R^2$ for 5-minutes intervals of car and PT passengers departures (216 observations between 05:00 to 23:00) in the mixed traffic set-ups, which is calculated for the baseline population ($k$ = 1, Figure 24a) and the same downscaled scenarios of 0.01 $\leq k \leq$ 0.5 (Figure 24b-h). As can be seen, for car departures, $R^2$ remains high up to $k$ = 0.05, while for the PT Passenger departures the $R^2$ drops for $k$ < 0.1.

Table 7. Sioux Falls 2014, mixed traffic scenario, $R^2$ between the number of car and PT departures for the case of $k$ = 1 and cases of $k$ varying between 0.01 ≤ $k$ ≤ 0.5

| $k$ | 1.00 | 0.50 | 0.40 | 0.30 | 0.20 | 0.10 | 0.05 | 0.01 |
|---|---|---|---|---|---|---|---|---|
| **$R^2$ - Car departures** | - | 0.994 | 0.991 | 0.989 | 0.988 | 0.982 | 0.974 | 0.887 |
| **$R^2$ PT Passengers departures** | - | 0.983 | 0.980 | 0.972 | 0.969 | 0.944 | 0.902 | 0.530 |

The MRD($k$) values for the car and PT Passenger departures (Figure 25) in the mixed traffic scenario are higher than car departures (in the car only scenario), but remain below 20% for $k$ ³ 0.3. The MRD($k$) for PT Passengers departures remains below 20% for $k$ ³ 0.1. In any case of $k$ < 0.1 the values of MRD($k$) are essentially higher for larger $k$.

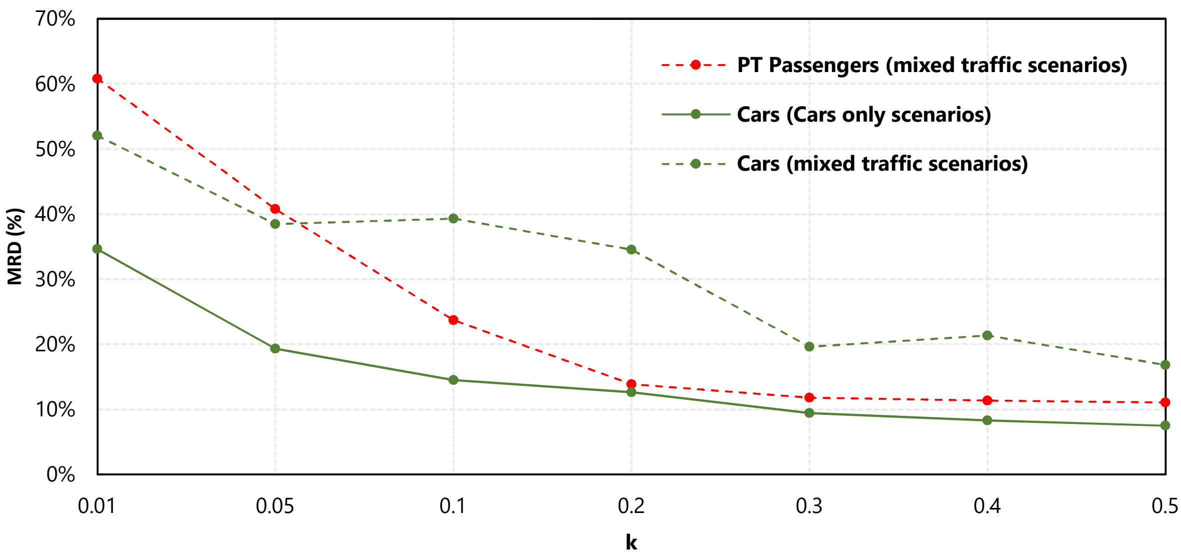


Figure 25. MRD($k$) for the number of Cars and PT passengers departures (equation 6) in the car only and mixed traffic scenarios as dependent on $k$, for 0.01 ≤ $k$ ≤ 0.5 (aggregated for the whole day).

