Marginal Congestion Cost Pricing in a Multi-Agent Simulation Investigation of the Greater Berlin Area

Ihab Kaddoura

Department of Transportation System Planning and Telematics
Technische Universitat Berlin (Berlin Institute of Technology)
Berlin, Germany

Correspondence address: kaddoura@vsp.tu-berlin.de

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Abstract

In this paper, for the first time, an innovative agent-based marginal congestion cost pricing approach was successfully applied to a real-world case study with a large-scale network. To the best of the author's knowledge, the general principles of marginal congestion cost pricing have never been applied to a real world city model on such a sophisticated level of detail. Each road segment is considered as a potential bottleneck and the entire queuing process is taken into account by computing marginal delay cost for each simulated time step at a microscopic, truly agent-based level. The results of the greater Berlin case study are checked for plausibility and analyzed with regard to their implications for pricing policies. Overall, the results are plausible and prove the conceptual innovative approach. Congestion is found to be a relevant externality and there is a great potential to reduce congestion by means of intelligent pricing and reconsiderations of route choice decisions. Especially, in areas with higher average congestion costs, the residents benefit very strongly from the pricing policy. Since the user-specific road prices are difficult to implement in reality, the results may be used to derive more practicable pricing strategies. The simulation experiments indicate that the home location is difficult to use for pricing purposes, and prices should rather depend on the type of road segment and time of day.

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1 Introduction

An efficient transport system is considered as a prerequisite for economic power and growth, thus an increase in transport efficiency directly translates into economic benefits (see e.g. European Commission, 2011). Due to the existence of transport related externalities, such as congestion, air pollution, noise and accidents, transport users only pay for parts of the total travel costs. External costs are defined as the difference between private user costs and total costs (or social cost). For the car mode, typically, the private part of the user costs (e.g. the transport user's own travel time) and the producer costs (e.g. fuel consumption, vehicle wear and tear) are already paid by the user. Whereas, the external part (e.g. other transport users' additional travel time due to congestion effects) is typically not paid by the user. Consequently, the wrong incentives are given which yields an inefficient use of transport resources. Pricing can be understood as a market-based instrument to make users take into account the full costs and thereby change individual travel decisions towards a higher level of efficiency (see e.g.; Maibach et al., 2008; Small and Verhoef, 2007). When applying marginal social cost pricing, introduced by Pigou (1920), marginal private user prices are set equal to the sum of marginal producer costs, marginal private user costs and marginal external costs. That is, the uncovered costs which are not borne by the transport user, are internalized. By charging road users a toll that is equal to the marginal cost imposed on other travelers or the society as a whole, external costs are included in decision making processes and people's behavior is changed towards a more efficient use of the transport system.

Several recent studies have shown that congestion causes the largest part of all transport related externalities which lead to an inefficient market equilibrium (see e.g.; Maibach et al., 2008; Small and Verhoef, 2007; de Borger et al., 1996; Parry and Small, 2009). Hence, this study focuses on congestion, whereas other externalities such as air pollution, noise and accidents are neglected. Applying the principles of marginal congestion cost pricing, road users must be charged by a toll that is equal to the marginal delay cost which they impose on other travelers.

In this paper, a newly developed simulation-based approach is presented to calculate external congestion effects at a microscopic, truly agent-based level. The innovative pricing approach is applied to a real-world case study of the greater Berlin area. The results are checked for plausibility and analyzed with regard to their implications for pricing policies.

The paper is organized as follows. Sec. 2 provides a short review of the relevant literature and states the problem which is addressed in this study. Sec. 3 gives a brief overview of the simulation framework and describes the newly developed approach to calculate dynamic and agent-based marginal congestion effects. Sec. 4 describes the simulation experiments that are carried out. The results and a discussion are given in Sec. 5 and Sec. 6. Finally, Sec. 7 provides a brief summary of the main findings.

2 Literature and Problem Statement

In the standard economic model, introduced by Alfred Marshall, which Pigou (1920) refers to, all transport activities are considered to take place in a single time-independent interval. That is, the dynamics within the considered time interval are ignored. Breaking down the demand curve into individual users is possible, however, the positioning of individual users follows each user's willingness-to-pay and can not be used for a dynamic interpretation. In the standard model, marginal social costs are defined as the increase in social costs from an additional user in the considered time interval (see e.g. Arnott et al. (1993)).

A simple dynamic model is obtained dividing the rush-hour or the day into finite time intervals and applying the standard model for each interval. However, a separate analysis of each time interval is problematic. In the standard model where a facility is subject to congestion for example, the time intervals are linked due to the dynamics of congestion. A solution to face this problem is provided by Vickrey (1969) who determine the equilibrium for a single bottleneck simultaneously over the entire rush-hour (Arnott et al., 1993). In that study, the network is to a very high degree stylized and congestion is considered to occur in form of a queue at the bottleneck. The optimal time-dependent toll is found to reduce the traffic flow to the capacity of the bottleneck. In several studies, the original bottleneck model introduced by Vickrey (1969) was extended, e.g. by proportional heterogeneity in the Values of Travel Time Savings (VTTS) and Values of Schedule Delay (Vickrey, 1973; Arnott et al., 1994), a price-sensitive demand (Arnott et al., 1993), a combination of continuous heterogeneity and price-sensitivity on the demand side (van den Berg, 2011). Lindsey and Verhoef (2001) discuss the economic concepts of static and dynamic congestion pricing models, considering dynamic approaches to extend time-independent models by a time-depending demand and a traffic flow model which specifies how traffic expands over space and time. For the latter, Lindsey and Verhoef (2001) distinguish between microscopic models, which allow to keep track of each vehicle's movement, and macroscopic models, in which individual vehicle movements are aggregated to traffic flows.

