DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics

# Analyzing Effects of Road Pricing on Travel Demand using MATSim

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# Analyse der Auswirkung von Straßenbenutzungsgebühren auf den Verkehrsbedarf mit MATSim


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I confirm that this master's thesis in informatics is my own work and I have documented all sources and material used.

Munich, 15.07.2021 Burak Öz

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# Abstract

The negative impact of congestion on the economy, the environment, and human health has reached critical levels. Although static road pricing policies reduced congestion to some extent, the problem still exists since prices do not adapt meaningfully to shifting demand in most of these policies. Littmann and Bichler propose a dynamic road pricing scheme to address this. Even though their findings suggest that dynamic pricing can reduce congestion and increase social welfare, there are concerns about the online optimization algorithm they used and the simulation program they utilized, SimMobility. In this master's thesis, the dynamic road pricing scheme proposed by Littmann and Bichler is optimized and further investigated using the state-of-the-art multi-agent simulation software MATSim. Using the individual and the equitable economic interpretations, the simulation findings are assessed in terms of mode usage, social welfare impact, and public approval.

# Zusammenfassung

Die negativen Auswirkungen von Verkehrsstaus auf die Wirtschaft, die Umwelt und die menschliche Gesundheit haben ein kritisches Ausmaß erreicht. Obwohl die statische Mautpolitik die Überlastung bis zu einem gewissen Grad reduziert hat, besteht das Problem immer noch, da sich die Preise in den meisten dieser Politiken nicht sinnvoll an die veränderte Nachfrage anpassen. Littmann und Bichler schlagen eine dynamische Mautpolitik vor, um dies zu adressieren. Obwohl ihre Ergebnisse darauf hindeuten, dass dynamische Preise Staus reduzieren und die soziale Wohlfahrt erhöhen können, gibt es dennoch Bedenken über den von ihnen verwendeten Online-Optimierungsalgorithmus und das von ihnen verwendete Simulationsprogramm SimMobility. In dieser Masterarbeit wird die von Littmann und Bichler vorgeschlagene dynamische Mautpolitik mit der hochmodernen Multi-Agenten-Simulationssoftware MATSim optimiert und weiter untersucht. Wir untersuchen unsere Ergebnisse in Bezug auf Transportmittel, Wohlfahrt und öffentliche Akzeptanz und unterscheiden dabei zwischen individuellen und gesellschaftlichen Effekten.

# Contents

# 1 Motivation

In 2017, traffic congestion caused a combined damage of $461 billion in the United States, Germany, and Britain (Cramton et al. 2018). Besides the economic cost, time spent in traffic also has an ecological cost. It is shown that traffic congestion can cause an 80% increase in fuel consumption, and four times longer traveling times (Greenwood et al. 2007). This means there is more carbon dioxide ($CO_2$) emission caused by fossil fuel combustion. Getting stuck in traffic can also affect mental health by causing stress and frustration (Cramton et al. 2018). Road pricing policies alleviate these problems by guiding drivers' road choices through meaningful prices and adding disincentives for driving when roads are congested.

A road pricing policy can be optimized based on the goal aimed to be reached. As done in London and Stockholm (Meyer de Freitas et al. 2016), a pricing scheme can be designed to increase social welfare by reducing the total travel time across the network. It can also be designed for maintaining a certain minimum travel speed or revenue maximization (Chakirov and Erath 2012).

A road pricing strategy can be unsuccessful against traffic congestion regardless of its design goal. As happened in Singapore and some cities in the United States, when prices do not adapt meaningfully to changing demand, policies become useless for mitigating congestion (Cramton et al. 2018; Martin and Thornton 2017). To overcome this problem, Cramton et al. (2018) propose **dynamic road pricing**, which adapts prices to demand in real-time by tracking the location of vehicles and measuring road usage. However, they also point out that dynamic road pricing has not progressed due to some research gaps such as the technology for tracking vehicles at a low cost and computational modeling of the market.

A dynamic road pricing scheme has been proposed by Littmann and Bichler (2020), where service providers (SP) sell their inventory of road capacity to end-users (e.g., private cars, taxis, freight). In their design, end-users submit queries for the origin-destination (OD) pair which they want to drive between. The SP in return responds with available routes and respective real-time prices. Since this scheme is referred to as **real-time dynamic congestion pricing** in their work, in this thesis, this term is used interchangeably with the term dynamic road pricing.

The SP has to compute prices for thousands of trips simultaneously, thus it is necessary to use fast, real-time pricing algorithms. To maximize welfare and decide which trip requests (bids) to accept, the SP needs to solve a very large-scale non-convex integer optimization problem (Littmann and Bichler 2020). Although the pricing scheme of Littmann and Bichler (ibid.) is a good starting point for filling the gap pointed out by Cramton et al. (2018), there exists room for improvement. Some of the components which are refined and extended in this thesis are: *the online optimization algorithm*, *the traffic simulation software (SimMobility)*, and the *analysis* part of the research. For extending the analysis part, social welfare is measured with respect to economic evaluation approaches. Moreover, public acceptance of dynamic road pricing is discussed for different income groups.

According to Hau (2005), the reason for public rejection of road pricing is mainly due to costs becoming dominant over advantages such as time-saving for individuals. To overcome this problem, the gained welfare should be returned to road users (e.g., increased public transport services) (Chakirov and Erath 2012). In order to make plans on how to return social welfare, the expected amount of it, in monetary terms, should be calculated first. Thus, it is critical to conduct an overall welfare analysis on road pricing schemes.

This master's thesis focuses on analyzing the effects of dynamic road pricing on social welfare and public acceptance of different income groups in a population, through running and optimizing the solution by Littmann and Bichler (2020). To achieve this goal, the state of art multi-agent simulation software *MATSim* is utilized. MATSim is a large-scale agent-based transportation simulation framework that contains features such as agent-based mobility simulation, re-planning (Allan and Farid 2015), and road pricing (Nagel 2016). Although MATSim supports road pricing, this is only in terms of pre-defined tolls. There is no known work for dynamic road pricing in MATSim.

For the practical part of this thesis, two Java applications developed by the MATSim team are used and extended. The first one is *MATSim Open Berlin Scenario*[1] which provides a MATSim model for Berlin. The real-time dynamic congestion pricing scheme proposed by Littmann and Bichler (2020) is integrated into the road pricing module of this project. Using the MATSim Open Berlin Scenario, different road pricing configurations are simulated.

The second application is *matsim-analysis*[2] which is used for analyzing the output produced by MATSim simulations. For the purpose of this thesis, the social welfare calculation module in matsim-analysis is re-implemented such that it considers personalized Value of Time (VOT) when converting utility into monetary terms.

[1]https://github.com/matsim-scenarios/matsim-berlin
[2]https://github.com/matsim-vsp/matsim-analysis

Besides social welfare, matsim-analysis also provides information about various outcomes of a simulation such as the collected revenue, the number of trips made by each vehicle type (e.g. private car, public transportation, bike), travel times, road usage, and kilometers traveled.

This thesis is structured as follows. In chapter 2, research on static road pricing schemes and a dynamically priced car-sharing service are reviewed. In the following chapter (3), the dynamic road pricing scheme proposed by Littmann and Bichler (ibid.) is presented and discussed for optimizations. Chapter 4 covers MATSim with a focus on how it works and how dynamic road pricing can be integrated into it. Chapter 5 explains the details of the simulated MATSim scenario. In the next chapter (6), simulation results are summarized and examined. In the final chapter (7), the thesis is concluded and questions are raised for future research.

# 2 Literature Review

There exists an extensive line of research that analyzes the effects of road pricing utilizing MATSim (Kickhöfer et al. 2010; Meyer de Freitas et al. 2016; Nagel et al. 2008; Rieser et al. 2008). However, these papers adopt static road pricing schemes. Unlike dynamic schemes, static schemes have fixed toll prices for certain hours of the day. Since tolls are pre-defined in these schemes, they are not responsive to demand like dynamic schemes and, as shown by Lo and Szeto (2004), the congestion problem can worsen by transportation management schemes which are based on static traffic assignment theory (Littmann and Bichler 2020).

Nevertheless, it is important for research to review different approaches for analyzing the impacts of road pricing schemes. Even though the real-time road pricing scheme used in this thesis differentiates from the pricing schemes reviewed here, the methods of analysis are still applicable since they are all simulated with MATSim. In the following section, some of the most common road pricing analysis methods are reviewed. Due to the lack of research in the literature on dynamic road pricing with MATSim, a dynamically priced car sharing service is also reviewed.

## 2.1 Analyzing Static Road Pricing Schemes

The impact of a road pricing scheme can be analyzed apropos to different aspects such as the congestion level, social welfare, public acceptance, or even environmental impact (e.g. pollution). Research shows that not all of these aspects can be optimized simultaneously (Kickhöfer et al. 2010; Meyer de Freitas et al. 2016). Thus, there is a trade-off and this must be considered while analyzing a road pricing scheme. Otherwise, a false-positive diagnosis may be made about a pricing policy, which could then lead to public opposition (e.g. deciding to apply a pricing scheme just because it is decreasing the travel times, without considering its public acceptance).

To get a better understanding of the relation between the aspects and how pricing policies impact them, a literature review on research analyzing road pricing schemes is conducted. Since, in all papers, the methodology used for simulating a road pricing scheme is the same as the one from this thesis (*MATSim*), the details of the simulation environment are not addressed. In chapter 4 of the thesis, an elaborate analysis of MATSim is presented.

### 2.1.1 Early Work with MATSim

In 2008, Rieser et al. (2008) conduct research on the impact of an evening toll on congestion. The simulated scenario covers the Zurich area. The representative network includes 10k nodes and 28k links. Inside the network, 260k agents is simulated. Each agent only has a single activity pattern, home-work-home, and they all commute by their private cars.

Inside the inner city of Zurich, an area with approximately 6 kilometers diameter is tolled. The toll is only applied during the evening time in order to show that MATSim considers impact for the whole day. According to Rieser et al. (ibid.), this is only possible with an agent-based model like MATSim, and it cannot be represented with a trip-based model.

The simulation results show that when compared to the no-toll case, the toll case has more traffic jams at the evening time (when the toll is applied) but less in the morning time (ibid.). Rieser et al. (ibid.) also explore how travelers react to the toll by changing their departure time. As expected, in order to avoid paying tolls, the number of agents departing before the toll begins is higher in the toll case than in the no-toll case. Since each traveler aims to work 8 hours, agents in the toll case tend to leave earlier in the morning as well (ibid.).

In conclusion, it is proven that MATSim, a multi-agent simulation tool, can capture the reaction of agents to a time-dependent pricing scheme. Since that day, MATSim has been one of the primary tools for analyzing road pricing schemes and the early work by Rieser et al. (ibid.) can be considered as a milestone.

Nagel et al. (2008) take the research to the next step by conducting an economic benefit analysis. They calculate the winners and losers of their road pricing scheme by aggregating agents' utilities. For aggregation, they sum up the utilities of individuals. The reason why this works is that since monetized utilities reflect the willingness-to-pay of an individual, summing them up would then yield the aggregated willingness-to-pay (ibid.).

Nagel et al. (ibid.) adopt the same Zurich scenario as (Rieser et al. 2008). 260k agents, each with a single activity pattern, are simulated in a network of 10k nodes and 28k links. However, this time, two different road pricing policies are tested:

(a) Time toll: time-based, applied across the whole simulation area.

(b) City toll: distance-based, applied in certain areas.

When time-toll is applied, road users are charged 13.13 *CHF* (12 *EUR*) for every hour they spent on the road throughout the day. Although this may be perceived by travelers as an incentive to speed, Nagel et al. argue that by placing in-car devices for tracking speed, this problem can be mitigated. According to Nagel et al. (2008), by using time-dependent tolls we can better approximate the optimal toll as links with higher congestion will become more expensive.

Similar to the road pricing policy in Rieser et al. (2008), links inside an area are priced when city-toll is applied. However, instead of 6 kilometers, the diameter of the toll area is 11 kilometers this time. Also differently from Rieser et al. (ibid.), the toll is applied only during the morning rush hour, with a fee of 1.09 *CHF* (1 *EUR*) per kilometer traveled (Nagel et al. 2008).

The results of the simulations show that when the time toll is applied, road users are motivated to minimize their travel time. Compared to no toll case, a significant decrease in the number of agents driving during the morning and evening rush hours can be observed (ibid.). However, there is no remarkable change in the arrival pattern of agents as they still try to arrive at work by 08:00 am.

When arrival times and the number of agents on the road are analyzed for the city-toll, one can see that it has an impact which is in between the no-toll case and the city-toll case (ibid.). Although agents show a reaction to the toll by departing earlier in the morning, a similar reaction is not observed in the evening. This is in a way a contrast to the agent reaction observed in the work by Rieser et al. (2008), where effects of an evening toll are also visible in the morning. The reason for this can be that, even after the toll is applied, the morning arrival pattern of agents does not change significantly in Nagel et al. (2008). As a result, since there is no evening toll, agents do not adapt their evening departure time.

The two road pricing policies (time-toll, city-toll) are also compared in terms of aggregated economic benefits. For each policy, the average travel time, monetized utility, and average/total paid fees are calculated. As expected, in the time toll case the sum of paid tolls is much greater than the city toll case due to the difference in the configuration of the two policies (fee, duration, area) (ibid.). Inevitably, this has a reflection on the monetized utilities as losing a greater amount of money causes a greater utility loss for an agent. Hence, the agents in the city toll have a much better overall utility, even better than the no-toll case.

Although the economic benefit analysis by Nagel et al. (2008) is a pioneer work (when it comes to simulating road pricing policies with an agent-based tool), it lacks the consideration of personalized Value of Time (VOT). This is significant as willingness-to-pay for road use varies from person to person in the real world. As it is seen in the upcoming reviewed works, a VOT can be realized for an agent by using their income data. Since there is no income data integrated to agents in Nagel et al. (ibid.), calculation of VOT is not possible.

### 2.1.2 Equity Effects

Meyer de Freitas et al. (2016) investigate the equity effects of road pricing by placing rush hour tolls to the city center of Zurich. The cordon tolls are applied when entering and leaving the inner city, during fixed time intervals in the morning and the afternoon. To set the correct amount to be charged, the toll fees are increased at each simulation, until the desired traffic reduction volume is reached.