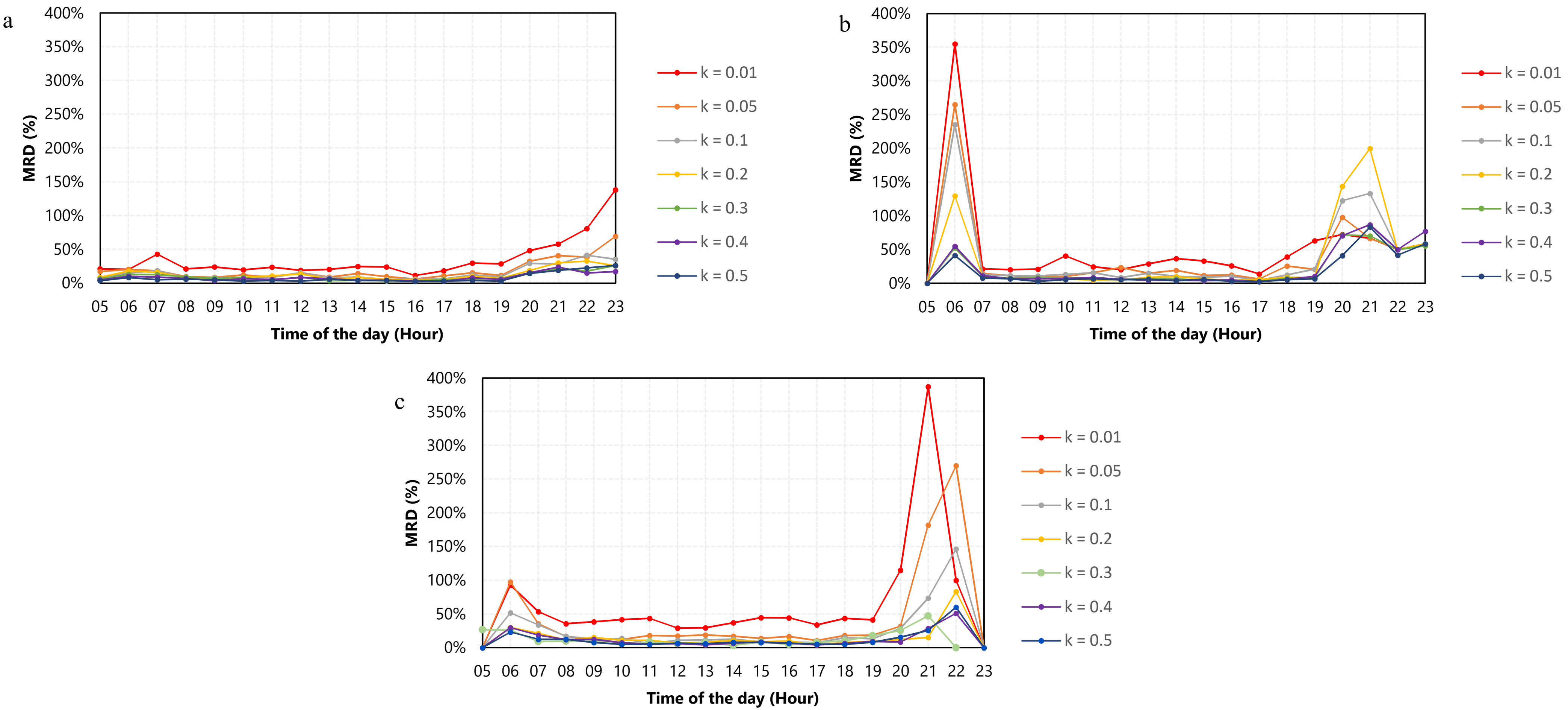


Figure 26. MRD($k$) calculated for each hour between 05:00-23:00 (equation 6). (a) Car departures in the car only scenario; (b) Car departures in the mixed traffic scenario and (c) PT Passenger departures in the mixed traffic scenario

The hourly variation of the MRD($k$, $t$), for the cars and PT passengers departures, is presented in Figure 26 above.

Similar to the aggregate outputs of the whole day (Figure 21 and Figure 25), the deviations for $k$ < 0.1 are essentially high than those of larger $k$ values, suggesting that the $k$ = 0.1 threshold should be applied for investigating hourly model dynamics.