Most studies on congestion pricing use stylized networks and build on the macroscopic modeling approach that can be solved analytically. Analytical modeling is well suited to understand the economic principles behind optimal price setting. However, due to their rather simplistic structure, these models are less appropriate for real-world scenarios, e.g. large-scale networks, multiple origin-destination points, non-deterministic demand, and dynamic congestion, including the emergence and decline of queues and spill-back. The agent-based simulation approach allows to account for such complexities that arise within real-world scenarios. It enables the evaluation of various transport policies, including dynamic pricing. However, when using a simulation approach, the equilibrium is not determined analytically.

Furthermore, the agent-based approach allows to consider the phenomenon "congestion" as a result of several small congestion effects that occur among the agents, i.e. delays that transport users ahead impose on the following (upstream) transport users. Therefore, optimal prices have to be set based on the simulated traffic flows, accounting for the dynamics of disaggregated user-user interactions. To the best of the author's knowledge, the general principles of marginal congestion cost pricing have never been applied to a real world city model on such a sophisticated level of detail. Spatially, each road segment is considered as a potential bottleneck, at which the demand may exceed the capacity, i.e. at which the capacity may be reduced compared to the sum of the ingoing road segment(s) plus the number of starting trips. Temporally, the entire queuing process is considered by computing the delay effects for each time step. That is, the time interval in which the marginal congestion cost are computed, is set to the duration of one time step.

Applying the agent-based simulation methodology, several studies address the reduction in congestion by a second-best pricing policy or an approximation of the optimal toll. In Kickhöfer et al. (2010) for instance, a manually designed second-best pricing scheme is applied which reduces traffic congestion during the morning rush-hour in the area of Zurich. Nagel et al. (2008) estimate the optimal toll based on the time spent traveling. Lämmel and Flötteröd (2009) developed an approach to approximate the marginal social costs assuming a stationary flow of vehicles. This approach and a modification by Lämmel (2011) were applied in a large-scale evacuation scenario to find the optimal routing solution. An alternative method was recently presented by Kaddoura and Kickhöfer (2014), however not applied to a large-scale real-world scenario. This approach directly builds upon the dynamics of a queue-based traffic model and calculates user-specific marginal congestion cost at a microscopic, truly agent-by-agent level. One advantage of the latter approach is that accounting for the heterogeneity of travelers is fairly straight-forward compared to the approximation using aggregated flows.

The applicability and effectiveness of a similar approach were previously demonstrated for public transport pricing by Kaddoura et al. (2015) and air pollution pricing by Kickhöfer and Nagel (2013).

The main objective of this study is to prove the applicability and effectiveness as well as the conceptual idea of dynamically calculating marginal congestion cost at a microscopic level for a large-scale real world scenario.

3 Methodology

3.1 Simulation Framework

In this study, the agent-based simulation framework MATSim[1] is used for the investigation of optimal road pricing. The transport demand is modeled as individual agents. In an initial step, for each agent, daily travel plans have to be provided, which describe the daily activity chains, including the initial transport modes and departure times for the trips in between each two activities. The demand adapts to the transport supply in an evolutionary iterative approach that involves the (1) traffic flow simulation, followed by an agent-specific (2) evaluation and a (3) learning process.

1. **Traffic Flow Simulation** The traffic flow simulation is based on a queue model developed by Gawron (1998). Each road segment (link) is modeled as a *First In First Out* queue that has three attributes: a free speed travel time t_{free}, a flow capacity c_{flow} (in the literature often referred to as 'bottleneck congestion' (see, e.g., van den Berg, 2011)), and a storage capacity $c_{storage}$ (causing spill-back effects). Each time step, typically 1 sec, the state of each link's queue is updated. A vehicle is only moved from link l_a to link l_b if (i) the free speed travel time (given by the freespeed and length of link l_a) has passed, (ii) the inverse of the flow capacity has passed since the last vehicle left link l_a, and (iii) there is space on link l_b. The resulting traffic flows are consistent with the macroscopic fundamental diagram (see e.g. Agarwal et al., 2013).

2. **Evaluation** Each agent evaluates his/her executed plan taking into account both the usually positive utility that is gained from performing an activity (see Charypar and Nagel, 2005) and a typically negative trip-related utility which usually includes the travel time, travel distance as well as monetary payments.

3. **Learning** A predefined share of agents generate new plans to be executed in the next iteration by modifying a copy of an existing plan. The remaining agents select a plan for the next iteration by choosing among their existing travel alternatives based on a multinomial logit approach.

Over many iterations, the agents improve, generate plausible travel alternatives, and the simulation outcome stabilizes. Considering each agents' travel alternatives to represent valid choice sets, the system state converges towards a stochastic user equilibrium (Nagel and Flötteröd, 2012). For a detailed description of the simulation framework, see Raney and Nagel (2006).