The scenario used by Meyer de Freitas et al. (ibid.) consists of a 10% sample of the population living in the 30 kilometers radius of Zurich city center. For all 162.157 simulated agents, demographic information including home and work location and income are taken from the national census of 2000 and travel diaries of 2005 (ibid.). This information is necessary for analyzing the impact of the pricing scheme on different income groups and spatial patterns.

Besides the demographic information, the work by Meyer de Freitas et al. (ibid.) also considers a VOT value for every agent. Since road pricing intends to provide shorter travel times at the expense of paid fees, each agent must have a VOT to determine their behavior. To calculate VOT for an agent, Meyer de Freitas et al. (ibid.) utilize existing models of VOT for Switzerland by Axhausen et al. (2006).

Meyer de Freitas et al. (2016) reach its goal of 20% traffic reduction, in terms of kilometers traveled, by setting a toll fee of 4.07 $CHF$ (3.72 $EUR$). Although this shows that a road pricing scheme like this can achieve the desired policy (in a simulated environment), the winners and losers must be analyzed to get an understanding of the possible public impact of the pricing scheme.

For determining the winners and losers, Meyer de Freitas et al. (ibid.) analyze how the aggregated utility of each group, filtered by home location and income, changes after the policy. This type of analysis yields information about which demographic groups are affected the most, and which the least. Meyer de Freitas et al. (ibid.) also explore behavioral changes of the agents after the introduction of tolls. They identify groups such as agents who have changed departure times to avoid toll or switched from driving private cars to using public transportation. Using this analysis, the policymakers can return the gained revenue in ways that would help the ones who get affected the most. In this thesis, a similar analysis of the demographic groups is also conducted (see section 6.3).

### 2.1.3 Economic Policy Evaluation

Kickhöfer et al. (2010) show new approaches for economic policy evaluation. They test 8 different toll levels, covering all roads within Zurich except motorways which lead into the city. Kickhöfer et al. (ibid.) exclude these roads since they are not owned by the city of Zurich, but the Swiss Confederation. Unlike Meyer de Freitas et al. (2016), they apply distance-based tolls where agents are charged per kilometer they travel on the tolled road. The toll levels range from 0.35 $CHF/km$ (0.32 $EUR/km$) up to 44.80 $CHF/km$ (40.99 $EUR/km$). By applying tolls only during the morning rush hours, Kickhöfer et al. (2010) aim to find the optimal toll for this period. The optimal toll can be defined as the one where welfare is maximized ibid.

Similar to Meyer de Freitas et al. (2016), Kickhöfer et al. (2010) also analyze the change in the traffic conditions. Percentage of private car trips and average speed are compared among different toll policies. Although this is an insightful analysis for comparing policies, they compute the overall welfare effect as well. The overall welfare is defined as the sum of monetized utility gains of agents and the total revenue (ibid.). To find the sum of monetized utility gains, Kickhöfer et al. (ibid.) utilize two different interpretations: the equitable interpretation and the individual interpretation. In the former interpretation, utility changes are summed up first and then converted into monetary value by multiplying with a population average VOT. On the other hand, in the latter one, each agent's utility change is multiplied with their personalized VOT and then summed up. With this interpretation, an individual willingness-to-pay is considered for each agent when calculating the overall welfare change (ibid.).

When effects of policies on overall welfare are analyzed using the equitable and the individual interpretations, Kickhöfer et al. (ibid.) show that sum of monetized utility changes can become negative with the equitable approach, while it always stays positive with the individual one. For example, when toll levels 11.20 $CHF/km$, 22.40 $CHF/km$, and 44.80 $CHF/km$ are applied, with the equitable approach, the sum of monetized utility gains become $-0.1$ million $CHF$, $-0.3$ million $CHF$, and $-1.3$ million $CHF$ respectively. However, with the individual one, they all stay positive. This proves that the same road pricing policy can cause vastly different welfare effects. Interestingly, Kickhöfer et al. (ibid.) find the optimal policy to be the same with both interpretations. Although it is not proven whether these interpretations will always yield the same optimal policy, when it happens, it is definitely an important outcome for policymakers who are comparing different road pricing policies.

To understand the reasons behind the unpopularity of road pricing among road users, Kickhöfer et al. (2010) analyze how each income group is affected by different pricing policies. Although they utilize the individual interpretation during this analysis, there is no explanation for the motivation of preferring it over the equitable interpretation.

In Figure 2.1 taken from Kickhöfer et al. (ibid.), the impact of the lowest (0.35 $CHF/km$) and the highest (44.80 $CHF/km$) toll levels on each income group are shown. In the figure, higher deciles correspond to richer people of the population. With the high toll level, half of the population has negative willingness-to-pay and 30% of it has no remarkable utility gain. Only the richest 20% of the population are better off with this toll level. Kickhöfer et al. (ibid.) believe this may be the reason why there exists a negative opinion towards road pricing although it has a positive impact on the overall welfare.

Although the fees are significantly different from each other, the low toll level has a similar effect on the public as the high one. Again, the highest two income groups are the ones who benefit the most from the pricing policy. As a result, even though the low-income groups have a positive utility gain on average, they may think that the rich is becoming richer with this new allocation of utilities, thus be against it (ibid.).

The economic policy evaluation methods utilized by Kickhöfer et al. (ibid.) prove that the overall welfare impact of a road pricing scheme depends on the valuation of utility. Not only the magnitude of the impact, but even the sign of it can change based on the chosen evaluation method (ibid.). However, since public acceptance is not analyzed with both of the interpretations, it is not possible to deduct something about the relation between the evaluation methods and public acceptance. This thesis fills the research gap by analyzing how public acceptance changes based on the chosen economic policy evaluation method.

## 2.2 Analyzing a Dynamic Pricing Scheme

A dynamic pricing scheme aims to match real-time supply and demand by continuously adapting prices.[1] In terms of road pricing, this helps to control the traffic flow and prevent traffic jams by adapting prices in real-time based on parameters such as road usage and capacity (Soylemezgiller et al. 2013). Although there exists a long line of work on dynamic road pricing schemes (Brent and Gross 2017; Joksimovic et al. 2005; Linghui et al. 2017; Soylemezgiller et al. 2013), none of them are using MATSim for simulating their pricing scheme and analyzing the effects on congestion, social welfare, and public acceptance. Thus, a literature review concerning dynamic road pricing with

[1] https://www.business.com/articles/what-is-dynamic-pricing-and-how-does-it-affect-ecommerce/

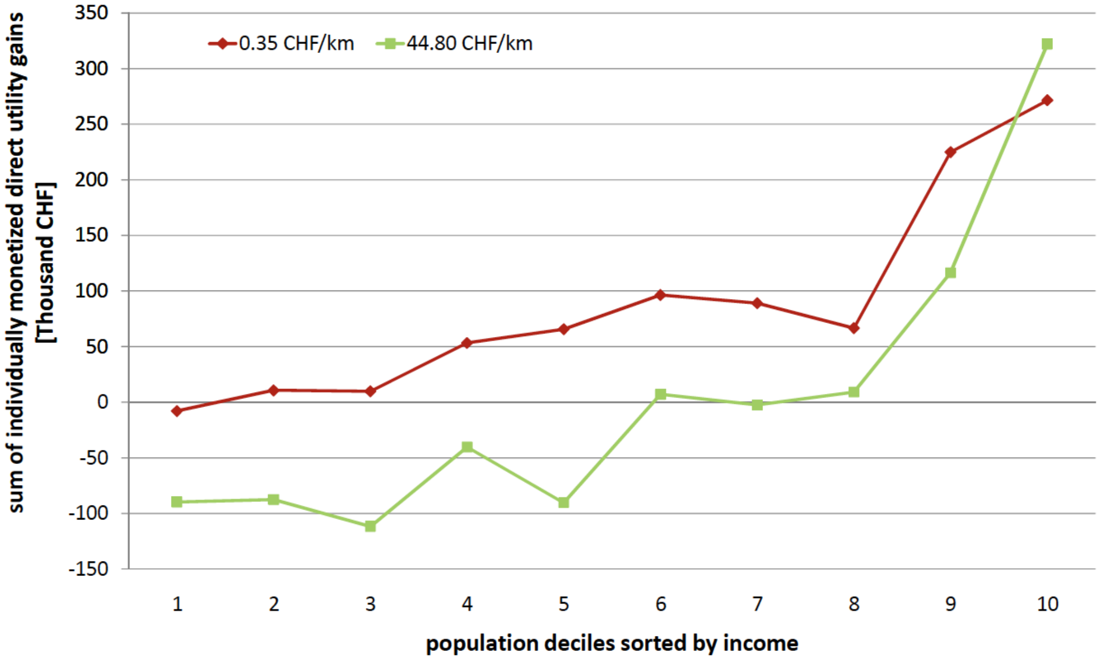


Figure 2.1: The impact of two extreme toll policies on monetized utility gains of different income groups (Kickhöfer et al. 2010). Higher deciles represent the richer people of the population.

MATSim is not possible to conduct. However, work on an availability-based dynamic pricing scheme for a car-sharing service that utilizes MATSim (Giorgione et al. 2019), is still worth reviewing.

### 2.2.1 A Dynamically Priced Car-sharing Service

Giorgione et al. (ibid.) investigate an availability-based dynamic pricing (*ABDP*) scheme for round-trip car-sharing services. Using ABDP, they price the car rental service based on real-time supply parameters such as the number of cars remaining in the rental station. Their study aims to understand the impact of ABDP on demand and whether it is socially fair. To simulate the change in demand realistically, Giorgione et al. (ibid.) calculate a VOT for each agent which then plays a role in an agent's decision for choosing a transport mode over another.

The results of the simulations with ABDP show that agents with the lowest VOT are the first ones to switch from car-sharing to another transport mode. While the high VOT group keeps their preferences, an increase in the car-sharing service utilization is observed for the average VOT group. However, a decrease in the rental duration for the average VOT group is also noticed (in order to keep the fee low) (Giorgione et al. 2019). The public reaction to ABDP can also be expected when the dynamic road pricing scheme by Littmann and Bichler (2020) is utilized. In the former, a trip becomes more expensive when there exists fewer cars in the rental station during the booking time. In the latter, a trip becomes more expensive when less road capacity is left during the time of request (see chapter 3).

# 3 A Dynamic Road Pricing Solution

Static congestion pricing models have been introduced all around the world in order to alleviate traffic jams. Such models can charge the road users based on the distance traveled on a road (distance toll) or for entering an area (area toll) or passing a certain road section (cordon toll) during a specific time interval (Cheng et al. 2017; Nagel 2016). Since 1975, Singapore has been applying an area-based tolling scheme. After the introduction of Electronic Road Pricing (ERP) in 1998, it has been observed that the traffic volume in the tolled area has reduced by 45% (Littmann and Bichler 2020). Congestion reduction targets have also been achieved in London and Stockholm, but this time by introducing a cordon-based tolling scheme (Meyer de Freitas et al. 2016). Although these schemes may have reached their policy goals, dynamic schemes are required for adapting prices to the time-dependent nature of traffic, since static schemes do not consider dynamic traffic flow (Littmann and Bichler 2020) or the impact of a toll on future congestion (Wie and Tobin 1998). Without dynamic pricing, problems such as overpricing or underpricing may occur which would then cause the pricing scheme to be ineffective against congestion and have a negative public impact.

Littmann and Bichler (2020) propose an update to an online optimization algorithm that can be used for dynamic road pricing. Their solution is called *real-time dynamic congestion pricing*. With this solution, they aim to alleviate the congestion problem by adapting prices according to supply and demand in real-time. In their solution, a service provider (SP), who owns capacity on roads of a city, sells its inventory to road users. The SP aims to avoid congestion by pricing trips in real-time based on the current traffic conditions and remaining road capacities. To use this service of the SP, road users (consumers) submit an online query including the origin and destination locations of their trip. The SP in return responds with available routes and their respective prices at that moment.

To implement the real-time dynamic congestion pricing scheme, really fast algorithms are required since the SP computes prices for thousands of trip requests dynamically and simultaneously. Since all bids (requests) are not known at the same moment, the optimization problem is not convex. Thus, the dual prices cannot be used as market prices for an offline optimization problem (ibid.). The problem, in this case, is a non-convex integer optimization problem and Littmann and Bichler (ibid.) solve this problem in dual space. To provide estimates for parameters in the online integer program, they use the recent developments in online linear programming and also forecasting.

Littmann and Bichler (2020) use the stochastic subgradient descent-based optimization algorithm by Li et al. (2020) in order to adapt prices in real-time with changing demand. Since stochastic gradient descent is frequently used for training neural networks, it is also a good fit for pricing a vast number of roads in real-time. The algorithm has an expected regret of $O(m\sqrt{n})$ which is a measure for comparing how well the algorithm works under the current stochastic input model versus the best dynamic decisions in hindsight. For the case of real-time dynamic congestion pricing, $m$ denotes the number of roads and $n$ the number of trips.

## 3.1 The Model for Offline Version

In a directed graph $N(V, E, c)$, $V$ represent vertices (nodes), $e \in E$ is a road segment, and $c\colon E \to \mathbb{R}_0^+$ denotes a road segment's capacity. In this model, road users $i \in I$ submit bids for routes $S \subseteq E$. For all the separate road segments $e$ in $S$, the vector $a_i$ (belonging to driver $i$) contains a binary value representing whether a road segment is included in $S$ or not. The valuation of a road user $i$ for route $S$ is then denoted by $v_i(S) \in \mathbb{R}_{\geq 0}$ and $x_i(S)$ is a decision variable standing for whether $i$ has won (got assigned) route $S$. Finally, the price of each road segment $e$ is indicated by $p(e)$.

With respect to these decision variables and constraints, an offline version of the resource allocation problem can be constructed which has an objective function aiming to maximize social welfare. Using the dual of the relaxed primal, Littmann and Bichler (2020) show that it is possible to get competitive equilibrium prices where each driver maximizes his payoff $\pi_i$ for price $p(e)$. Nonetheless, the problem must be solved online since road users are not arriving at the same moment but over time and the problem has integer variables.