For $k$ ³ 0.1, the values of MRD($k$, $t$) remain relatively steady for $t$ between 7:00-19:00. However, at the early morning (before 7:00) and evening (after 20:00) periods, when the total numbers of departures is low, the MRD($k$, $t$) values double and even triple.

Given $k$ > 0.1, the value of the MRD($k$) remains below ~20%, for all $k$ between 7:00 – 19:00. For later hours, the MRD($k$, $t$) remains below 40% for the car departures in the car only scenario, but is essentially higher (up to 200%) for the cars and PT passengers departures in the mixed scenario. The reason for these deviations is the low total number of travelers in the early morning/late evening, but deeper study of this phenomenon is delayed to the future stages of my study.

Importantly, in the mixed traffic set-up, the value of MRD($k$, $t$) after 20:00 does not necessarily decreases with an increase in $k$ (Figure 26b). Furthermore the, MRD($k$) values are substantially low for car departures reaching only 150% in the car only scenario (Figure 26a) when compared to a 350%-400% MRD($k$) value in the mixed traffic scenarios (Figure 26b, c).

The MRD($k$) difference between the car only and the mixed traffic scenarios for low $k$ values could be explained by the emerging traffic dynamics of downscaling a mixed traffic set-up which mixes PT vehicles and private cars on the same road space, which could cause issues:

- The number of the PT vehicles cannot be reduced proportionally to the percentage of travelers participating in the scenario, as conducted with private cars: The use of 10% instead of 100% of buses would reduce the frequency of buses 10-fold.

- As a result, the size of the PT vehicle should be scaled down proportionally to the reduction of the flow/storage capacities.
- Generally, traffic simulation of a low-value $k$ exacerbates congestion as traffic flow is not so fine-grained anymore. Because private cars can change their route to avoid congestion, while PT vehicles must follow fixed routes, in large network configurations the PT vehicles are those who are most affected by downscaling. In the case of small networks like the Sioux Falls 2014 scenario. The network is relatively small with not many re-routing options for cars especially during the PHDs. Thus, in smaller networks with a low value of $k$, PT vehicles which are stuck in traffic also affects the private cars and vice versa.

To demonstrate the above problems which arise when downscaling a mixed traffic scenario, one bus line in the baseline scenario ($k$ = 1) is compared to $k$ = 0.01. "Line 2" is chosen for comparison (see Figure 27d) as it contains enough PT flow (204 bus departures from 06:00-23:0 across 23 bus stops). Each bus traverse across the network from south to north.