[1] Multi-Agent Transport Simulation, see www.matsim.org

3.2 Dynamic and Agent-based Calculation of Marginal Congestion Cost

The agent-based pricing approach developed by Kaddoura and Kickhöfer (2014) computes marginal external congestion effects based on the simulated traffic flows in each iteration. An agent who leaves a road segment prevents all following agents from leaving that road segment for the time of $\frac{1}{c_{flow}}$. This is depicted in Fig. 1, assuming a flow capacity of 1200 vehicles per hour and three agents 1, 2 and 3 arriving at the end of the link at time step $t = 0$, $t = 1$ and $t = 2$. Accordingly, each time an agent leaves a road

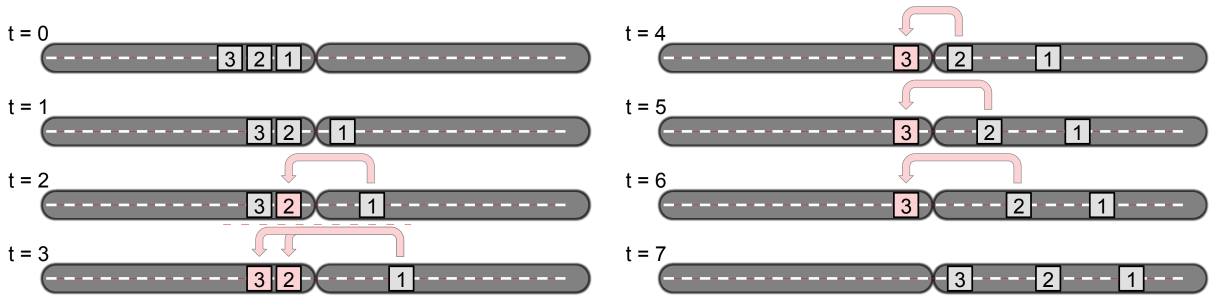


Figure 1: Example: Congestion effects due to the flow capacity. A red arrow indicates an external delay effect.

segment the delay effect imposed on the following agents are computed and a local optimal user-specific toll is calculated. The first external delay effect appears at time step $t = 2$, when agent 2 cannot leave the first road segment. Since agent 1 has left the road segment and the flow capacity constraint limits the number of leaving agents per time, 3 sec ($\frac{1}{c_{flow}}$) have to pass until the next agent can be moved to the next road segment. At time step $t = 3$, both agents 2 and 3 are delayed by agent 1. At time step $t = 4$, agent 2 is allowed to leave the road segment, however, agent 3 is still queued. This time, agent 2 is considered as the causing agent that imposes a delay of 3 sec ($t = 4...6$) on agent 3. Summing up for each agent the private and external delay cost results the following. Agent 1 causes 3 sec congestion and is not affected by any delay. Agent 2 causes 3 sec delay and is exposed to 2 sec. Agent 3 causes no delay and is exposed to 4 sec delay. That is, especially for longer queues, the first agent(s) will cause more congestion than they are exposed to compared to the agents at the back of a queue. When applying a marginal congestion cost pricing scheme, depending on the cost of the alternatives (routes, transport modes, departure times), transport users will change their travel behavior to reduce the sum of the private and (internalized) external congestion cost.

To extend the example towards an elastic demand, a travel alternative is introduced. Agent 1, 2 and 3 can alternatively use the bicycle on an uncongested bicycle lane, the alternative specific cost for taking the bicycle (instead of the car) is 4.5 sec. Other cost components such as the free speed travel time on either mode are ignored. Without any form of road pricing, for all agents, the congested car mode is the "better" option. However, the overall welfare loss amounts to 6 sec (2 sec delay of agent 2 plus 4 sec delay of agent 3). However, applying a marginal congestion cost pricing scheme in which the agents also take into account their external cost, for agent 2, the bicycle-option is the “better”-one, since the alternative-specific constant of 4.5 sec is below the sum of the private congestion cost (2 sec) and the marginal extern congestion cost (3 sec). The overall welfare loss would then amount to 5.5 sec only (1 sec remaining congestion on the car mode plus the 4.5 sec bicycle offset “payed” by agent 2).

As described in Sec. 3.1, the simulation framework accounts for a second capacity constraint, namely the storage capacity $c_{storage}$, which limits the number of vehicles that can be placed on a road segment. That is, in case the queue which results from c_{flow} has dissolved, the remaining delay is ascribed to $c_{storage}$ of a *downstream* in combination with c_{flow} of a *downstream* road segment at the queue’s origin, e.g. the bottleneck link. At this stage, several approaches are implemented to internalize these delays. A reasonable compromise between computational performance and precise calculation seems to save the spill-back related delay, and then to charge for these delays in case the affected agent drives along the bottleneck link at which the queue has not yet dissolved.