## 3.2 The Online Optimization Algorithm

The algorithm starts with forecasting the number of trip requests $n$ expected to arrive in the next time period (e.g. 30 minutes). This is done by using the planned trips data from the activity schedules of agents. During the time period, a subgradient descent algorithm, $f(p)$, is applied for adapting the prices continually in real-time (Li et al. 2020). With a single pass in the dual space, the algorithm finds the primal solution. Besides $n$, the algorithm also takes a vector of prices from the last time period ($p_{lastperiod}$) and a vector of capacities ($c$) as inputs. To have the same notation as Littmann and Bichler (2020), the subscript $i \in I$ is replaced with $t \in I$. The motivation for this replacement is to highlight that each trip request of a road user is submitted at a specific time and order.

For each incoming trip request $t$ in a time period, the online algorithm applies the same three steps. First, a decision variable $x_t(S)$ is computed for denoting whether a trip request $(v_t(S), a_t)$ is accepted or not (see line 3). Following that, the subgradient decent is applied. The price is not increased for road segments which are not in $S$ (not requested) or when $(v_t(S), a_t)$ is rejected, since $a_t x_t(S) = 0$. Only when a road segment $e \in S$ and the respective trip request is accepted, the price is increased by $\gamma_t(1 - \frac{c}{n})$ (see line 4). $\gamma_t$ refers to the step size and in order to comply to the regret constraint ($O(m\sqrt{n})$ (Li et al. 2020)), it is chosen as $\gamma_t = \frac{1}{\sqrt{n}}$. In the last step, the algorithm makes sure that the updated price $p_{t+1}$ is in the feasible region by using an element-wise maximum operator $\vee$ (see line 5). The algorithm finally returns an approximation to the solution of the primal (Littmann and Bichler 2020).

**Algorithm 1:** The Original Online Optimization Algorithm

**Data: Input:** c, n, $p_{lastperiod}$

1 Initialize $p_1 = p_{lastperiod}$

2 **for** $i = 1, \ldots, n$ **do**

3 $\quad x_t(S) = \begin{cases} 1, & v_t(S) > a_t^T p_t \\ 0, & v_t(S) \leq a_t^T p_t \end{cases}$

4 $\quad p_{t+1} = p_t + \gamma_t(a_t x_t(S) - (\frac{c}{n}))$

5 $\quad p_{t+1} = p_{t+1} \vee 0$

6 **end**

7 **return** $x = (x_1(S), \ldots, x_n(S))$

Using the provided input $(c, n, p_{lastperiod})$, the algorithm already succeeds to find an integer solution to the relaxed linear program and an approximation to the integer linear program (ibid.). However, Littmann and Bichler (ibid.) believe that the subgradient decent step should be improved such that it considers the remaining capacity of a road segment while updating its price. The motivation for this improvement is to prevent exceeding capacity constraints (ibid.). To integrate this improvement into the algorithm, they replace Line 4 with two new steps.

In the updated version of the online optimization algorithm, the residual capacity $c_t$ of a road segment at request $t$ is calculated at Line 4. $c_t$ stays the same for road segments which are not requested or when the trip request is rejected as both causes $a_t x_t(S) = 0$. Otherwise, it is decremented.

In Line 5, two updates to the initial subgradient decent step are applied. The first update is, instead of using the default capacity $c$ of a road segment, the residual capacity $c_t$ is used. According to Littmann and Bichler (ibid.), by using the residual capacity, the prices will increase more significantly when demand increase since $c_t$ approaches 0. Also, for road segments that are not requested or when the trip request is not accepted, the prices will decrease less significantly.

The second update is applied to the denominator. By replacing $(n)$ with $(n - t)$, the algorithm now considers the number of trip requests yet to come while updating prices. The current situation of congestion is reflected better on prices with this update (Littmann and Bichler 2020). Since $n >> c$, this change has a little impact on the first incoming requests of a time period $t$. However, when most of the trip requests are processed since $n - t$ would approach 0, the update will cause the price of not requested road segments to drop more substantially.

**Algorithm 2:** The Updated Online Optimization Algorithm

**Data: Input:** c, n, $p_{lastperiod}$

Initialize $p_1 = p_{lastperiod}$

**for** $i = 1, \ldots, n$ **do**

$$x_t(S) = \begin{cases} 1, & v_t(S) > a_t^T p_t \\ 0, & v_t(S) \leq a_t^T p_t \end{cases}$$

$c_t = c_{t-1} - a_t x_t(S)$

$p_{t+1} = p_t + \gamma_t(a_t x_t(S) - (\frac{c_t}{n-t}))$

$p_{t+1} = p_{t+1} \vee 0$

**end**

**return** $x = (x_1(S), \ldots, x_n(S))$

## 3.3 Methodology

Littmann and Bichler (ibid.) utilize SimMobility[1] for testing the impact of their dynamic pricing algorithm. SimMobility is an integrated, agent-based, mobility simulation platform. It supports simulating scenarios for short, medium, and long-term travel behavior. The development of the platform continued until June 2019, by the Intelligent Transportation System Lab at the Massachusetts Institute of Technology (MIT) and the Singapore-MIT Alliance for Research and Technology (SMART).

Using the mid-term framework of SimMobility, Littmann and Bichler (ibid.) simulate a prototypical city that has 100k households and 254 separate road segments. Agents of this simulated city can use private or public transportation modes such as car, bike, taxi, or bus. Although prices and travel times of public transportation modes are already known by agents (since they are constant), the cost or the travel time of a private vehicle trip is unknown since they both depend on congestion levels. To incorporate this into the agents' mode decision, Littmann and Bichler (ibid.) come up with a quasi-linear utility function,

[1]https://github.com/smart-fm/simmobility-prod

$$u_t(S) = v_t(S) - \Big(p_t(S) + 10 * \big(tt_t(S) - (tt_t(Q_s))\big)\Big). \qquad \text{(Agent's Utility Function)}$$

In the utility function, $v_t(S)$ represents the valuation of a trip and it is drawn from a uniform distribution between 5 and 15. While $p_t(S)$ denotes the price of a route $S$ at time $t$, $10 * (tt_t(S) - (tt_t(Q_s)))$ stands for the additional travel time ($tt_t$), relative to the minimal travel time $tt_t(Q_s)$ on that OD pair at $t$. It is assumed that the range where $v_t(S)$ is drawn from and the constant co-factor (10) in the additional travel time calculation are chosen on-purpose for making the utility function work as expected.

A utility value ($u_t(S)$) is calculated for all different route options between the OD pair that an agent wants to travel between. Among the options, the agent chooses the one which has the highest, positive utility. In case no route option has positive utility, the agent either prefers a public transportation mode or postpones the trip.

## 3.4 Results

Littmann and Bichler (ibid.) analyze the change in social welfare, revenue, and the total number of traffic jams among three different scenarios: no road pricing (base case), zonal-static road pricing (low and high fee), and dynamic road pricing. While social welfare is calculated by summing all the $v_t(S)$ values for realized trips, the revenue is computed by adding up the paid amounts by agents. Finally, for finding the number of traffic jams, a measure that counts a road as congested if the average density is greater than 185 cars per lane kilometer is defined.

The simulation results show that dynamic pricing is better at every comparison. First of all, it drops the number of traffic jams to one-third of the base case. Although the other zonal pricing cases are also doing better than the base case, they are not as good as the dynamic pricing case. Moreover, while the base case outputs \$1,002,940 (845.293 *EUR*) social welfare, the dynamic road pricing case outputs \$1,396,007 (1,176,575 *EUR*). Again, both of the zonal pricing cases do worse than the dynamic pricing (the low fee zonal pricing case does even worse than the base case). Finally, the most revenue is raised when dynamic road pricing is applied.

## 3.5 Discussion

Littmann and Bichler (2020) prove that a dynamic road pricing scheme is computationally feasible and can perform better than both zonal-static road pricing and no road pricing schemes. They show that dynamic pricing can guide road users to better decisions and can make better use of finite resources. However, there exist some discussion points related to the original version (1) and the updated version (2) of the online optimization algorithm they utilize. Besides the algorithm, the transport simulation software they use, SimMobility, is also debatable.

### 3.5.1 Issues Related to the Original Version of the Online Optimization Algorithm (1)

The main issue with the original version of the online optimization algorithm is regarding the subgradient decent step. As seen at Line 4 in 1, when a road segment $e$ is included in an accepted trip request, its price will increase by $\gamma_t(a_t - \frac{c}{n})$. However, in the inverse situation, the price of $e$ will decrease the same amount, taking the price back to 0. This may not be a problem if the number of requests is sufficiently high for every road segment so that the price is not always set back to 0, but there is no guarantee for that. Thus, when this version of the online optimization algorithm is applied, market prices for road segments tend to rapidly fluctuate which then can cause overpricing or underpricing. Hence, congestion can increase and dynamic road pricing may fail to achieve its goal. To alleviate this problem, the amount of increment and decrement should be different from each other. The amount should depend on parameters like the residual capacity of a road segment and the expected number of trip requests still to arrive.

### 3.5.2 Issues Related to the Updated Version of the Online Optimization Algorithm (2)

Two major issues are introduced with the update by Littmann and Bichler (ibid.) on the original version of the online optimization algorithm. The first one is about what happens when the number of expected trip requests yet to arrive ($n - t$) becomes less than the residual capacity ($c_t$) of a road segment that is included in an accepted trip request. The expected behavior from the algorithm is to increase the price when there is demand and keep the prices fixed when expected demand becomes less than supply. However, in this case, the subgradient decent step will decrease the price since $\frac{c_t}{n-t} > 1$ and $a_t x_t(S) = 1$, hence $a_t x_t(S) - \frac{c_t}{n-t} < 0$. The problem with this is that, unless the total number of expected trip requests ($n$) is significantly greater than road capacities ($c$), $n - t$ can approach $c_t$ real quickly. In this case, if the algorithm is allowed to decrease the price of a demanded road segment, then just like in the original version of the algorithm, the market prices will approach 0 right away. To avoid this, in this thesis, the prices are fixed when $n - t$ becomes less than $c_t$ (see Lines 5-10 in Algorithm 3).

The second issue is a more obvious one, the denominator becoming 0 when the number of current trip requests ($t$) matches the total number of expected trip requests ($n$). Although Littmann and Bichler (ibid.) may be handling this situation in the actual implementation of the algorithm, there is no addressing of it in their work. Thus, it can be considered as an issue. In this thesis, it is handled by taking the maximum of $n - t$ and a small constant number (e.g., 0.01) (see Line 6 in Algorithm 3).

**Algorithm 3:** The Online Optimization Algorithm After the Modifications For This Thesis

**Data: Input:** c, n, $p_{lastperiod}$

1 Initialize $p_1 = p_{lastperiod}$

2 **for** $i = 1, \ldots, n$ **do**

3 $\quad x_t(S) = \begin{cases} 1, & v_t(S) > a_t^T p_t \\ 0, & v_t(S) \leq a_t^T p_t \end{cases}$

4 $\quad c_t = c_{t-1} - a_t x_t(S)$

5 $\quad$ **if** $n - t > c_t$ **then**

6 $\quad\quad p_{t+1} = p_t + \gamma_t (a_t x_t(S) - (\frac{c_t}{\max(n-t, 0.01)}))$

7 $\quad\quad p_{t+1} = p_{t+1} \vee 0$

8 $\quad$ **else**

9 $\quad\quad p_{t+1} = p_t$

10 $\quad$ **end**

11 **end**

12 **return** $x = (x_1(S), \ldots, x_n(S))$

### 3.5.3 Issues with SimMobility

The main discussion point regarding SimMobility is about agent behaviors during simulations. For example, it is known that 80% of the traffic in simulations of Littmann and Bichler (ibid.) is caused by taxis cruising around the airport without any passengers. Since this type of flaw compromises the whole simulation data, any kind of analysis made on this data becomes open to discussion.

Another issue with SimMobility is the poor documentation and the lack of support available online. In a meeting held with Richard Littmann (for the purpose of this thesis), he also approved this and emphasized how difficult it was to work with SimMobility when it comes to implementing and integrating a custom module such as their dynamic pricing scheme. In order to take the work by Littmann and Bichler (2020) to the next step, a new simulation tool that does not have any issues like this and has many more features, MATSim, is utilized in this thesis (see chapter 4).

# 4 MATSim Transport Simulation

There exists three different types of transport software based on the simulation modeling they use: *microscopic*, *macroscopic*, and *mesoscopic* (Aljamal et al. 2018). While microscopic models are simulating each element in traffic in detail, macroscopic models are handling the whole traffic based on fluid dynamics concepts. To fill the gap between them, mesoscopic models are developed which define behavioral properties for individual vehicles while describing the whole traffic flow in aggregate terms (e.g., probability distribution)(Kessels 2019). Thus, to capture the impact of a macroscopic traffic management strategy on a microscopic level, a **mesoscopic** model is required (Meyer de Freitas et al. 2016).

MATSim[1] is an agent-based mesoscopic traffic simulation software that utilizes dynamic traffic assignment for incorporating the travel demand of each individual agent based on their activity schedules (Chakirov and Erath 2012). It was started by Kai Nagel during his time at ETH Zurich and developed further with collaboration by Kay W. Axhausen after he moved to TU Berlin in 2004 (Horni et al. 2016b). Today, MATSim is still continuously developed[2] and used for various types of projects which require agent-based transport modeling such as evacuation analysis (Aljamal et al. 2018), carsharing (Giorgione et al. 2019), or road pricing (Kickhöfer et al. 2010; Meyer de Freitas et al. 2016; Nagel et al. 2008; Rieser et al. 2008).

## 4.1 Building Blocks of MATSim

A MATSim simulation is an iterative process that aims to reach an equilibrium where an agent cannot do any better, in terms of utility, by itself (Horni et al. 2016b). In every iteration, agents try to optimize their daily activity schedule (plan) while being in competition with other agents for space-time slots (ibid.). This approach is also called *MATSim's Co-evolutionary Algorithm* and it is carried out by a simulation structure called the **MATSim loop** (see Figure 4.1). The MATSim loop contains four main building blocks for conducting a simulation: *initial demand*, *traffic flow simulation*, *scoring*, and

[1] https://matsim.org/
[2] https://github.com/matsim-org

*re-planning*. Upon the completion of a simulation, the process is followed by an output analysis which can be considered as the fifth block.