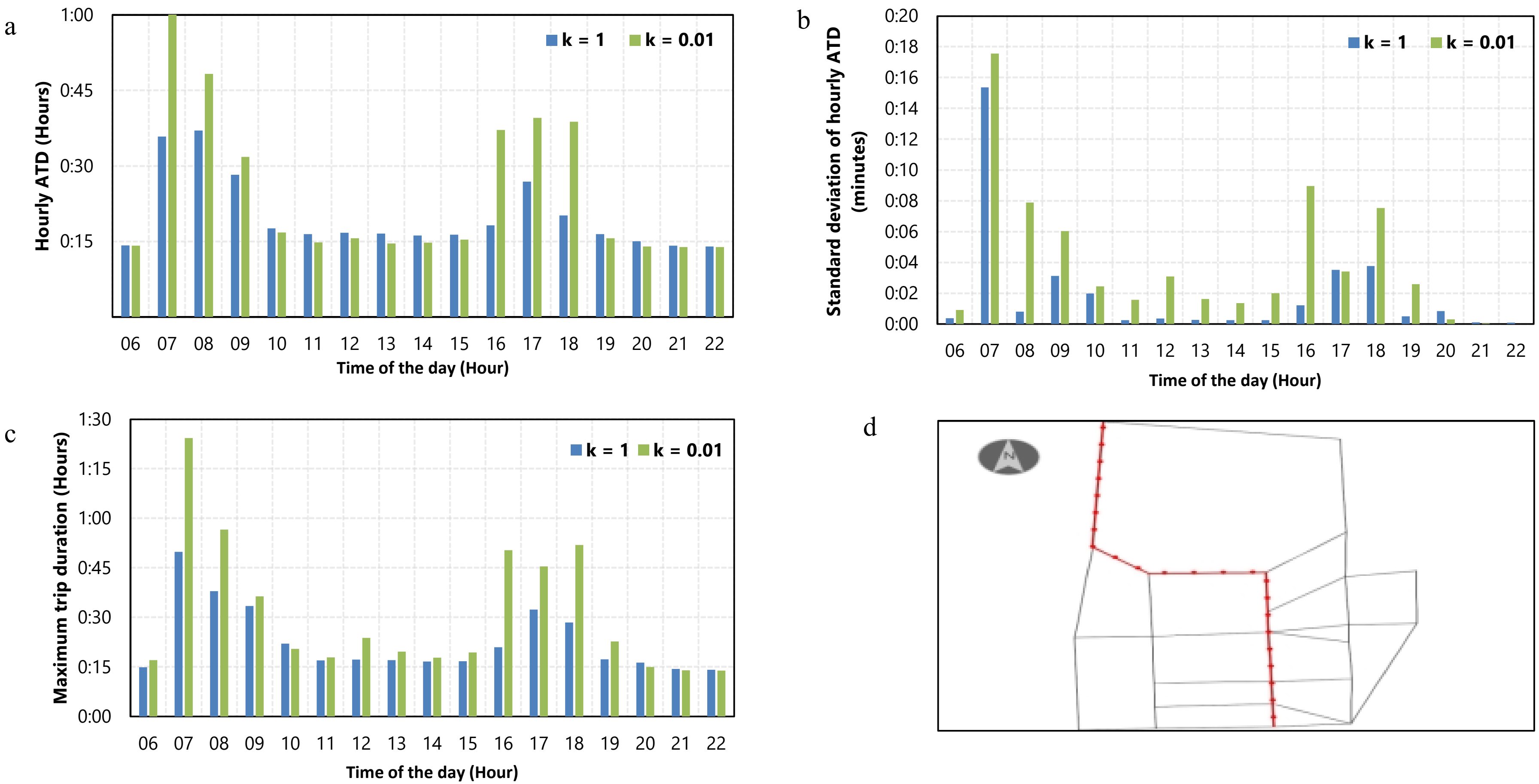


Figure 27. Hourly comparison of the aggregate statistics for the PT vehicles (T2T) of "Line 2" (12 buses per hour) between k =1 and k = 0.01. (a) Hourly ATDs; (b) Standard Deviations of hourly ATDs; (c) the maximum hourly recorded trip durations and (d) PT "Line 2" in the Sioux Falls 2014 scenario.

Figure 27(a-c) above shows an hourly comparison (between 06:00-23:00) of the PT vehicles driving from T2T, in "Line 2". Compared between $k$ = 1 and $k$ = 0.01. Figure 27a is the hourly ATDs, Figure 27b is the *Standard Deviation* (STDEV) of the hourly ATDs and Figure 27c is the maximum trip duration recorded in a given hour.

It is apparently evident in Figure 27(a-c) that for $k$ = 0.01 the values across the whole day (06:00-23:00) are almost always higher when compared to $k$ = 1, this is especially true during the PHDs.

Figure 27 suggests that in small networks (like the Sioux Fall 2014 scenario) and with a small downscaled mixed traffic set-ups, PT vehicles create and are caught in unrealistic traffic dynamics which in turn worsen the travel times for all the system.

The primary goal of downscaling is a reduction of the computation time, and this is indeed substantial and close to linear for $k$ decreasing from 1 to 0.1 (Figure 28). For the lower $k$, the common computational overhead overcomes the computation time reduction caused by a decrease in the number of agents. Comparing between scenarios for a given $k$, mixed traffic scenarios demand less time than the car only ones, due to a 16%-18% "Walk" legs which are implemented as teleportation.