4 Simulation Experiments

The agent-based approach to calculate individual congestion cost is applied to a real-world scenario of the greater Berlin area. In this study, the scenario by Neumann et al. (2014) is used who converted a static trip-based model into a dynamic activity-based MATSim model. The transport network contains all major and minor roads. The travel demand is comprised of a SrV survey-based (see Ahrens (2009)) population and additional traffic, such as freight, airport and tourist traffic, which is modeled as “non-population representative” agents. The demand was calibrated with regard to the mode shares, travel times and distances. For a better computational performance, a sample size of 10% is used and the network capacity is accordingly reduced. As input demand for the simulation experiments described in the following sections, the executed plans of the relaxed travel demand generated by Neumann et al. (2014) are used.

Since this study focuses on road congestion, the traffic flow simulation described in Sec. 3.1 is only applied to the car mode. For all other modes, namely public transport, bike and walking, in this study, the travel time is calculated based on the beeline distance. That is, the simulated public transport is disabled. Normally, this modification would require a recalibration of the scenario. However, in this study, the agents are not enabled to choose their mode of transportation, and a recalibration is not needed. Since the choice dimension *departure time* widens each agent’s search space and requires a larger number of iterations, in this study, the agents are forced to stick to their initial time schedule. For all simulation experiments, a total of 100 iterations are run. During the first 80 iterations choice sets are generated, i.e. each iteration 10% of the agents are enabled to experience new routes, whereas for the final 20 iterations the agents' choice sets are fixed and travel alternatives are chosen based on a multinomial logit model. For each agent the maximum number of travel alternatives is set to 4 plans.

The following two simulation experiments are carried out:

1. **Base case (No pricing):** In this simulation experiment, the scenario generated and calibrated by Neumann et al. (2014) is run without any modification. The outcome is considered as the current traffic situation (Nash equilibrium) and is therefore used as the reference case.

2. **Policy case (Marginal congestion cost pricing):** In this simulation run, the user-specific marginal congestion cost pricing policy described in Sec. 3.2 is implemented. The outcome is considered as the predicted equilibrium of the system optimum subject to the model's assumptions, e.g. transport users are only enabled to adjust their routes (sequence of road segments) in order to avoid road charges or being stuck in traffic.

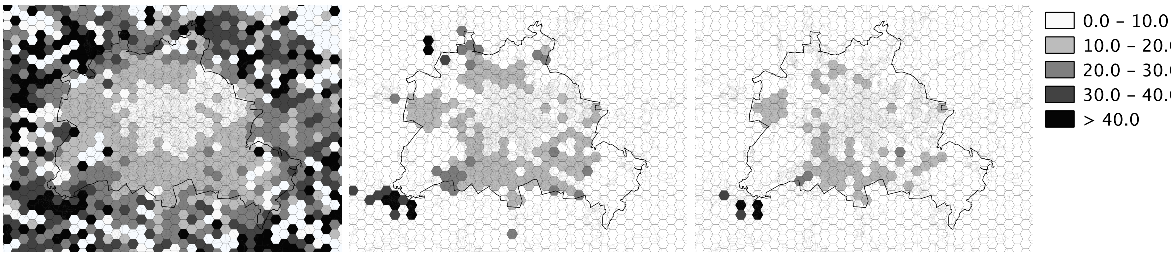
5 Results

5.1 Base case: No pricing

In this section, the base case situation is investigated regarding the external congestion effects travelers impose on each other. In this simulation experiment, external congestion effects are not internalized. That is, each agent only pays for the private congestion cost, i.e. the own time spent in traffic jam.

The average congestion cost per trip within the car mode which is imposed on other travelers results in 86 sec with a standard deviation of 597 sec, including additional traffic such as freight, airport and tourist traffic. Only accounting for the "population representative" agents (see Sec. 4), the average congestion effect results in 21 sec per car trip with a standard deviation of 50 sec. Depending on the level of traffic, the average external congestion cost per car trip vary by time of day. During peak times, the average congestion effect per trip is much higher compared to the off-peak periods. To give an example, for the "population representative" agents, the external congestion effect amounts to 9 sec for trips starting between 10.00 and 11.00 a.m. and 48 sec for trips between 3.00 and 4.00 p.m. (see Fig. 4 in Sec. 5.2). Average external congestion cost are also observed to increase with the trip length, e.g. 7 sec for a trip length between 4 and 5 km and 17 sec for a trip length between 10 and 11 km ("population representative" agents only).

To begin with a more detailed spatial analysis, the external congestion costs are mapped back to the home location of each causing agent and aggregated on a zone-based level. Since the additional traffic (freight, tourists) is modeled as "non-population representative" agents without a home location, the following analysis only refers to the "population representative" agents. Fig. 2 depicts the average congestion cost in sec per resident for each zone of the greater area of Berlin (Fig. 2a), for zones with more than 5,000 residents (Fig. 2b), and for zones with more than 10,000 residents (Fig. 2c). The average external congestion cost are observed to be higher in areas outside of Berlin compared to the inner Berlin area. However, since the population density is lower in most of the outer zones, the absolute level of congestion cost caused by the residents of these zones can be neglected. Nevertheless, for some areas the average congestion cost as well as the number of residents are on a higher level, e.g. Potsdam, the inner-city suburbs, especially in the southern region (see Fig. 2b and Fig. 2c). This indicates that residents in these areas contribute to a very large extent to the overall congestion cost.