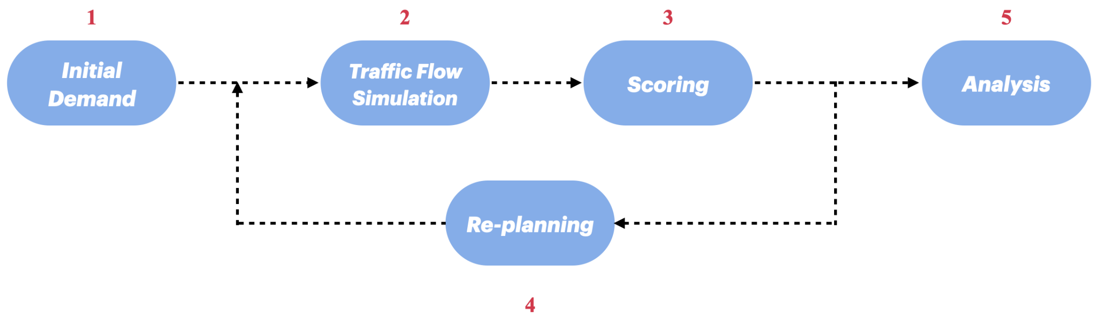


Figure 4.1: The MATSim loop (Horni et al. 2016b).

In the rest of this section, the displayed input and output files are all belonging to the same MATSim scenario called *equil*.[3] This scenario contains the minimum amount of details that are required for running a MATSim simulation. It has 15 nodes, 23 road segments (links), and 100 agents. In the scenario, all agents share the same home location and the same work location. Also, the activity plan of the agents are identical (*home-work-home*). The only difference is in their departure times and activity durations.

### 4.1.1 The Configuration

The configuration of the MATSim loop is the first step of every simulation. This is possible by a *config file* which is provided to MATSim as an input by the user. This file contains parameters that determine the details of the simulation to be conducted such as the number of iterations, plan selection strategies, or network and plans files to be used. The file is in XML format and each parameter is grouped under so-called modules. Some of the most fundamental modules are *controller* (iteration information and other metadata), *strategy* (plan selection strategies), and *planCalcScore* (scoring parameters).

In Figure 4.2, the config file of the equil scenario is displayed. Under the module global, the coordinate system to be used is set. Following that, the network and plans files are determined. While the controller module includes parameters about the iterations to be conducted, the qsim module contains information regarding the mobility simulation. The rather interesting modules are planCalcScore and strategy. In the former, parameters which are part of the utility function of MATSim are defined. These parameters can be either global like *learningRate*, *lateArrival*, and *traveling* or they can be specific to

[3] https://github.com/matsim-org/matsim-example-project

an activity such as *typicalDuration* and *openingTime*. In the latter module, strategy, the approaches to be used during plan selection are defined with respect to their weights. In the current setup, the agents of the equil scenario will choose the plan with the highest score with 90% probability and come up with a new plan with 10% probability.

```xml
<?xml version="1.0" ?>
<!DOCTYPE config SYSTEM "http://www.matsim.org/files/dtd/config
<config>
    <module name="global">
        <param name="randomSeed" value="4711" />
        <param name="coordinateSystem" value="Atlantis" />
    </module>
    <module name="network">
        <param name="inputNetworkFile" value="network.xml" />
    </module>
    <module name="plans">
        <param name="inputPlansFile" value="plans100.xml" />
    </module>
    <module name="controler">
        <param name="outputDirectory" value="./output" />
        <param name="firstIteration" value="0" />
        <param name="lastIteration" value="10" />
    </module>
    <module name="qsim">
        <param name="startTime" value="00:00:00" />
        <param name="endTime" value="00:00:00" />
        <param name = "snapshotperiod"   value = "00:00:00"/>
    </module>
    <module name="planCalcScore">
        <param name="learningRate" value="1.0" />
        <param name="BrainExpBeta" value="2.0" />
        <param name="lateArrival" value="-18" />
        <param name="earlyDeparture" value="-0" />
        <param name="performing" value="+6" />
        <param name="traveling" value="-6" />
        <param name="waiting" value="-0" />
        <parameterset type="activityParams">
            <param name="activityType"    value="h" /> <!-- home -->
            <param name="priority"        value="1" />
            <param name="typicalDuration" value="12:00:00" />
        </parameterset>
        <parameterset type="activityParams">
            <param name="activityType"            value="w" /> <!-- work -->
            <param name="priority"        value="1" />
            <param name="typicalDuration" value="08:00:00" />
            <param name="openingTime"     value="07:00:00" />
            <param name="latestStartTime" value="09:00:00" />
            <param name="earliestEndTime" value="" />
            <param name="closingTime"     value="18:00:00" />
        </parameterset>
    </module>
    <module name="strategy">
        <param name="maxAgentPlanMemorySize" value="5" /> <!-- 0 means unlimited -->
        <param name="ModuleProbability_1" value="0.9">
        <param name="Module_1" value="BestScore"/>
        <param name="ModuleProbability_2" value="0.1"/>
        <param name="Module_2" value="ReRoute"/>
    </module>
</config>
```

Figure 4.2: A simplistic config file belonging to the MATSim equil scenario.

### 4.1.2 Initial Demand

In MATSim, the initial demand is provided by the *plans file* which includes the daily plans of the study area's population. The daily plans of a population are usually generated using the survey data of the study area (Meyer de Freitas et al. 2016; Ziemke et al. 2019). During a simulation, agents optimize their initial plans by adapting their mode, route, and departure time choices. Although each agent is restricted to selecting a single plan for every iteration, they can store a pre-defined number of plans and their associated scores (utility) in their memory. This is useful for agents as they can compare their former plans and select the one that provides the highest utility.[4] However, the number of stored plans should be set carefully as it causes a performance drawback by consuming more memory.

An essential part of an agent's plan is the location information about activities and trips since every activity takes place in a specific location and trips are conducted depending on the routes between these locations. To build the road network infrastructure, MATSim expects a *network file* to be provided by the user. In the network file, nodes and links are defined again in an XML format. For each node, a coordinate and an id is assigned. Links on the other hand have parameters such as capacity, free-speed, permlanes (number of

[4]This is how the plan selection is done when the chosen strategy is BestScore.

lanes available in the specified from-to direction), and length besides from and to nodes and id.

To get a better understanding of a road network, the visualization tool Via[5] can be used. Via accepts input and output files of MATSim and provides insights about key inspects of a simulation (e.g. link volumes, activity times). If Via is only provided a network file and no events file, then the raw network infrastructure of a simulation can be observed. In Figure 4.3, the road network of the equil scenario is visualized.

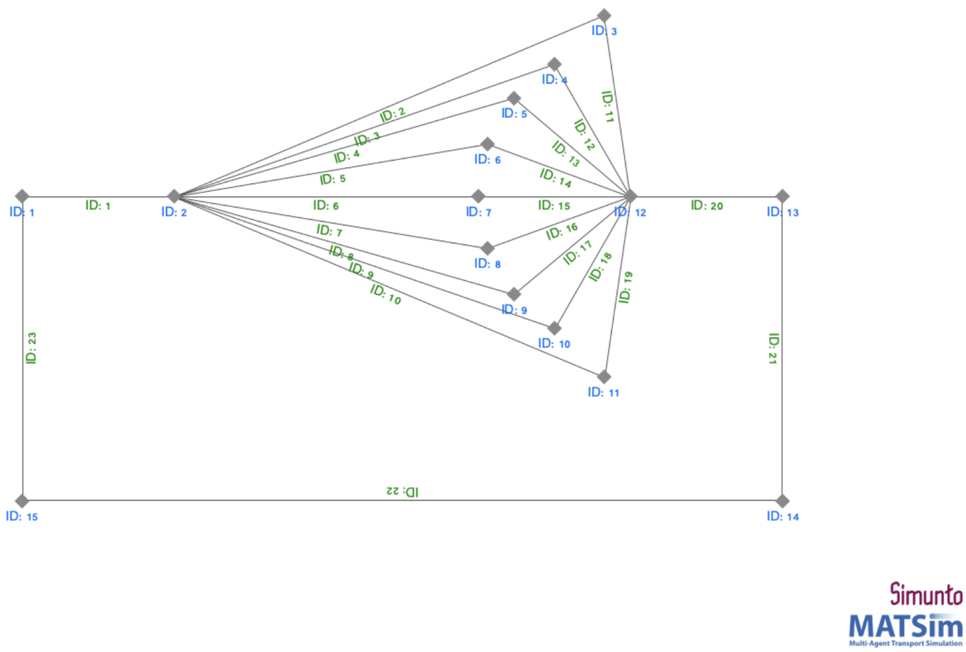


Figure 4.3: The network file of the MATSim equil scenario visualized with Via.

Using the nodes and links in the network file, MATSim users are able to define plans for agents. Each plan is a chain of activities and trips following each other. An activity has parameters such as type (e.g. work, home, leisure), end time (except the last activity of a plan), and either a coordinate or a link that determines the location of the activity. Trips or legs, as referred to in MATSim book (Horni et al. 2016a), defines the journey from the ending activity to the one to begin. Each leg is required to have a mode and can optionally have an expected duration attribute (ibid.). Also, every leg must include route information so that it can be simulated. A route is simply either a list of links (when the mode is car) or a list of stop locations (when the mode is public transportation). If there is no pre-defined route information included in a leg, MATSim computes it automatically.

[5] https://simunto.com/via/

A plan belonging to one of the agents from the equil scenario is displayed in Listing 4.1. According to this plan, the respective agent is going to leave her home at 6.00 *AM* and use her car to travel to work which is located on link 20. After staying 8 hours at work, the agent will travel back to her home, passing from nodes 13, 14, 15, and 1.

Listing 4.1: Activity Schedule of a MATSim Agent.

```
<person id="1">
        <plan>
                <act type="h" x="-25000" y="0" link="1" end_time="06:00" />
                <leg mode="car">
                        <route>2 7 12</route>
                </leg>
                <act type="w" x="10000" y="0" link="20" dur="08:00" />
                <leg mode="car">
                        <route>13 14 15 1</route>
                </leg>
                <act type="h" x="-25000" y="0" link="1" />
        </plan>
</person>
```

### 4.1.3 Traffic Flow Simulation

MATSim runs all selected plans of the agents simultaneously using its default mobsim (mobility simulation) *QSim*. In order to process large-scale scenarios, MATSim adopts a queue-based approach. With this approach, a car entering a link from an intersection is placed on the tail of the waiting queue (Horni et al. 2016b). Once the car is at the head of the queue and the duration for traveling the link with free-flow speed has passed, then it is allowed to leave the intersection and join the link. Since QSim adopts a time-step-based approach (iterates through time-steps (e.g. 1 sec) and handles events occurring during that step), a link's storage capacity and flow capacity are key factors for the traffic flow model of MATSim. While the storage capacity represents the number of cars that can travel on the link simultaneously, the flow capacity denotes the number of cars that can exit the link per time-step (ibid.).

### 4.1.4 Scoring

In MATSim, after each iteration, plans which were executed by mobsim get scored with MATSim's *Charypar-Nagel utility function* (Horni et al. 2016c). This function is loosely based on the Vickrey congestion model and it was first introduced by Charypar and

Nagel (2005). Since that day, the function has been adapted and extended for different purposes such as road pricing, car sharing, and parking (Horni et al. 2016c).

In the basic version of the Charypar-Nagel utility function, utility from activities $S_{act,q}$ and disutility from trips $S_{trav,mode(q)}$ are summed up to find the overall score of an executed plan $S_{plan}$ (Chakirov and Erath 2012). Let $q$ denote the trip that comes after activity $q$, then for $N$ activities, $S_{plan}$ can be computed as follows:

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

The first summand of the Eq. (1) represents the sum of utilities gained from activities $q = \{0, 1, \ldots, N-1\}$. For each activity $q$, the utility of the activity $S_{act,q}$ is computed by adding up the following utility contributions:

(i) $S_{dur,q}$: utility gained from performing an activity.

(ii) $S_{wait,q}$: utility lost by waiting for an activity to start.

(iii) $S_{late.ar,q}$: utility lost by arriving late to an activity.

(iv) $S_{early.dp,q}$: utility lost by departing early from an activity.

(v) $S_{short.dur,q}$: utility lost by activity shorter than shortest activity limit.

Thus, the formula for calculating the utility of an activity $q$ results in

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

Each summand in Eq. (2) denotes a different contribution to the total utility of an activity $q$. In the config file, under the module *planCalcScore*, users are able to set values to variables that are used in the calculation of these contributing components. This way, the utility function can be customized based on users' specific interests. For example, one can find no negative utility in waiting for an activity to start and set the parameter *waiting* to 0.

The second summand of the Eq. (1) denotes the total disutility caused by traveling between activities. Just like the utility of an activity, the disutility of a trip is also a combination of different contributors, and these contributors are controlled by variables that can be set in the config file. The list of contributors include:

(i) $C_{mode(q)}$: mode constant.

(ii) $\beta_{trav,mode(q)}$: marginal utility of time spent traveling with given mode.

(iii) $t_{trav,q}$: duration of travel between activities $q$ and $q+1$.

(iv) $\beta_m$: marginal utility of money.

(v) $\Delta m_q$: monetary change.

(vi) $\beta_{d,mode(q)}$ marginal utility of distance.

(vii) $\gamma_{d_m ode(q)}$ monetary distance rate of given mode.

(viii) $d_{trav,q}$ distance travelled between activities $q$ and $q+1$.

(ix) $\beta_{transfer}$ transfer penalties with public transportation.

(x) $x_{transfer}$ binary variable for whether a transfer occurred.

Using these contributors, the disutility of a trip $q$ can be computed by

$$\begin{aligned} S_{trav,q} &= C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,q} + \beta_m \cdot \Delta m_q \\ &+ \left(\beta_{d,mode(q)} + \beta_m \cdot \gamma_{d_m ode(q)}\right) \cdot d_{trav,q} + \beta_{transfer} \cdot x_{transfer}. \end{aligned} \tag{3}$$

### 4.1.5 Re-planning

The re-planning stage of the MATSim loop covers the plan modification and selection of the agents for the upcoming iteration. The strategy to be followed while choosing a plan depends on the parameters set in the config file. Usually, the strategy with the highest weight is to select the plan with the best score. However, with a small probability, agents are also able to modify their plans and generate new ones (Horni et al. 2016c). This is called the *innovation* step and it is executed by modules of MATSim with respect to three different choice dimensions: *time*, *route*, and *mode* (Kickhöfer et al. 2010).