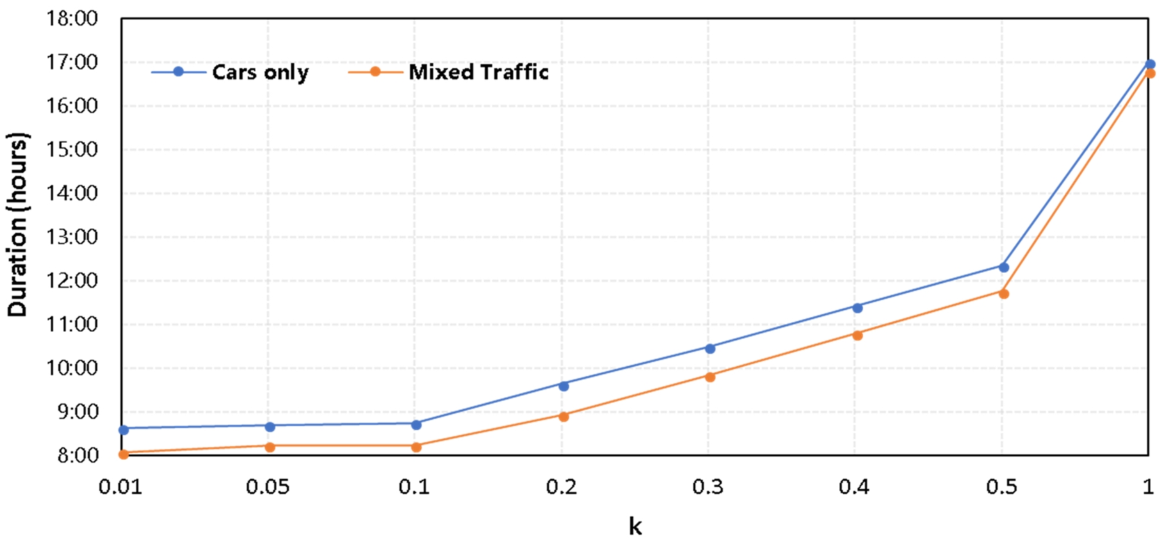


Figure 28. Sioux Falls 2014 runtime of Mixed Traffic vs. Cars only scenarios.

To summarize, for the assessment of hourly model dynamics, downscaling should be done with care primarily in the mixed traffic state. In future research, the appropriateness of downscaling will be investigated further in terms of the spatial deviations which could arise from downscaled outputs.

Combining all the comparisons of this section, a general conclusion arises, that downscaling up to $k$ = 0.1, properly represents the MATSim model dynamics of $k$ = 1. Lower values of $k$ cause disproportionally high deviations from the baseline scenario (and do not improvement the model performance).

# 7 Conclusions

The primary goal of the thesis is to investigate, with the MATSim ABM, the consequences of DBL network - a subject that was not thoroughly investigated before. Using Sioux Falls setup for the year 2014, it was demonstrated that the addition of DBLs at the city level fundamentally improves PT's effectiveness. Furthermore, the results established that the introduction of DBLs equalizes travel times of PT Passengers during the peak and off-peak hours. Two scenarios of the DBL establishment were compared: Added DBLs, where a new DBL is added to every street link; Converted DBLs, where one of the lanes on each street link which is exploited by PT is converted into a DBL. *The Converted DBLs* scenario results in higher modal share for PT but converting a car lane to DBL generates more congestion on the rest of the lanes, particularly during peak hours. The impact of the DBLs critically depends on the level of congestion in the city that is defined by the travelers' population size. For a high level of congestion, DBLs cause a 20% rise in the PT usage.

Prior studies did not investigate the effects of multiple DBLs on a city-scale scenario. Most of them were limited to studying the effects of a single DBL. The advantage of MATSim is in a direct simulation of human mode choice, which previous studies ignored (Basso et al., 2011; Luo & Qian, 2014; Shu & Yong, 2009; Thamizh Arasan & Vedagiri, 2010; Yu et al., 2015; Zhou & Peng, 2013). MATSim is thus the next logical step towards the holistic assessment of DBLs at the resolution of a single traveler.

This thesis also studies the adequateness of the "downscaled" scenarios, which aim at representing the transportation dynamics of the entire city by the fraction of the agents' and vehicles' population. MATSim provides the tools for adjustment of downscaled scenarios but their adequateness was always taken for granted and never investigated properly. The likely results of the thesis have demonstrated that the MATSim downscaling rules guarantee adequate representation of the system dynamics for $k$ > 0.1. Downscaling below $k$ = 0.1 causes substantial changes in model outputs.