(a) all zones (b) zones with >5k residents (c) zones with >10k residents

Figure 2: Average congestion cost in sec per resident mapped back to the home location of the causing agent

Analyzing how much each agent delays other agents (external cost) and how much each agent is delayed by other agents (private cost) results in an average external and private congestion effect of 68 sec per agent (including non-population representative agents) with a standard deviation of 534 sec (external cost) and 551 sec (private cost). For the "population representative" agents the average external and private congestion effect amounts to 16 sec with a standard deviation of 54 sec (external cost) and 71 sec (private cost). It is very likely that travelers who produce congestion are stuck in traffic themselves. However, depending on the time when an agent passes a bottleneck, the external and private delays deviate from each other. Therefore, Fig. 3, addresses the *difference* between the external congestion cost that is imposed on other agents and the private congestion cost which an agent is affected him-/herself.

Starting with an aggregated (zone-based) analysis, Fig. 3 (left-hand side) depicts the difference between caused and incurred congestion cost for each zone's residents. A red colored zone indicates a negative balance, which means the residents cause more than 1 hour congestion compared to the delays they are affected by others. A green colored zone indicates a positive balance, which means the residents cause less than 1 hour congestion compared to the congestion cost that they are affected. A white colored zone indicates that, in sum, the (absolute) difference between caused and affected congestion is below 1 hour. As shown in Fig. 3 (left-hand side), the different zones (red, green, white) are spread all over the area of Berlin, with a higher tendency of red zones along the northwestern corridor via Spandau.

A more detailed look on a microscopic level is given in Fig. 3 (right-hand side) for the inner-city area around the Ernst-Reuter-Platz. Each agent's home location is colored in red, green or grey to indicate whether the external congestion effect is exceeded by the private delay effect or not. Again, the additional traffic ("non-population representative" agents) without any home location is not displayed. It is shown that the difference between the caused and affected congestion strongly differ from agent to agent, even among agents with neighboring home locations. For the greater Berlin area, the average absolute difference between each agent's external and private congestion effect amounts to 7 sec with a standard deviation of 46 sec not taking into account the additional traffic. Including the additional traffic, such as freight and tourists, the average absolute difference per agent amounts to 30 sec with a standard deviation of 322 sec.

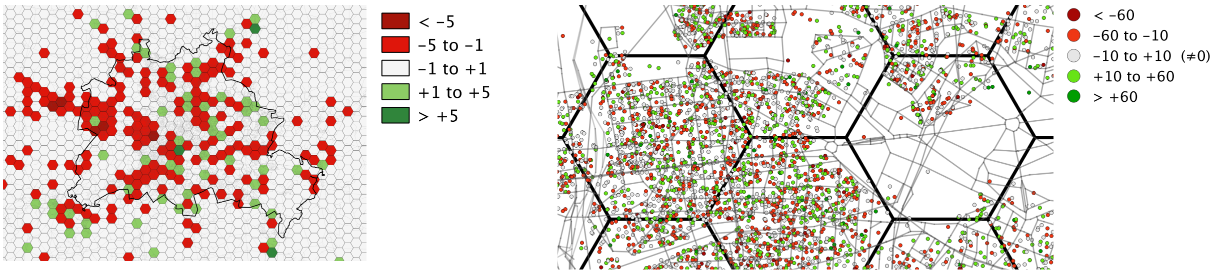


Figure 3: The difference between the agents' private and external congestion cost (red: external cost > private cost; green: external cost < private cost); Left: aggregated zone-based difference in hours; Right: agent-specific specific difference in seconds (coloring the agents' home locations with difference ≠ 0; 10% sample size)

Finally, the external congestion effects are analyzed where they are actually induced, namely for the (bottleneck) road segments. Very high average congestion effects per agent that passes by are observed on road segments of the inner-city motorway, e.g. the southwestern corridor A115, the southwestern parts of the inner-city ring road A100, but also on minor roads inside the city center. Due to the high demand on these road segments, also the absolute level of congestion cost is very high.

5.2 Policy case: Marginal Congestion Cost Pricing

This section provides the results of the second simulation experiment, i.e. the policy case in which the user-specific congestion pricing approach described in Sec. 3.2 is applied. As expected, the optimal pricing approach leads to an overall lower congestion level compared to the base case (no pricing): The average travel time per trip within the car mode decreases by 9 sec. Relative to the average travel time per trip, which amounts to 1,075 sec in the base case situation, the change seems minor ($\approx 1\%$). However, relative to the average private/external congestion effect per trip which is 68 sec (see Sec. 5.1) in the base case, a change of 9 sec describes a significant reduction in congestion ($\approx 13\%$).

Fig. 4 only considers the "population representative" agents and depicts the average external congestion effect per trip for each time period in the base case situation and the pricing equilibrium in which the external congestion costs are internalized. Especially during the congested peak periods, the average internalized external delay effect is much lower in the optimal pricing equilibrium compared to the (not internalized) average external delay effect in the base case situation.