Since MATSim adopts a co-evolutionary algorithm, agents try to optimize their plans during the simulation process and this can be done in the innovation step. During this step, a newly generated plan gets added to an agent's memory and, as mentioned previously, MATSim agents can store a fixed number of plans in their memories (e.g., 5).

Due to the capacity constraint, when the memory of an agent is full, the plan with the lowest score is dropped. Hence, agents tend do eliminate *bad* plans (poor score) and keep the *good* ones.

After a certain amount of iterations are executed (e.g., 80%), it is a good practice to turn off the innovation step of MATSim and let agents stick to the plans in their memory. This can be done with a configuration in the config file. Switching off the innovation step prevents agents from coming up with bad plans and makes the scores converge to an equilibrium. This way, the simulation reaches a relaxed state, and no remarkable improvement in agents scores' can be observed anymore.

### 4.1.6 Analysis

MATSim creates various output files which can be used for analyzing a simulation on a whole or on an iteration basis. These files include score, link, and mode statistics, trip duration and distances, and much more information about the conducted simulation run (Horni et al. 2016a). However, it may not be trivial to understand the impact of a road pricing scheme on social welfare just by analyzing the output produced by MATSim since the data it provides is too disperse. To overcome this problem *matsim-analysis*[6] can be used. matsim-analysis takes a MATSim simulation's output files as an input and produces elaborate analysis about them. This tool is again developed by the working team of MATSim.

matsim-analysis provides six different types of analysis using the MATSim output data: *person-based analysis*, *trip-based analysis*, *aggregated analysis* (e.g., number of trips per OD pair, total utility change of agents), *spatial analysis*, *temporal analysis* (e.g., total toll payments), and *scenario comparison* (e.g. how scores change). Among them, one of the most significant contributions (compared to the raw output of MATSim) is the aggregated analysis results. matsim-analysis calculates both the monetized utility gain of all agents which is referred to as **travel-related user benefits** and the total revenue. Although travel-related user benefits can be used to find the social welfare impact of a road pricing policy, by adding it up with the total revenue, one can also compute the change in the overall system welfare (Kaddoura and Nagel 2016).

Although the default way which matsim-analysis adopts for calculating the travel-related user benefits is valid for analyzing the impact of a road pricing scheme on social welfare, it is not the only way and in some cases it requires adaptations. According to (Kickhöfer and Nagel 2016), there exist four strategies to aggregate an agent's scores into utility for the purpose of economic evaluation:

[6] https://github.com/matsim-vsp/matsim-analysis

(a) Using the logsum of scores,

(b) Using the score of the last executed plan (matsim-analysis),

(c) Using the average score, or

(d) Using the highest score.

The strategy to be used for aggregating an agent's scores depends heavily on the plan choice model defined in the config file of the simulation. If the plan choice model assigns the highest weight to the best score selection (*BestScore* as it is denoted in the config file), then it makes sense to use the strategy (*d*) (ibid.). On the other hand, if the plan choice model is a logit model (*SelectExpBeta* as it is denoted in the config file), then using the strategy (*a*) fits the best to the model. Although there may be cases where strategies (*b*) and (*c*) may be useful, according to Kickhöfer and Nagel (ibid.), either strategy (*a*) or (*d*) should be adopted in order to be consistent with the choice model.

### 4.1.7 Economic Interpretation

The overall utility change of an agent has to be monetized in order to conduct an economic evaluation such as a benefit-cost analysis (ibid.). There exists two main interpretations for monetizing utility with respect to the income data: *the individual interpretation* and *the equitable interpretation* (Kickhöfer et al. 2010). When the individual interpretation is adopted, the overall utility change of an agent $\Delta U_n$ is divided by the personalized marginal utility of money $\lambda_n$ which then yields the consumer surplus $\Delta Y_n$ (Kickhöfer and Nagel 2016).

$$\Delta Y = \frac{\Delta U_n}{\lambda_n} \tag{4}$$

By summing up consumer surplus for a population of $n = \{1, \ldots, N\}$, one can compute the overall social welfare change $\Delta W$.

$$\Delta W = \sum_{n=1}^{N} \Delta Y_n (Consumer\ Surplus) \tag{5}$$

When the equitable interpretation is utilized, instead of a personalized marginal utility of money value ($\lambda_n$), the population average $\overline{\lambda}$ is used.

$$\overline{\lambda} = \frac{1}{N} \sum_{n=1}^{N} \lambda_n \tag{6}$$

Thus, the monetized utility calculation of an agent $n$ yields,

$$\Delta Y_n = \frac{\Delta U_n}{\overline{\lambda}}, \tag{7}$$

and again the change in social welfare ($\Delta W$) can be computed by summing up monetized utility values ($\Delta Y_n$) of a population.

$$\Delta W = \sum_{n=1}^{N} \Delta Y_n. \tag{8}$$

The motivation for this application is to prevent rich people with the lower marginal utility of money from having more impact on the economic evaluation compared to the poor people (Kickhöfer and Nagel 2016). As mentioned by Kickhöfer et al. (2010), the equitable interpretation is influenced by the following argument by Mackie et al. (2001):

"Society needs to agree that the welfare of all individuals is equally important." (Mackie et al. (ibid.))

When the equitable interpretation is not used, the policymakers can possibly return the revenue gained from road pricing in favor of those with higher income by investing in expensive public transportation solutions which the low-income population cannot afford. To prevent this unevenness, the equitable interpretation utilizes the average marginal utility of money ($\overline{\lambda}$) while calculating the monetized utility change of an agent $n$.

## 4.2 Road Pricing in MATSim

The concept of road pricing is integrated into MATSim in a fairly simple way. An event handler catches every time a vehicle enters a link and checks whether there are any active tolls during that time period on that link (Nagel 2016). If there is, then the driver (agent) gets charged according to the pre-defined toll fare. When the score of a plan is calculated at the end of a simulation (see Eq. (1)), the toll charges of an agent get picked up by the third summand of the trip disutility equation (Eq. (3)), which is the product of the marginal utility of money $\beta_m$ and the change in the monetary budget $\Delta m$.

Since the score of a plan gets affected by the road pricing charges, agents do consider the route, mode, and departure & arrival time choices based on their VOT and income when they make plan decisions (ibid.). With this, MATSim ensures that any kind of heterogeneity in the time values of travelers is considered.

MATSim supports four different toll schemes: *link toll*, *cordon toll*, *distance toll*, and *area toll*. While the link toll charges drivers every time they enter a tolled link, the cordon toll only charges them when they move to a tolled link from an untolled one (e.g., when a cordon is passed). The area toll, on the other hand, charges the drivers when they enter a pre-determined area (e.g., inner-city) during specific hours of the day. Finally, the distance toll charges the drivers based on the length they travel on the tolled link. When configuring a distance toll in MATSim, instead of a one-time toll amount, the traveling cost per length unit (e.g, 0.01 *EUR* per kilometer) is defined.

To introduce a road pricing scheme, MATSim requires a few configurations and a toll file as an extra input. The user has to add the *RoadPricingModule* to the driver class of their MATSim build and include a module called *roadpricing* which contains the path to the toll file, in their config file. The toll file includes the list of links to be charged and their respective cost structures.

In the example toll scheme in Listing 4.2, cordon tolls are placed on three different links. While there is a specific cost structure defined for link 6, links 10 and 15 share the general cost structure. The general cost structure is assigned automatically to any link without a specific structure. With the current toll scheme, link 6 is charged only in the afternoon (4-5 *PM*), and links 10 and 15 are charged only in the morning (6-10 *AM*). Any link which is not included in this file is free of charge.

Listing 4.2: A simple cordon toll scheme for integrating road pricing into MATSim.

```
<roadpricing type="cordon" name="equil-net␣cordon-toll">
      <links>
           <link id="6">
               <cost start_time="16:00" end_time="17:00" amount="4.50" />
           </link>
           <link id="10" />
           <link id="15" />
      </links>
      <cost start_time="06:00" end_time="10:00" amount="2.00" />
</roadpricing>
```

## 4.3 Integrating Dynamic Road Pricing into MATSim

The dynamic road pricing scheme proposed by Littmann and Bichler (2020) is based on the idea that agents can make decisions during simulations. In theory, agents should be able to choose between different route options which are priced in real-time when taking a trip. In SimMobility, agents can make decisions *during* simulations, thus the integration of the scheme is possible.

In the default, *iterative* approach of MATSim, agents stick to their selected plan during iterations, and make changes on the plan or choose a new plan only during the re-planning stage. This means, during an iteration, an agent cannot choose between different options before taking a trip and must execute the trip which is pre-defined in her plan. Initially, this is against how dynamic pricing works. However, the iterative approach of MATSim converges to a demand-supply equilibrium eventually (Dobler and Nagel 2016). Thus, after a sufficient number of iterations (e.g. 500), agents' reaction to market prices during re-planning becomes the same as if they are reacting during iterations. Hence, the market prices converge.

In the implementation for this thesis, agents keep taking the next trip in their plans without making new decisions during iterations. Then, trip prices are calculated with the updated version[7] of the online optimization algorithm, as if the trip requests are always accepted. Finally, agents adapt their plans during the re-planning stage which takes place after every iteration.

In MATSim, there already exists modules for applying road pricing schemes. However, they are all static schemes where the prices cannot be updated in *real-time*. To implement the online optimization algorithm, the current RoadPricingModule of MATSim has to be extended. In the following subsections, the details of this implementation and improvements regarding the discussion points of the algorithm (see section 3.5) are explained.

### 4.3.1 RpTollCalculator Class and Event Handlers

The *RpTollCalculator* is the main listener class which is bound to the RoadPricingModule of MATSim. This class makes it possible for mobsim to compute tolls and generate money events. In the default version of it, there exist four sub-classes, one for each tolling scheme. Each sub-class implements the same generic interface *TollBehaviourI*. This interface includes an abstract event handler method that catches the link entry events (*LinkEnterEvent*). For example, the *CordonTollBehaviour* class implements this method in

[7] Referring to the updates made for the purpose of this master's thesis, not version by Littmann and Bichler (2020).

a way that applies a cordon toll to the driver of the vehicle which entered a link if there is any cost associated with that link at that time period.

To implement the dynamic road pricing scheme, a similar event handler method must be added to the RpTollCalculator class. However, instead of catching the link entries, it should catch the moment which an agent can book their next trip. The reason for that is, in the dynamic pricing scheme, agents are charged based on the trip they are planning to take, and not by the individual tolls on a link.

MATSim generates an event right at the moment when an activity ends (*ActivityEndEvent*). However, the end of an activity does not have to be followed by a trip right away since each trip has a specific departure time. Thus, it is not realistic to assume that an agent would book a trip when an activity ends. Hence, the price of an upcoming trip should not be calculated when the ActivityEndEvent is triggered.

The *PersonDepartureEvent* of MATSim catches the moment which an agent leaves an activity and heads for taking a trip. In a real-world use case, drivers are booking their trips just before taking them. In MATSim, PersonDepartureEvent captures this moment. Thus, it is the ideal time for calculating a trip cost and charging it to the driver. With this motivation, this thesis implements the online optimization algorithm for dynamic road pricing into an event handler that catches PersonDepartureEvent(s).

### 4.3.2 The Variables

To implement the online optimization algorithm for dynamic road pricing, some variables must be initialized either at the beginning of every iteration or at every forecasting interval (e.g., 30 minutes). These variables include:

- **pricedLinks**: The list of links that are located in the inner city of the simulated scenario. The cost of a trip depends on the use of these links.
- **legTracker**: Tracks the next trip to be taken by each agent.
- **linkCapacities**: Tracks the remaining capacity of each link.
- **linkPrices**: Tracks the current price of each link.
- **nEstimatedTrips**: The number of expected trip requests to arrive in the next interval.
- **initialDemand**: Stores the number of trip requests which arrived during the first iteration of a previous simulation run. The data is used for forecasting during the first iteration of the current simulation.

### 4.3.3 The Constructor

In the constructor of the RpTollCalculator class, some variables such as *network*, *scenario*, *links*, and *persons* are initialized first. Then, a text file that includes the list of links that reside in the inner city of the simulated network is processed. Each link id in this file is stored in the *pricedLinks* variable. Once the read is complete, the *resetLinkPrices* method is called. This method is responsible for resetting both the *legTracker* and the *linkPrices* variables. While the legTracker is just emptied, the linkPrices variable is first emptied and then filled with a starting price (usually 0) for each link in pricedLinks. Finally the *forecast* method is called. It must be noted that the resetLinkPrices method is also called after each iteration.

### 4.3.4 Forecasting

The forecasting method is responsible for estimating the number of trip requests to arrive in the upcoming interval. The method gets called after each iteration and interval. It first calls the *resetLinkCapacities* method which sets the link capacities stored in *linkCapacities* variable back to their original values. This is required due to the assumption that all road capacities are reset after each interval (Littmann and Bichler 2020).

After link capacities are reset, the method checks whether the current iteration is the first one or a later one. If it is the first one, the method uses the demand data for the upcoming interval from the *initialDemand* variable. Otherwise, it uses the demand data from the previous iteration of the same interval. Once the *nEstimatedRequests* variable is set with the new estimation data, the current number of requests which arrived in the just ended interval gets stored in the *requestsByIntervals* variable (to be utilized in future iterations). Finally, the method resets the current request tracker to 0 and sets the step size, which is used during the subgradient decent step of the online optimization algorithm, to $\frac{1}{\sqrt{nEstimatedRequests}}$.

To demonstrate an example, let's assume the simulation is running the first iteration and 250 trip requests arrive in the 8.30-9.00 *AM* interval. Then, right before the 9.00-9.30 *AM* interval begins, the forecasting method gets called. Since this is the first iteration, the method does not have any stored data in the requestsByIntervals variable from a previous iteration. Therefore, it uses the pre-defined number available in the initialDemand variable as the estimate for the 9.00-9.30 *AM* interval. Then, it stores the number of trip requests that arrived during the 8.30-9.00 *AM* interval (250) in the requestsByIntervals variable. Finally, when the 8.30-9.00 *AM* interval is reached during the second interval, the forecasting method estimates the number of trip requests to arrive as 250.