# 8 Future Outlook

As a next step, the developed methodology of this thesis will be employed in an extensive case study of the highly congested *Tel-Aviv Metropolitan area* (TLVM) which includes over 3,000,000 inhabitants, ~13,000 road links, and ~1000 bus lines, where the effectiveness of the proposed DBL schemes will be compared. Looking ahead, Sioux Falls 2014 configuration for $k$ = 1 that results in 250 travelers per link, is similar to the travelers per link value for TLVM. However, the difference in the network size may result in a much higher level of congestion for TLVM. Therefore, it is hypothesized that the TLVM case will resemble the Sioux Falls case for $k$ » 3.

In a future study, a thorough analysis of the spatial patterns of the TLVM traffic will be done. Different from the aggregate model outputs, random variation of the model spatial patterns may be substantial. In particular, I will investigate the variation in traffic congestion emerging, due to the variation of local conditions, at different locations and at different moments in time.

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# Appendix A

Table A1. Sioux Falls 2014 scoring utilities and values

| General Utility Functions | Value |
|---|---|
| Performing an activity ($S_{dur,q}$) | 0.96 |
| Waiting ($S_{wait,q}$) | 0 |
| Late arrival ($S_{late.ar,q}$) | 0 |
| Early Departure ($S_{early.dp,q}$) | 0 |
| Utility per monetary unit ($\beta_{\mathrm{m}}$) * | 0.062 |
| **Car Utility Functions** | |
| Car Mode-Specific constant *($C_{mode(car)}$)* | -0.562 |
| Time spent traveling by a car mode *($\beta_{trav,mode(car)}$)* | 0 |
| Car marginal utility Distance *($\beta_{d,mode(car)}$)* | 0 |
| Car Monetary Mode Distance *($\gamma_{d,mode(car)}$)* | -0.0004 |
| **Bus Utility Functions** | |
| Bus Mode-Specific constant *($C_{mode(bus)}$)* | -0.124 |
| Time spent traveling by a Bus mode *($\beta_{trav,mode(bus)}$)* | -0.18 |
| Bus marginal utility Distance *($\beta_{d,mode(bus)}$)* | 0 |
| Bus Monetary Mode Distance *($\gamma_{d,mode(bus)}$)* | 0 |
| Waiting time at bus stations *($\beta_{wait.bus}$)* ** | -0.18 |
| **Walk Utility Functions** | |
| Walk Mode-Specific constant *($C_{mode(walk)}$)* | 0 |
| Time spent traveling in a Walk mode *($\beta_{trav,mode(walk)}$)* | -0.14 |
| Walk marginal utility Distance *($\beta_{d,mode(walk)}$)* | 0 |
| Walk Monetary Mode Distance *($\gamma_{d,mode(walk)}$)* | 0 |

* The monetary values of the Sioux Falls 2014 scenario are stated in Australian Dollar 1 AUD = 0.88 USD (21.01.2014).
** MATSim provides an option for additionally penalizing the waiting time at transit stations

# תקציר

נתיבי תחבורה ציבורית (נת"צים) יכולים לשפר באופן משמעותי את הביצועים של שירותי האוטובוסים, תוך עידוד המעבר של הנוסעים מרכב פרטי לתחבורה ציבורית דבר שיפחית את זמני הנסיעה ויקל על העומס העירוני. מטרתה העיקרית של התיזה המוצגת, היא להעריך את השפעתם של נת"צים על מצב תנועת התחבורה העירונית, בעזרת סימולציה מבוססת סוכנים - MATSim. בתזה זו נבדקו ההשפעות של הוספת נת"צים חדשים והמרת נתיבים קיימים לנת"צים.