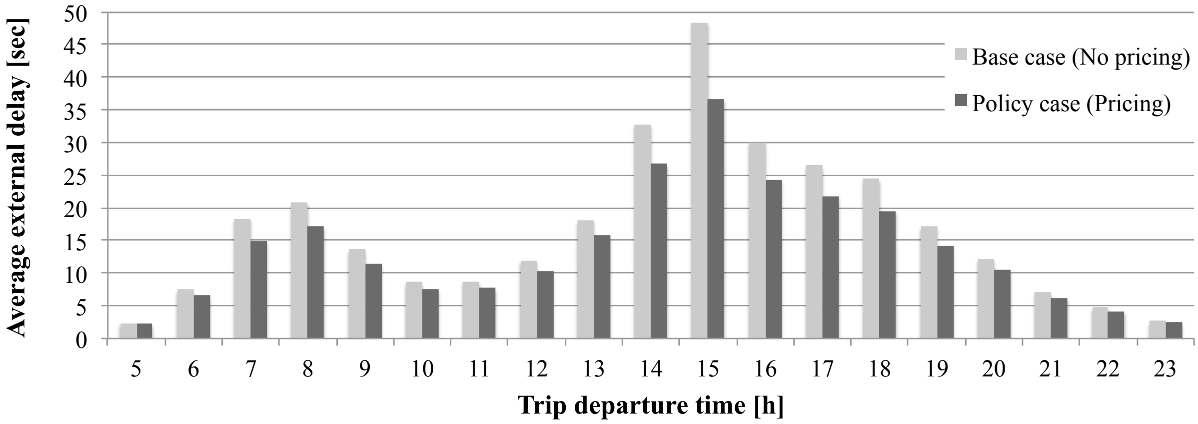


Figure 4: Average (internalized) external congestion effect (in sec per car trip, without additional traffic, greater Berlin region) depending on the time of day (in hours)

In Fig. 5, the changes between the base case (no pricing) and the policy situation (marginal congestion cost pricing) are given for zones with more than 5,000 residents. On the left-hand side of Fig. 5, the

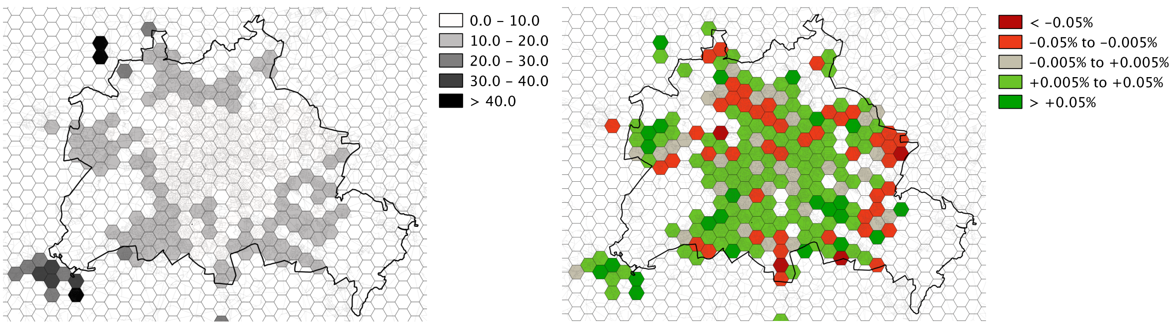


Figure 5: Left: average toll payments (= internalized congestion cost) in sec per resident; zones with <5k residents are not depicted; Right: relative increase (green) / decrease (red) in welfare (user benefits + toll payments) due to pricing; grey: change <0.005%

toll payments, which are equal to each agents' (internalized) external delay effect, are mapped back to the agents' home locations and given for each zone as average in sec per resident. A comparison of the spatial plots in Fig. 5 (left-hand side) with the base case situation, depicted in Fig. 2b, reveals that the average congestion cost is lower in many zones, especially in the southern region of Berlin. Nevertheless, the spatial structure is similar to the base case with an overall tendency of higher average congestion cost for residents outside the inner-city area. A home location-based analysis of the relative increase in social welfare due to the marginal congestion cost pricing policy is given on the right-hand side in Fig. 5. Thereby, the welfare is defined as the sum of the user benefits which include the positive utility earned when performing activities and the trip-related negative utility (e.g. travel time, tolls). Internalized external congestion costs, shown on the left-hand side in Fig. 5, are considered as transfer payments and therefore assumed to be repaid to the causing agents. That is, on the right-hand side in Fig. 5, for each aggregated zone, it is shown whether the residents win (green colored zones) or lose (red colored zones) in terms of reduced travel times due to the pricing policy compared to the base case. A reduction in travel time increases the welfare in two ways. First, the trip-related disutility is smaller. Second, there is more time available to be spent at an activity location, which may yield a higher positive utility gained from performing an activity. Comparing both plots in Fig. 5 reveals that for zones with the highest average congestion cost, e.g. the area of Potsdam, the increase in welfare (reduction in travel times) is observed to be very high (more than +0.05%). The results also show that without repaying the toll revenues to the transport users, the relative change in user benefits is negative for most of the zones in the study area.