### 4.3.5 PersonDepartureEvent Handler

As explained in the section 4.3.1, the PersonDepartureEvent is the ideal place to calculate the cost of the upcoming trip of an agent and charge it. Thus, a method that handles these events can be used for implementing the online optimization algorithm for dynamic pricing. The method requires a single parameter which is a PersonDepartureEvent. Using this parameter, information such as event time and person id are accessed.

First, the method detects the time interval of the current event by dividing the event time, which is in seconds, to 1800 (30 minutes in seconds). If the event interval is larger than the *currentInterval*, then the currentInterval is set as the interval of the event, and forecasting is done. Otherwise, no further action is required. After the interval is set, the person who is the actor of this event is initialized. To do this, the person id attribute of the event variable is cast into a *Person* class object. If the object is not null, then the algorithm understands that the event is triggered by a valid agent, thus, starts the trip cost calculation process.

The first step of calculating the cost of a trip is to detect the upcoming trip of the person. MATSim person object has an attribute that stores the list of activities and trips to be taken by that person, in chronological order. However, there is no pointer for the current activity or trip. This is where the *legTracker* variable comes in. This variable stores a pointer for the next trip to be taken by each agent who has triggered the PersonDepartureEvent handler method. Instead of initializing an empty slot for each agent at the beginning of every iteration, the variable only stores agents' data after they trigger the method. This is done for the sake of performance issues.

Once the next trip of the current person is found, then it is checked whether the mode of the trip is car or not. For the purpose of this thesis, only car trips are charged and if the mode of the trip is not car, the method ends there. If the mode is car, then the route of the trip is accessed, divided into links, and stored in a list format at *requestedLinks* variable.

In the next step, a new price is calculated for each link. For each priced link in pricedLinks, the method first checks whether the link is included in the requestedLinks or not. If it is included, this means the link is a part of the requested route, thus, its price must be increased and get added to the total cost of the trip. If it is not included, then the price of the link should be decreased since it is not requested.

The Listing 4.3 shows the algorithm for increasing the price of a link that is a part of the requested route. After the capacity of the link is updated accordingly, the price update takes place between Lines 7-13. At Line 7, the algorithm checks whether the remaining number of expected requests is still larger than the unused road capacity of the respective link. The algorithm only proceeds if this case is true. Otherwise, a price decrease occurs as discussed in the section about issues related to the updated version of the online optimization algorithm (see section 3.5). Thus, in the case where the remaining capacity is larger than the remaining number of expected requests to arrive, the price is kept still (Line 13). This application also makes sense according to economic theory as there is no point in increasing the price of a product where the supply is greater than the expected demand.

At Line 8, the subgradient descent is applied and the new price of the respective link is calculated. During the calculation, in order to prevent the denominator becoming 0, the maximum between the remaining number of expected requests (*nEstimatedTrips - currentRequest*) and a constant number is selected. Once the new price is calculated, it is also checked if it is a valid, positive number. Finally, the price of the respective link is updated with the new computed price and it is added to the total cost of the trip.

Listing 4.3: The algorithm for increasing the price of a requested link.

```
1  if pricedLink in requestedLinks {
2      newLinkCapacity = pricedLink.capacity − 1
3      if newLinkCapacity is not negative
4          update pricedLink.capacity with newLinkCapacity
5      else newLinkCapacity = 0
6      remainingRequests = nEstimatedTrips − currentRequest
7      if remainingRequests > newLinkCapacity {
8          newLinkPrice = pricedLink.price + stepSize ∗ (1 − (newLinkCapacity /
               max(remainingRequests, 0.01)))
9          if newLinkPrice is negative or NaN or infinite
10             newLinkPrice = 0
11         update pricedLink.price with newLinkPrice
12     }
13     else keep the pricedLink.price unchanged
14     add pricedLink.price to totalPrice
15 }
```

When a priced link is not a part of the requested route, its price must be decreased since there is no demand for it. The Listing 4.4 displays the part of the algorithm which is responsible for handling this case. As seen in the algorithm, the capacity of a link is not changed and the subgradient decent step is updated in order to decrease the price. However, the check at Line 3 is pretty similar to the one in Line 7 of the Listing 4.3. The motivation for this check is now to prevent the price decrease to be too *steep*. Again, the new price is finally checked for validity before assigning it to the respective link.

Listing 4.4: The algorithm for decreasing the price of a not requested link.

```
if pricedLink not in requestedLinks {
    remainingRequests = nEstimatedTrips − currentRequest
    if (remainingRequests > pricedLink.capacity) and pricedLink.price is positive {
        newLinkPrice = pricedLink.price + stepSize ∗ (0 − (pricedLink.capacity /
            max(remainingRequests, 0.01)))
        if newLinkPrice is negative or NaN or infinite
            newLinkPrice = 0
        update pricedLink.price with newLinkPrice
    }
    else keep the pricedLink.price unchanged
}
```

# 5 Scenario

An accurate analysis of a transport policy (e.g., road pricing scheme) requires an agent-based transport model where people can react to the policy according to their individual properties such as Value of Time (VOT), income, or home and work locations (Ziemke et al. 2019). Since MATSim is an agent-based transport tool, a transport simulation scenario developed for MATSim is suitable for analyzing a transport policy. For the purpose of this thesis, the dynamic road pricing scheme proposed by Littmann and Bichler (2020) is simulated with the *MATSim Open Berlin Scenario*.[1] This scenario models the greater Berlin metropolitan area which includes 73,689 nodes and 159,039 car-only links. In this thesis, a link is priced only if it resides inside the inner-city and it is *non-residential*. An overview of the priced links on the network (highlighted with red) can be seen in Figure 5.1, which is produced with the visualization tool Via.

## 5.1 Overview

The main difference between the MATSim Open Berlin scenario and most of the other MATSim scenarios is that it only requires *open data* which is accessible for almost any region of the world (Ziemke et al. 2019). By using the travel demand generation technique from the MATSim Open Berlin Scenario, a scenario for any other region can be developed. However, most of the other MATSim scenarios use census data which is difficult to obtain by the public. Thus, a similar application using their scenario development techniques is not possible.

The MATSim Open Berlin Scenario contains initial daily plans for the simulated population of Berlin and Brandenburg. These plans utilize all available transport modes such as car, public transportation (based on real-time schedules), walk, and bicycle. To generate these plans, a procedure based on the traffic-count data and personalized activity scheduling models are utilized (ibid.). Since this generation procedure is integrated inside the re-planning module of MATSim, the plans of the agents become more realistic with every iteration. Thus, it is a good practice to run simulations with as many iterations as possible with respect to the server properties.

[1] https://github.com/matsim-scenarios/matsim-berlin

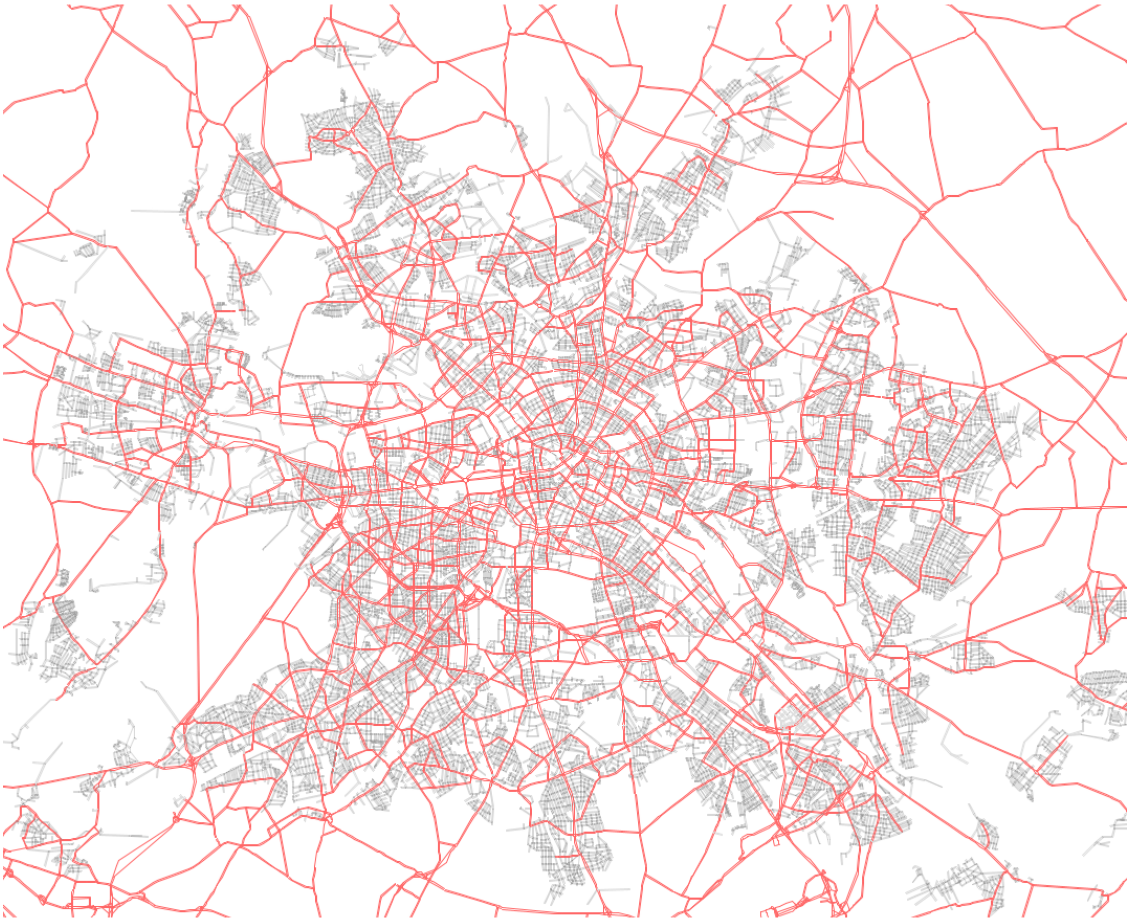

Figure 5.1: The links highlighted in red represent the priced links of the MATSim Open Berlin Scenario.

In MATSim Open Berlin Scenario, agents are assigned income values based on the distribution in Germany. The income groups in this data set range from 826 *EUR* to 4329 *EUR*. Using the income information, a personalized VOT for each agent is calculated. Since agents experience different time pressure, the Value of Travel Time Savings (VTTS) also becomes personalized for each agent. The heterogeneity in VOT and VTTS is then automatically picked up by the scoring function of MATSim (Nagel 2016).

The MATSim Open Berlin Scenario is also discussed in literature by Ziemke et al. (2019). In this paper, they explain the utilized population data generation procedure in detail. To show how realistic the simulation is, they conduct a comparison with survey data (MiD 2008 and SrV 2008). The data sets are compared in terms of mode share rates, mode-specific trip distances and duration, departure times, and activity types.

The results show that the traffic data produced by the MATSim Open Berlin Scenario simulations are significantly similar to the survey data. For example, 29.6% of the simulated agents use their personal cars for transportation, while this number is 30.0% according to the MiD Survey 2008 (ibid.). Trip distances and duration, and the distribution of activity types are also similar between the simulation and the survey data. The only major difference is observed between the departure times with the car mode. This is due to the fact that while simulation accounts for the freight traffic, the survey only includes personal traffic data.

## 5.2 Configuration Details

The MATSim Open Berlin Scenario is configured in a config file just like any other MATSim scenario. The parameters of this file are initialized in a way that fits its overall scenario generation procedure. For the purpose of this thesis, the only changes made on this file are: setting the number of iterations based on the simulated road pricing scenario (e.g., 500 iterations for dynamic road pricing on the default network, 100 iterations for dynamic road pricing on the network with decreased link capacities), initializing the number of global and qsim threads according to the server properties, and adding the road pricing module.

### 5.2.1 Strategy Settings

An important configuration in the config file of the MATSim Open Berlin Scenario is the strategy choice settings. In the default configuration, these settings are set as shown in Table 5.1. The strategy with the most probability, *ChangeExpBeta*, is a logit model. Thus, to be consistent with the choice model when aggregating the plan scores of agents for finding the utility, a valid strategy such as using the logsum of scores must be selected.

| Strategy | Description | Weight |
|---|---|---|
| ChangeExpBeta | Switch plan with a probability dependent on score differences of plans. Uses Multinomial Logit Model(MNL). | 85% |
| ReRoute | Rerouting the current route. | 5% |
| SubTourModeChoice | Randomly change all of the modes used in a randomly chosen subset of a plan which starts and ends at the same link. | 5% |
| TimeAllocationMutator | Randomly shifts activity end times with respect to a configurable range. | 5% |

Table 5.1: Default strategy settings defined in the config file of the MATSim Open Berlin Scenario.

The motivation for using the logsum of scores for finding the utility change of an agent $n$ is based on the literature which proposes the use of logsum term for welfare analysis with Discrete Choice Models since it also yields the change in consumer surplus (Jong et al. 2007; Kickhöfer and Nagel 2016). For $i = \{1, \ldots, J\}$ executed plans of an agent, where the utility of plan $i$ is $V_i$, the logsum term yields the Expected Maximum Utility (EMU) of the agent and it can be calculated with

$$logsum_n = EMU_n = ln \sum_{n}^{J} e^{V_i}. \tag{1}$$

### 5.2.2 Computing the Change in Utility

The calculation of the change in utility of an agent is the first step of social welfare analysis. In this thesis, this calculation is handled by matsim-analysis. In matsim-analysis, the module responsible for carrying out this calculation uses the score of the last executed plan as the default strategy for finding the change in the utility of an agent. However, since using the logsum of scores is a more consistent strategy to be used with the MATSim Open Berlin Scenario, the respective module of matsim-analysis is updated in this thesis.

The function responsible for computing the utility change of an agent is called *getPersonId2UserBenefit* and it is located under *MatsimAnalysis* class of matsim-analysis. The function is updated such that computes the logsum of the agent's executed plan scores. Once the logsum is calculated, it is divided by either a person-specific (if it is defined) or a default marginal utility of money value which then yields the individual consumer surplus. By summing this value over the whole population, the change in social welfare is computed.