יעד משנה של תזה זו, הוא להעריך את היכולת של MATSim לייצר פלט עקבי ודומה בתרחישים בעלי גודל אוכלוסייה מדגמי (Downscaling). Downscaling הינו הליך של הסקת מידע ברזולוציה גבוהה ממשתנים ברזולוציה נמוכה לשם שיפור יכולות המחשוב. תוצאות ה-Downscaling ברשת הדרכים של העיר Sioux Falls, אחת הרשתות המוכרות למבחני רגישות בתחבורה, מדגימות כי עדיף לבצע Downscaling לכ-10%-20% של האוכלוסייה בכדי לשמור על סטייה נמוכה (15% או פחות) מהתוצאות של תרחיש הבסיס לפי פרמטרים עיקריים כגון זמני הנסיעה הממוצעים, שיעורי בחירת אמצעי הנסיעה ושעות היציאה של הסוכנים. כפי שהוכח בתזה,Downscaling מתחת ל-10% אינו תורם לשיפור ביצועי מחשוב (זמן ריצה מתייצב על כ-~8.5 שעות ולא יורד יותר). המסקנות אלה נכונות גם לתרחישי של רכב פרטי כאמצעי תחבורה היחיד (פרק 6.2), וגם לתרחישים של תחבורה מעורבת (פרק 6.3).

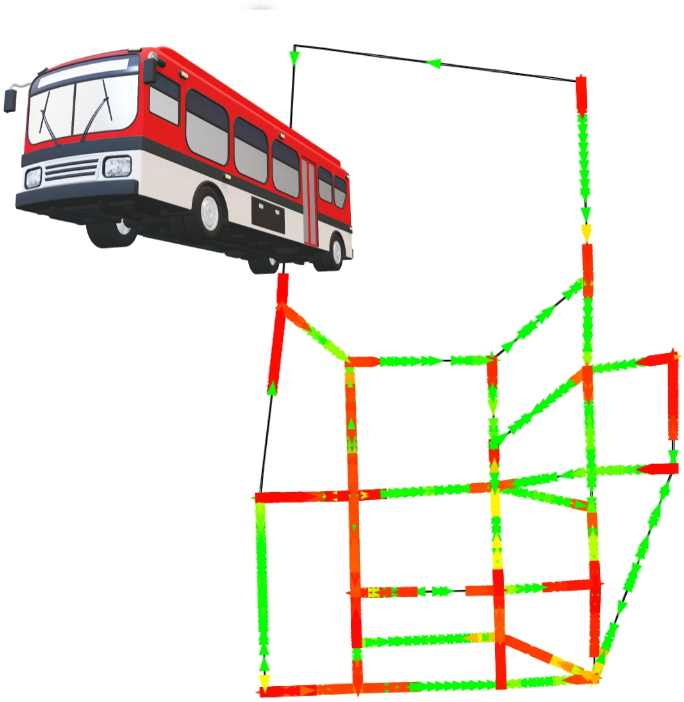
בבחינת ההשלכות של פריסת הנת"צים, נמצא שהוספת נת"צים גוררת שינויים מהותיים במעבר של נוסעים לתחבורה ציבורית, זאת תוך שימור זמן הנסיעה של הנוסעים במהלך שעות העומס ומחוצה להם. בגודל האוכלוסייה הנוכחי של העיר Sioux Falls תוספת של נת"צים חוסכת לנוסעי האוטובוס בממוצע כ-4% בזמן הנסיעה, כאשר לתרחיש של אוכלוסייה מוכפלת השיפור הינו 14% ולאוכלוסייה משולשת השיפור הינו 26% (פרק 6.1). אי לכך, היכולת של MATSim לייצג הסתגלות של סוכנים להזדמנויות הנסיעה חדשות בעקבות הוספת נתיבים יעודים, מדגימה יעילות גבוהה לנת"צים בערים שבהן רמת עומסי התנועה היא גבוהה.

Porter School of
the Environment and
Earth Sciences

בית הספר לסביבה
ולמדעי כדור הארץ
על שם פורטר

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

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

# הערכת ההשפעה של נתיבי תחבורה ציבורית על מצב התנועה העירוני באמצעות מודל מבוסס סוכנים

חיבור זה הוגש כעבודת מחקר שקולה לתיזה כתנאי קבלה ללימודי תואר שלישי


## גולן בן-דור

העבודה נעשתה בחוג לגיאוגרפיה, בית הספר למדעי כדור הארץ הפקולטה למדעים מדויקים שבאוניברסיטת תל אביב:

בהנחייתם של פרופ' בננסון (אוניברסיטת תל-אביב) וד"ר ערן בן-אליא (אוניברסיטת בן-גוריון)


ח׳ בחשוון התשע״ט