In Fig. 6 the changes in traffic volume (agents per day) are shown. Red colored road segments indicate an increase in traffic when applying marginal social cost pricing compared to the base case. Whereas, green colored road segments indicate a decrease in traffic volume due to the optimal pricing approach. Absolute changes up until 500 agents per day are not displayed. A network wide analysis for the area of

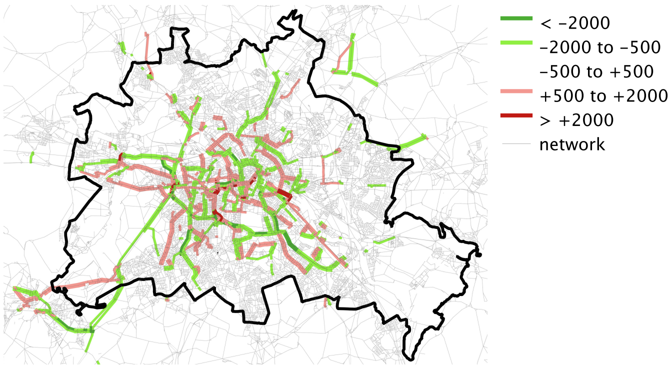


Figure 6: Link-specific changes in agents per day (base case vs. pricing policy); red: increase in traffic due to pricing; green: decrease in traffic due to pricing; not displayed: changes of +/- 500 agents

Berlin reveals that the average toll per agent is much higher on major road segments compared to minor road segments. Hence, the demand is shifted from major roads to minor roads. Along the southwestern corridor towards Steglitz-Zehlendorf and Potsdam, for example, the agents switch from the inner-city motorway A115 to the primary road B1. The same effect is observed for the inner-city ring road A100 and the southeastern corridor towards Schönefeld, where the agents are observed to avoid the motorway and switch to primary and secondary roads.

6 Discussion

The aggregated (zone-based) and disaggregated (agent-based) comparison of the external and private congestion cost, given in Fig. 5, reveals that for some areas as well as some parts of the population the external congestion cost and the private congestion cost are on a similar level. Nevertheless, for most areas, i.e. for the areas with the highest average external congestion effects, the external and private part of the congestion effect differ very strongly. This indicates that congestion is not per se internalized, and the importance to consider congestion as an external effect which has to be internalized by policies.

The comparison of the two simulation experiments (marginal congestion cost pricing vs. no pricing) reveals the great potential to increase the transport efficiency by means of pricing. However, the model accounts for route choice as the only choice dimension, other choice dimensions such as time choice or mode choice are disabled. Hence, the way how transport users can react to the road charges is limited to a change of the network route, i.e. the sequence of road segments between two activity locations. In particular, the time-dependent tolls cannot be avoided except by a change to another transport route. However, for many transport users, a change of the transport route is no meaningful option because the alternative routes go along with longer travel times, and may be congested and tolled as well. Therefore, the simulation experiments may underestimate the actual increase in welfare due to (i) transport users that avoid the tolled car mode and switch to alternative transport modes or (ii) those transport users that avoid the congested peak periods and decide to travel earlier or later. In that case, presumably, also without a reinvestment of the toll revenues, the change in user benefits will be positive due to the improved transport efficiency when applying marginal congestion cost pricing.

A distinction must be made between direct congestion effects and indirect delay effects. The first effect is computed based on the marginal congestion cost, i.e. the delays the agents impose on each other due to the direct interaction at bottleneck road segments (see Sec. 3.2). Whereas, the second delay effect is related to the additional travel time which is spent in order to avoid congestion, e.g. to drive around the traffic jam. Hence, it has to be taken into account that the additional travel time due to congestion is much higher compared to the direct private/external congestion effects.

An optimal user-specific pricing scheme which depends on the current congestion level on each (bottleneck) road segment is rather difficult to implement in real world. Since theoretical first best conditions do not exist in reality (e.g. due to underpriced competing modes, difficult computation, unfeasible implementation), second best solutions are required that are easy to implement and to be understood by the transport users (Verhoef, 2001; Proost and van Dender, 2001; Small and Verhoef, 2007; Tirachini and Hensher, 2012). Common pricing schemes which are applied in many municipalities are for instance area-pricing (e.g. London) or cordon-pricing (e.g. Stockholm) (Beckers et al., 2007). Insights from the first best solution may help to develop second best pricing strategies, which make more precise distinctions and combine time dependent tolling (peak pricing), vehicle-specific tolling and differentiated network pricing, as for instance applied in Singapore. Different technologies such as camera systems, Dedicated Short Range Communication (DSRC) or satellite-based systems may be used for a differentiated collection of tolls. That is, the theoretical first-best user-specific tolls provided by the pricing experiment (Sec. 5.2) may be used as a starting point for policy design and to develop more practicable pricing solutions which are less complex but can still be used to control traffic and increase the transport efficiency. The marginal congestion pricing approach may then be used as a benchmark to evaluate these policies. The results also confirm general finding that optimal tolls should not be set according to the observed external delay effects in the base case situation (see e.g. de Borger et al. (1996)). This is due to the fact that optimal toll levels depend on the number of road users which in turn depends on the toll levels. As shown in Fig. 4, this is especially important for higher congestion levels observed during the peak periods in which the average external delay effects in the base case and policy situation deviate from each other by a very significant amount.