# 6 Results

This thesis utilizes the 1% sample of the MATSim Open Berlin Scenario for testing the impact of the dynamic road pricing scheme proposed by Littmann and Bichler (2020). The sample includes 49,290 agents and the road capacities of the links are reduced accordingly. Although the actual network includes 159,039 links, only 34,139 links that reside inside the inner-city of the greater Berlin metropolitan area that is non-residential are priced.

Besides the default scenario configuration, the dynamic pricing scheme is also tested under different configurations. The motivation for testing these configurations is to simulate scenarios where prices change faster or slower than the default case. By observing the reaction of the agents and the change in the overall social welfare, the impact of dynamic pricing can be analyzed for scenarios with different demand levels.

In this thesis, simulations are executed in a virtual machine that has 60 GB RAM and 20 VCPU. The number of iterations ranges from 100 to 500 depending on the tested configuration. In all simulations, after 80% of the iterations are executed, the innovation module of MATSim is disabled. This operation is performed in order to keep the set of plans fixed for agents after some point. After simulations are complete, outputs are processed using matsim-analysis.

The rest of this chapter contains the results of the simulations and their analysis. The simulations are compared in terms such as mode share, travel time and distance, and social welfare. Moreover, a public acceptance analysis is conducted based on the economic evaluation approaches introduced by Kickhöfer et al. (2010). The simulation results are also compared with the results from Littmann and Bichler (2020). The purpose of this comparison is to analyze how the impact of the scheme changes based on the chosen simulation tool (MATSim vs. SimMobility).

## 6.1 Mode Analysis

The dynamic road pricing scheme guides the incentive of agents to minimize travel times and distance when they are using their private cars. Through real-time pricing, the scheme adds disincentives for driving when roads are congested. This reinforcement is realized by drivers either through changing routes based on real-time market prices or changing transport mode. Either way, the scheme aims to decrease the travel time and distance made with private cars.

In Table 6.1, mode shares are compared between no road pricing (NRP) and dynamic road pricing (DRP) schemes. Both schemes are simulated for 500 iterations. The mode share of freight is not included in the table as it is handled separately in the MATSim Open Berlin Scenario. The results in the table prove that DRP succeeds in shifting agents' mode preference from car to other alternatives such as public transportation (PT), walk, or bicycle. While 33% of the agents preferred using their private cars in the NRP case, when DRP is applied, this number drops to 30%. The 3% shift is evenly distributed between PT, walk, and bicycle modes.

| **Mode** | **NRP** | **DRP** |
|---|---|---|
| Car | 33% | 30% |
| Public Transportation (PT) | 18% | 19% |
| Bicycle | 18% | 19% |
| Walk | 21% | 22% |
| Ride | 10% | 10% |

Table 6.1: Mode shares of no road pricing and dynamic road pricing schemes.

In Table 6.2, the shift from car to other modes such as pt can be seen more clearly. The table compares NRP and DRP in terms of the number of trips, travel time, and distance for car and PT modes. The results show that DRP decreases the total number of car trips by 7.76%. It also reduces the travel time with car by 7.75% and the distance by 5.37%.

| | **NRP** | **DRP** | **Difference** |
|---|---|---|---|
| Number of trips | 182,545 | 182,545 | *0* |
| Total delay (hours) | 20,436 | 19,885 | *-551(-2.69%)* |
| Number of car trips | 60,241 | 55,564 | *-4,677(-7.76%)* |
| Car travel time (hours) | 30,029 | 27,700 | *-2,329(-7.75%)* |
| Car travel distance (km) | 834,278 | 789,442 | *-44,836(-5.37%)* |
| Number of PT trips | 32,484 | 35,185 | *2,701(8.31%)* |
| PT travel time (hours) | 23,188 | 25,353 | *2,165(9.33%)* |
| PT travel distance (km) | 365,873 | 398,408 | *32,535(-8.89%)* |

Table 6.2: Detailed mode and trip analysis of no road pricing and dynamic pricing schemes.

As shown in Table 6.1, PT is one of the modes which agents prefer over the car when DRP is applied. The results in 6.2 also support this. When DRP is applied, the number of PT trips increases by 8.31%, which also increases the travel time and distance taken with PT. This outcome is also in line with the results from Littmann and Bichler (2020) where more agents prefer PT when dynamic road pricing is applied. Approximately *4.5* times more agents switch from driving to PT when dynamic road pricing is applied instead of a static road pricing scheme.

Table 6.2 also includes the total number of trips and the total delay for all modes. As seen in the table, the total number of trips is the same for both NRP and DRP. This is due to the default configuration of MATSim. In MATSim, agents do not cancel trips when they do re-planning, they either change the route or the mode of it. When total hours of delay are compared between NRP and DRP, it is observed that RPP decreases the total delay by 2.69% or *551 hours*. This is another point that proves DRP adds disincentives for driving when roads are congested and eventually decreases the time spent waiting in traffic.

When dynamic road pricing is analyzed in terms of travel time per departure hour, its impact on travel demand is still noticeable. Figure 6.1 depicts how travel time with car changes over the duration of a day. The blue line represents the default case where no road pricing is applied, and the red line represents the case where dynamic road pricing is applied. In the default case, the peak hours are 5 *AM* and 20 *PM*. When dynamic pricing is applied, a subtle decrease in the traveling time at those hours is observed. A more significant reduction occurs during the morning hours. For example, the traveling time at 2 *AM* drops from 27 minutes to 20 minutes when dynamic pricing is applied.

## 6.2 Welfare Analysis

According to Kickhöfer et al. (2010), there exist three motivations behind road pricing: allocating scarce resources (e.g., road capacities) in a more efficient way, causing less environmental impact, and raising revenue which can be returned to road users based on their needs (e.g., new public transport services). The common point when it comes to measuring the success of these motivations is calculating the monetized utility change of agents. With this data, a policy can be reviewed in terms of how better or worse it leaves the whole system (ibid.). In this section, the dynamic road pricing policy is analyzed in terms of its impact on overall welfare. The results are compared with the no road pricing policy case, in order to observe if the system benefits from road pricing.

In Table 6.3, NRP and DRP are compared in terms of gained social welfare, raised revenue, and total system welfare which is the sum of total monetized utilities and total revenue. The results show that DRP increases social welfare by 0.01% and the overall system welfare by 0.18%. Although the positive impact of DRP is not too significant in terms of total utility gain by the public, it is sufficient to prove that DRP succeeds in leaving the system in a better state than the starting point (NRP).

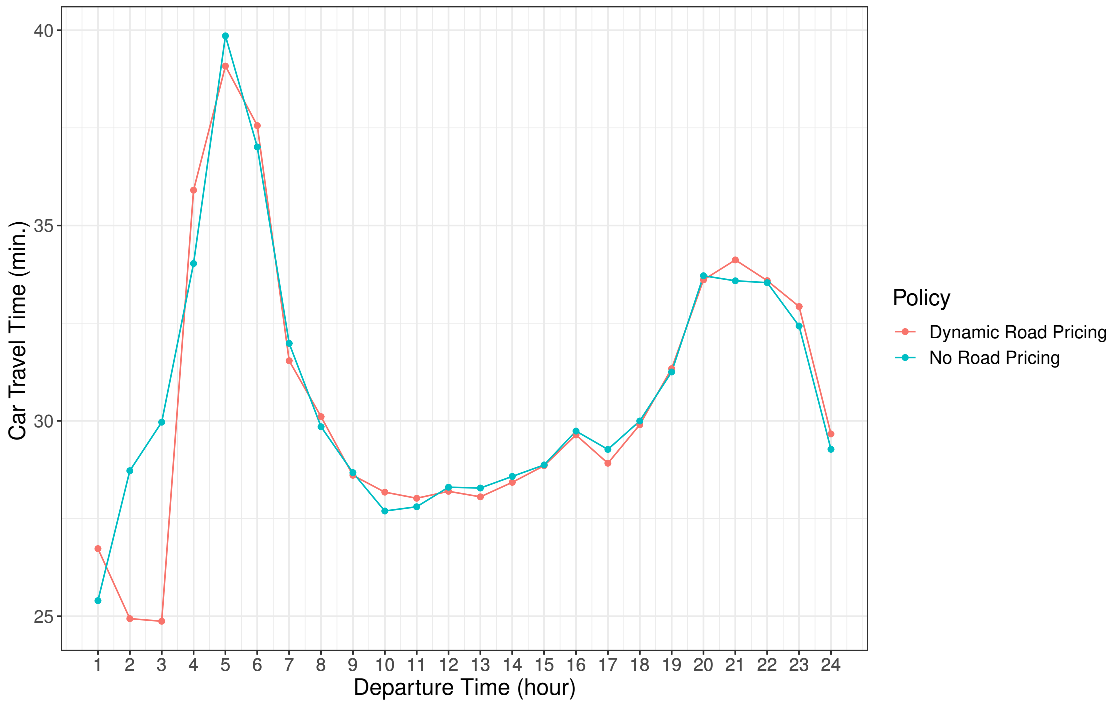


Figure 6.1: Travel time with car per departure time, compared between no road pricing (blue) and dynamic road pricing (red) schemes.

| | NRP | DRP | Difference |
|---|---|---|---|
| Avg. monetized utility per agent ($EUR$) | 198.67 | 198.71 | *0.04 (0.02%)* |
| Social welfare ($EUR$) | 9,792,913 | 9,794,677 | *1,764 (0.01%)* |
| Total revenue ($EUR$) | 0.0 | 16,455 | *16,455* |
| System welfare ($EUR$) | 9,792,918 | 9,811,133 | *18,219 (0.18%)* |

Table 6.3: Welfare analysis of no road pricing and dynamic road pricing schemes.

When the impact of dynamic road pricing on social welfare is compared between this thesis and the results from Littmann and Bichler (2020), a similarity in the direction but a difference in the magnitude is observed. Although results by both papers show that dynamic road pricing increases social welfare, the increment is much more significant in Littmann and Bichler (ibid.) where dynamic road pricing provides a 39.19% raise in the overall welfare gain. The difference in welfare gain between the two works is due to the difference in the simulated networks and the number of realized private car trips.

While the network simulated by Littmann and Bichler (ibid.) includes only **254** road segments (that are all priced), the one utilized in this thesis includes 159,039 road segments where **34,139** of them are priced. Since the road segment domain is much smaller in the network utilized by Littmann and Bichler (ibid.), even if the total number of realized trips is to be the same as in this thesis, the impact of dynamic road pricing on market prices is going to be more significant since each priced road segment is going to be requested more often. Moreover, the number of realized private car trips is also significantly different between the two works. While 109,457 trips are realized (by agents from 100,000 households[1]) when dynamic road pricing is applied in Littmann and Bichler (ibid.), only 55,564 trips are executed (by 49,290 agents) in this thesis.

## 6.3 Economic Evaluation

Table 6.4 summarizes the same measures from Table 6.3 for dynamic road pricing, but using the individual and the equitable economic interpretations (see section 4.1.7). The results yield a significant difference between the two interpretations. When the monetized utility of an agent is calculated with the equitable interpretation, the average per agent reduces by 19.71%. Since the total revenue is constant, social welfare and system welfare are affected similarly. When equitable interpretation is adopted, while social welfare decrease by 19.7%, system welfare reduces by 19.67%.

| | **Indiv.** | **Equit.** | **Difference** |
|---|---|---|---|
| Avg. monetized utility per agent ($EUR$) | 198.71 | 159.54 | *-39.17 (-19.71%)* |
| Social welfare ($EUR$) | 9,794,677 | 7,864,219 | *-1,930,458 (-19.7%)* |
| Total revenue ($EUR$) | 16,455 | 16,455 | *0* |
| System welfare ($EUR$) | 9,811,133 | 7,880,674 | *-1,930,458 (-19.67%)* |

Table 6.4: Welfare analysis of the dynamic road pricing scheme with the individual and the equitable economic interpretations.

The results in Table 6.4 yield an important outcome regarding the dynamic road pricing scheme and its public impact. When high and low-income groups are treated differently during utility calculation, the gained social welfare becomes greater. This can be possible in two ways. Either the size of the high-income group is significantly greater than the low-income group (such that due to their lower marginal utility of money values, they do more impact with the individual interpretation) or agents belonging to the high-income group have utility gains (score) at least as the agents belonging to the low-income group. Since the first option is not the case with the MATSim Open Berlin Scenario (see chapter 5), the second option becomes the only possible explanation.

To prove that individual interpretation yields greater social welfare when agents belonging to the high-income group have utility gains at least as the low-income agents, let's assume a population of two agents, one belonging to the high-income group and

[1]No information about the total number of agents is available in Littmann and Bichler (2020).

one to the low, that have 0.4 and 0.8 marginal utility of money values respectively. In the following Table 6.5, three different simulation outcomes are compared in terms of monetized utility gain per agent and the overall raised social welfare. The measures are calculated with both the individual and the equitable interpretations (see section 4.1.7).

*In Table 6.5, 1 and 2 stands for high and low-income agents respectively. While (I) denotes the individual interpretation, (E) denotes the equitable interpretation. Finally, MU stands for monetized utility, and SW stands for social welfare (e.g., 2-MU(I) denotes the monetized utility of agent 2 under the individual interpretation).*

| Scenario | 1-MU(I) | 2-MU(I) | SW(I) | 1-MU(E) | 2-MU(E) | SW(E) |
|---|---|---|---|---|---|---|
| 1 Score: 100<br>2 Score: 80 | 250 | 100 | *350* | 166.66 | 133.33 | *300* |
| 1 Score: 100<br>2 Score: 100 | 250 | 125 | *375* | 166.66 | 166.66 | *333.33* |
| 1 Score: 100<br>2 Score: 200 | 250 | 250 | *500* | 166.66 | 333.33 | *500* |

Table 6.5: Change in monetized utility (*MU*) and social welfare (*SW*) when individual (*I*) and equitable (*E*) interpretations are utilized in three different scenarios. The simulated population contains two agents and in each scenario, score of the low-income agent (2) changes.

The results in Table 6.5 show that social welfare gain is greater with the individual interpretation when the score of the high-income agent (*1*) is greater or equal to the score of the low-income agent (*2*). When the score of the low-income agent increase, the overall social welfare gain with the equitable interpretation also increase. Since this is not the case in results from Table 6.4, it is proven that high-income group agents benefit at least as the low-income group agents when dynamic road pricing is applied.

## 6.4 Public Acceptance

The results from the economic evaluation are discussed to be valid for interpreting the public acceptance of a road pricing policy (Kickhöfer et al. 2010). In this section, the dynamic road pricing scheme is investigated for this matter. Unlike Kickhöfer et al. (ibid.), the public acceptance of a policy is not just explored with the results from the individual interpretation, but also with the results from the equitable interpretation.

In Figure 6.2, results from Table 6.4 are broken down to the income-based population groups. Each data point in the figure represents the willingness-to-pay of an income group for direct utility gains. The blue data points denote the gain when the individual interpretation is utilized, and the red data points denote the gain with the equitable interpretation. In the figure, group *1* represents the lowest income group (826 *EUR*) and *10* the highest (4,329 *EUR*).

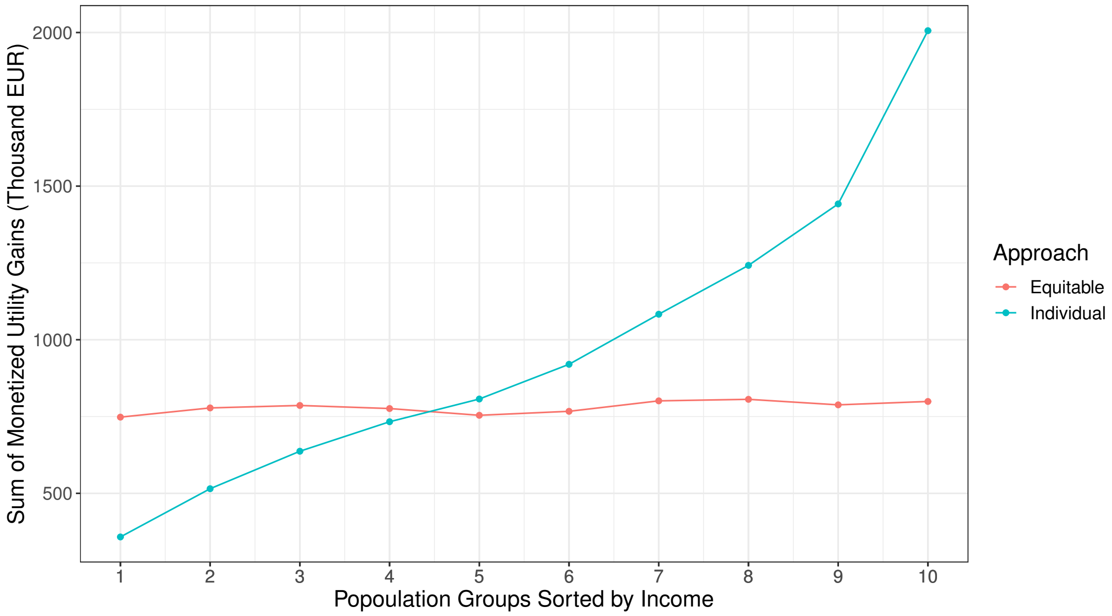


Figure 6.2: Sum of monetized utility gains when dynamic road pricing is applied. Blue data points represent the willingness-to-pay for each income group when the simulation results are analyzed with the individual interpretation and red data points represent the same for the equitable interpretation.

The outcome in Figure 6.2 shows that, with the individual interpretation, the monetized utility gain is increasing with the income. For example, monetized utility gain of the highest income group (*2,006,959 EUR*) is 5.6 times greater than the gain of the lowest group (*358,522 EUR*). If policymakers decide to return the raised revenue in favor of those who contributed the most to social welfare, under this interpretation, high-income groups (*8*, *9*) will be highly favored. Due to this possible unequal reallocation of utilities, the dynamic road pricing policy is subject to be rejected by the majority of the public. Although the policy has an overall positive welfare effect, the possible significant difference between the gains can cause a negative public opinion.

On the other hand, when the equitable interpretation is adopted, the monetized utility gains by all income groups are almost equal. This is in line with the main motivation of the equitable interpretation which states that the welfare of all individuals should be equally important for the society (ibid.). If policymakers utilize this interpretation when returning the raised revenue by the dynamic road pricing policy, a more positive public opinion can be expected (compared to the individual interpretation) since the reallocation of utilities will be fairer.

## 6.5 Alternative Scenarios

The impact of the dynamic road pricing policy can be amplified or reduced by changing the road network infrastructure or the population data of a scenario. For this matter, an alternative approach is applied in this thesis. Since changing the actual number of agents require other configuration changes in the scenario, it is not preferred.[2] Instead, road capacities are manipulated. For example, by increasing the capacity of each road segment, a scenario on the same network that has lower demand can be imitated. This configuration works since increasing road capacities will cause market prices to rise slower. On the other hand, when road capacities are decreased, the amount of the price increment increases. Thus, market prices rise more rapidly and the impact of the policy is felt more by the drivers. Since this is also the case when a scenario with higher demand is simulated on the same road network, the approach becomes valid.

In Table 6.6, results of the simulations under modified road capacities are summarized and compared with the results from the default scenario. While DRP denotes the default scenario where dynamic road pricing is simulated with the 1% sample of the MATSim Open Berlin Scenario, DRP(-50) and DRP(+50) stand for scenarios with 50% decreased and increased road capacities respectively. Due to server limitations, each scenario is simulated only for 100 iterations.

| | **DRP** | **DRP(+50)** | **Diff.(%)** | **DRP(-50)** | **Diff.(%)** |
|---|---|---|---|---|---|
| Total revenue (*EUR*) | 20,500 | 16,384 | *-20.07%* | 27,206 | *32.71%* |
| Social welfare (*EUR*) | 9,772,608 | 9,768,421 | *-0.04%* | 9,780,075 | *0.07%* |
| Total delay (hours) | 20,763 | 20,810 | *0.22%* | 20,695 | *-0.32%* |
| Number of car trips | 60,340 | 60,753 | *0.68%* | 59,994 | *-0.57%* |
| Car travel time (hours) | 30,344 | 30,609 | *0.87%* | 30,143 | *-0.66%* |
| Car travel distance (km) | 836,910 | 843,076 | *0.73%* | 833,039 | *-0.46%* |
| Number of PT trips | 32,155 | 31,801 | *-1.10%* | 32,247 | *0.28%* |
| PT travel time (hours) | 23,282 | 22,985 | *-1.27%* | 23,374 | *0.39%* |
| PT travel distance (km) | 364,910 | 359,924 | *-1.36%* | 365,795 | *0.24%* |

Table 6.6: Detailed analysis of the dynamic road pricing policy under alternative scenarios. While DRP stands for the default scenario where dynamic road pricing is simulated with the 1% sample of the MATSim Open Berlin Scenario, DRP(+50) and DRP(-50) denote simulations of the same scenario with 50% increased and decreased road capacities.

[2] Although it is possible to increase demand by duplicating agents in the plans file, this is not in line with the plan generation procedure of the MATSim Open Berlin Scenario.

The results show that, when road capacities are reduced (or demand is increased), the impact of dynamic road pricing also increases. For example, the total raised revenue in DRP(-50) is 32.71% greater than DRP. On the other hand, when road capacities are increased in DRP(+50), the total revenue drops to 20.07% of the revenue raised in DRP.

A similar impact is also observed when social welfare is compared among the three scenarios. However, the difference is not as significant as the difference in revenue. This is due to market prices not changing as remarkably as they should when road capacities are doubled or halved. Since the network contains too many links (34k priced links, 159k car-only links) compared to the amount of incoming demand (55k realized private car trips in the default DRP scenario), during a simulation, the set of requested priced links grows too large, although the frequency of each link getting demanded stays low. Thus, market prices do not rise in a significant manner. Hence, agents pay low trip fees and their utility does not get impacted by a lot from road pricing which then causes the overall raised social welfare to remain similar between scenarios with different road capacities (or different demand levels).

When mode shares are compared among the three scenarios, it is observed that the positive impact of dynamic road pricing on congestion increases with more significant market prices (e.g., when road capacities are reduced). In DRP(-50), the total delay is 0.32% less than DRP which then has 0.22% less delay than DRP(+50). This is because more drivers prefer less congested roads or switch from driving to other modes when market prices become more prominent. This impact is also observed in car and PT trips. While the number of trips, travel time, and distance decrease for car, they all increase for PT.

# 7 Conclusion

In this master's thesis, the effects of dynamic road pricing on travel demand and social welfare were analyzed. For this purpose, the real-time dynamic congestion pricing scheme proposed by Littmann and Bichler (2020) was utilized and optimized further. The solution offered an online optimization algorithm that adapts market prices in real-time based on changing demand. To simulate the algorithm, a large-scale agent-based transportation simulation software, *MATSim*, was utilized. The results of the simulation with MATSim were discussed in terms of mode usage, social welfare impact, and public acceptance. Even though there exists a line of literature that analyzes road pricing schemes using MATSim, most of them are conducted on static road pricing schemes where prices do not adapt to changing demand meaningfully. Thus, the work done in this thesis filled a research gap.

Littmann and Bichler (ibid.) prove the positive impact of dynamic road pricing on congestion and social welfare. However, the utilized online optimization algorithm and the simulation tool, *SimMobility*, are open to discussion. While the algorithm misses some case handlings (e.g., what happens when expected demand becomes less than supply or current request becomes equal to the expected number of requests), SimMobility produces flawed traffic data which compromises the reliability of the simulation results. This master's thesis provided a solution for the points missing in the online optimization algorithm and utilized MATSim to produce more realistic traffic data.

The results in this thesis show that dynamic road pricing reduces congestion by guiding drivers' road choices through meaningful prices and adding disincentives for driving while roads are congested. Compared to a scenario with no road pricing, dynamic pricing provides a remarkable amount of savings in total hours of delay. This is because, when dynamic pricing is applied, a decrease in personal car usage and an increase in alternate transport modes usage (public transportation, bicycle, walk) occurs. This result is also in line with the results from Littmann and Bichler (ibid.) where a significant amount of drivers switch to public transportation solutions when dynamic pricing is applied.

When the impact of dynamic road pricing on social welfare is investigated, it is discovered that the policy leaves the system in a better state than it was before the policy is implemented. The social welfare increase in this thesis, however, is less impressive when compared to the results from Littmann and Bichler (2020). This is because the simulated network and the quantity of completed private car trips vary between two works.

The network employed in this thesis has 159,039 road segments, with 34,139 of them priced, but the network simulated by Littmann and Bichler (ibid.) only has 254 road segments that are all priced. Because the road segment domain in the network used by Littmann and Bichler (ibid.) is much smaller, even if the total number of completed trips is to be the same as in this thesis, the influence of dynamic road pricing on market prices is going to be more significant since each priced road segment is going to be requested more frequently. In addition, the number of completed private car trips also differs greatly between the two works. When dynamic road pricing is used in Littmann and Bichler (ibid.), 109,457 trips are made by agents from 100,000 households, whereas only 55,564 journeys are made by 49,290 agents in this thesis.

To conduct a more accurate comparison between MATSim and SimMobility, two modifications should be made. First, the number of road segments has to be decreased in the MATSim Open Berlin Scenario. To accomplish this, adjacent road segments can be joined based on a set of rules (e.g., minimum road capacity). Furthermore, instead of using the 1% sample, the MATSim Open Berlin Scenario's 10% sample (which comprises almost 400,000 agents) should be used. The simulated network and produced demand are expected to be more similar to Littmann and Bichler (ibid.) after these modifications. Thus, a more realistic assessment of the impact of dynamic road pricing on social welfare may be made.

The public acceptance of dynamic road pricing is examined in this thesis using both the individual and the equitable economic interpretations. It is observed that the average monetized utility gain per agent becomes much higher when the individual interpretation is used. As a result, the calculated amount of social welfare also becomes greater. When the cause for this outcome is investigated, it is discovered that when dynamic road pricing is applied, the high-income agents get more or at least as much utility as the low-income agents. Because high-income agents have a lower marginal utility of money value, when utilities are monetized using the personalized marginal utility of money values, they have a stronger influence on social welfare. Since this is the case with the individual interpretation, as opposed to the equitable interpretation, which uses the population average marginal utility of money for every agent, a greater amount of social welfare can be computed.

To get a better understanding of the public acceptance of the dynamic road pricing policy, the simulated population is divided into income-based groups. For each group, the sum of monetized utility gains is computed with both of the economic interpretations. The results show that high-income groups get a significantly better utility than low-income groups when the individual interpretation is adopted. However, when the equitable interpretation is utilized, the utility gains turn out to be much closer to each other. If policymakers decide to return the raised revenue in favor of those who contribute the most to social welfare, the high-income groups will be benefiting the most under the individual interpretation. In that case, a public rejection can be expected due to unequal reallocation of utilities. However, this will not be the case if the equitable interpretation is adopted.

Even though this thesis provided insights about the positive impact of dynamic road pricing on congestion and social welfare, the research is still open for further analysis. Due to computing power constraints, a more populated scenario (*10% sample of the MATSim Open Berlin Scenario*) was not utilized in this thesis. Although it is assumed that the impact of dynamic pricing becomes more remarkable with increasing demand, is this the case when a more populated scenario is simulated in MATSim? Which factor does influence the market prices more, the road network or the demand? When dynamic pricing becomes more significant, can agents actually improve their monetized utility gains? With an appropriate MATSim scenario, does the increase in social welfare become as notable as in Littmann and Bichler (ibid.)? If not, why?

Comparing the impact of a dynamic road pricing policy to a static road pricing policy is another intriguing analysis to make. A tolling scheme can be defined on priced links of the dynamic pricing policy to generate a static pricing policy. The daily average price of each link from dynamic pricing simulations can be used as fixed toll prices and certain hours can be selected for applying the scheme (e.g., rush hours). For each metric utilized in this thesis, the simulation results can be studied and compared.

# Acronyms

**SP** Service Provider.

**VOT** Value of Time.

**VTTS** Value of Travel Time Savings.

**NRP** No Road Pricing.

**DRP** Dynamic Road Pricing.

**DRP(-50)** Dynamic Road Pricing simulated with 50% decreased road capacities.

**DRP(+50)** Dynamic Road Pricing simulated with 50% increased road capacities.

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