In order to develop a second-best pricing scheme, the external congestion effects may be aggregated for each road type (e.g. motorway toll), network area (e.g. inner-city toll), time of day (peak-pricing), vehicle type (HGV toll) or area of residence. Also a combination of several specifications may be useful, e.g. a motorway toll during peak-hours with differentiated prices depending on the vehicle size. Fig. 4 for instance may be used to introduce a peak pricing scheme, i.e. to define the pricing periods (for example 7 – 9 a.m. and 2 – 5 p.m.) and to define the toll level (a monetary amount which is equivalent to approx. 15 sec in the morning peak and approx. 25 – 30 sec in the afternoon/evening peak). The spatial plots in which the congestion costs are mapped back to the home location of the causing agent, i.e. Fig. 5 (left-hand side), may be used to develop home location oriented policies, in particular, to identify in which areas the residents should be motivated to avoid the private car mode. However, in the base case and policy case, the average congestion effect as well as the difference between external and private congestion are observed to vary extremely from agent to agent, even among agents with neighboring home locations. This is due to the heterogeneous demand, i.e. that two agents may have their home location close to each other but travel at different times and/or along different routes. That is, the spatial distribution of the home location seems difficult to use for pricing purposes (zone-based pricing), and pricing strategies should rather address the route and time of day.

The changes in traffic volume per road segment (see Fig. 6) that result from the pricing policy exhibits a shift from motorways and primary roads to smaller roads. However, an increase in traffic on smaller roads, i.e. in residential areas, may lead to an increase in other externalities such as environmental effects, accidents and noise. That is, congestion effects are interrelated with other externalities, i.e. the extent of one effect strongly affects the extent of the other effects (see e.g. Calthrop and Proost, 1998; Barth and Boriboonsomsin, 2009). In this study, other external effects than congestion are not accounted for. Including these effects in the internalization approach would presumably weaken the observed effect, and less agents would be shifted to smaller roads in residential areas. It is therefore crucial to set up an integrated study which takes into account all relevant external effects. A first step towards an integrated study is taken by Agarwal and Kickhöfer (2014) who combine an agent-based emission internalization approach developed by Kickhöfer and Nagel (2013) with the agent-based congestion pricing approach developed by Kaddoura and Kickhöfer (2014) and applied in the present study.

The applied scenario generated by Neumann et al. (2014) considers freight traffic as "non-population representative" agents. However, in this study, the applied queue model (see Sec. 3.1) only accounts for an identical vehicle type. That is, in the model, heavy goods vehicles (HGV) will cause the same delay effects as cars. However, in real-world, the external delay effects imposed on other transport users are strongly influenced by the vehicle type, i.e. the driving behavior, vehicle size, acceleration and deceleration patterns. A possible approach is to extend the calculation of marginal congestion cost towards a calculation in passenger car-equivalents. Hence, in this study, congestion which is induced by freight traffic or larger vehicles, also buses, may be underestimated. Nevertheless, the results of the pricing policy described in Sec. 5.2 may still be right estimates due to the fact that also the willingness-to-pay for a travel time reduction is considered to be equal for all vehicle types, even though, in real world the willingness-to-pay of freight traffic is observed to be higher compared to car traffic.

7 Conclusion

In this paper, for the first time, the newly developed agent-based marginal congestion cost pricing approach was successfully applied to a real-world scenario with a large-scale network.

Congestion effects were computed at a sophisticated level of detail, i.e. for each traveler, for each road segment, and for each time step. The dynamic approach to calculate marginal congestion effects explicitly accounts for non-stationary traffic flow conditions, i.e. the emergence and decline of queues, including spill-back effects. The disaggregated approach allows to calculate external congestion effects depending on the vehicle type or driving behavior and to convert these congestion effects into monetary units taking into account different values of travel time savings. Furthermore, by applying a simulation framework that allows for several user reactions (e.g. route choice, time choice, mode choice), optimal pricing can be investigated for a sophisticated representation of the demand side.

As a proof of concept, the case study of the greater Berlin area was investigated with a particular focus on private and external congestion effects. Overall, the results seem plausible and prove the conceptual innovative approach to compute external and private congestion effects at a microscopic, truly agent-based level. It is shown that congestion is a relevant eternality which is not per se internalized, i.e. some users cause much more congestion than they are exposed to, and the other way round. By comparing the optimal pricing policy with the base case situation, a great potential is revealed to increase the transport efficiency by means of intelligent pricing and transport users' reconsiderations of route choice decisions. In particular, for zones with higher average congestion costs, the residents benefit very strongly from the pricing policy. Since the user-specific road prices are difficult to implement in reality, the results may be used as a starting point for a manual optimization, i.e. to derive more practicable pricing strategies. The results of the case study indicate that the spatial distribution of the home location is difficult to use for pricing purposes, and pricing strategies should rather address the route and time of day (road specific tolling, peak pricing). Hence, the presented approach allows to develop or improve the pricing system for any study area. By this means, the efficiency within the transport system is increased without any costly expansion on the transport supply side (e.g. building a new road, extending a road). The approach may therefore help municipalities to reconsider their pricing schemes and to support the usage of more advanced pricing approaches, such as peak/off-peak pricing or GPS-based distance- and time-dependent tolling.

In future studies, the question will be addressed how to derive more practicable pricing strategies based on the theoretical first-best solution. Furthermore, an integrated study will be set up in which other external effects such as environmental effects (Kickhöfer and Nagel, 2013; Agarwal and Kickhöfer, 2014), as well as externalities within alternative modes, i.e. the public transport (Kaddoura et al., 2015), will be included.

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