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Agent-Based Simultaneous Optimization of Congestion and Air Pollution: A Real-World Case Study

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Abstract

The exclusion of external costs from the behavioral decision making process of individuals yields travel demand beyond the system optimum which implies inefficiencies in the transport system. The present study investigates the effect of congestion optimization on emissions levels and vice versa while considering heterogeneity in individual attributes and choice behavior. In consequence, the resulting correction terms (tolls) are highly differentiated. Furthermore, and going beyond existing literature, the present study proposes a joint optimization of vehicular congestion and emissions. The proposed model uses a microscopic agent-based simulation framework which is applied to a real-world scenario of the Munich metropolitan area in Germany. The combined pricing scheme accounts for both external effects and in an iterative process, agents learn how to adapt their route and mode choice decisions in presence of this combined toll. The results indicate that the combined pricing strategy moves the car transport system towards the optimum, measured by a strong decrease of congestion and emission costs. Furthermore, it is found that pricing emissions only pushes users on routes with shorter distances, whereas pricing congestion only steers users on routes with shorter travel times, and potentially longer distances. That is, the two pricing strategies influence behavior by tendency into opposite directions.

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Keywords: Air Pollution, Congestion, Vehicle Emissions, Road Pricing, Simultaneous Pricing, Optimization, Agent-based Modeling

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1. Introduction

Car traffic in urban areas has led to an increase in negative externalities such as road congestion, damage to the environment, and human health.[27,18] These externalities yield efficiency losses which can sum up to a significant

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part of a country's GDP (Gross Domestic Product). For example, total external costs by motorized traffic in Beijing range between 7.5% and 15% of GDP.[8] The total external costs in the EU-27 for year 2008 was 373 billion EUR – equivalent to 3.0% of the region's GDP.[4]

Congestion externalities occur, since every vehicle on the network imposes costs on other vehicles in terms of increased travel times which could be used to perform a beneficial activity. Similarly, exhaust emission externalities occur, since vehicular traffic emits exhaust emissions such as CO, NO_x, PM, SO_2 which are the main components for polluting air and these in turn are responsible for adverse effects on health and living conditions. However, exclusion of congestion and/or emission externalities in people's mobility decisions deviates demand from system optimum.

In order move the transport system towards the optimum, planners and policy makers may look for measures which reduce the efficiency losses caused by the negative externalities. From the literature, it is known that pricing schemes can be used to achieve this goal of shifting the system from the user equilibrium towards the system optimum.[21] This lead to many studies on road pricing which focus on finding the theoretically optimal tolls for road congestion.[17,24,25,11,1] However, there is only a limited number of contributions that aimed at finding optimal toll levels for emissions[16] or for congestion and emissions simultaneously.[26,22] The former solve the problem using a simulation-based optimization for large-scale scenarios considering dynamic traffic flows. The latter use an analytical approach for a small six-node network, and a large-scale scenario of Brussels (Belgium) with static traffic flows, respectively. None of these studies attempted a combined optimization for congestion and emissions in a large-scale scenario with dynamic traffic flows and activity-based demand. More practically oriented contributions investigated the impact of various pricing strategies on congestion and emission levels and find that these two externalities are positively correlated.[22,3,9,5,20,2]

The present study extends the existing literature by applying a combined optimization approach for automobile emissions and congestion in a large-scale scenario with dynamic traffic flows and activity-based demand. For that purpose, the congestion pricing approach by Kaddoura and Kickhöfer[13] and the emission pricing approach by Kickhöfer and Nagel[16] are simultaneously applied to a real world scenario of the Munich metropolitan area in Germany. The contribution of the combined approach is to determine individual vehicle-specific, time-dependent toll levels that include both externalities under consideration. The study calculates the effects of the correction term, which increases system efficiency, for a particular case study. The methodology can, however, be applied to any scenario worldwide.

2. Modeling

Travel demand simulator. MATSim[19] provides a framework for simulating transport in large-scale scenarios. Every individual is considered as an agent who learns within an iterative process that is composed of three steps: (1) Execution: Selected plans of all agents are executed simultaneously in the physical environment. (2) Evaluation: The performance of the executed plan is calculated using a scoring function. In this study, the MATSim default scoring function[7] is used with behavioral parameters from Kickhöfer (2014).[14] (3) Re-planning: A new plan is generated for some agents by modifying an existing plan (e.g. route or transport mode)[1].

Emission pricing. The existing emission modeling tool along with MATSim framework is used for the calculation of cold and warm emissions which depend on parking duration, traveled distance, vehicle characteristics, and engine type, road category, speed of vehicles, respectively.[15] Furthermore, time-dependent, vehicle-specific emission tolls are calculated using the methodology developed by Kickhöfer and Nagel[16] and the emission cost factors provided by Maibach et al[18]. In the simulation, every time an agent leaves a road segment, it is charged with a toll equivalent to the produced emissions.

Congestion pricing. Following the methodology developed by Kaddoura and Kickhöfer[13], dis-aggregated delays on each link for each agent are computed. It is defined as the difference of actual and minimum link travel time. A tracking of agents identifies causing and affected agents. The former can then be charged with the equivalent monetary amount of the delays. Since congestion is – in contrast to emissions – inherent to road traffic, the behavioral

[1] In the present study, dropping or re-scheduling of activities is not considered.

parameters of MATSim[14] can directly be used to convert delays into toll levels. These monetary payments are then charged to the causing agent.

All monetary payments are considered in the performance-based learning cycle of MATSim, and hence, the external effect is taken into account by the agents for their route and mode choice behavior.

3. Real-World Application

The initial scenario is taken from Kickhöfer and Nagel[16] and shortly described next:

Input. Raw data provided by the municipality of Munich[23] is used to create the road network. Activity-based demand is created using different data sources: (i) 1.4 million inner urban travelers[10], (ii) 0.3 million commuters and 0.2 million reverse commuters[6], and, (iii) roughly 0.15 million freight trips[12]. For the present study, 1% of the total population is used for computational performance reasons.

Scenario set-up. Initially a base case is set up by running the simulation for 1000 iterations. It is used as the reference scenario for the different pricing strategies. Four strategies namely, Business As Usual (BAU), Emission Internalization (EI), Congestion Internalization (CI), and combined Emission Congestion Internalization (ECI) are then simulated. These strategies are differentiated based on internalization of external costs as their names depict. Each strategy is run for another 500 iterations. For 80% of the iterations, 15% agents switch route and 15% shifts travel mode between car and public transport (PT). The rest of the agents choose plans according to a multinomial logit model. After 80% of the iterations, all agents choose plans from their generated choice set following the latter strategy. In the study, travel modes other than car are assumed to run emission free and as without capacity constraints and thus, such travel modes are grouped together as *non-car* travel modes.

Analysis. Time-dependent and person-specific emission costs are calculated and aggregated for each strategy in order to obtain total emissions costs. Similarly, dis-aggregated delays are calculated for each affected agent and then converted into toll levels. Afterwards, these values are summed up to get the total congestion costs for each strategy.

Table 1: Comparison of pricing strategies in terms of modal split, external costs and travel times

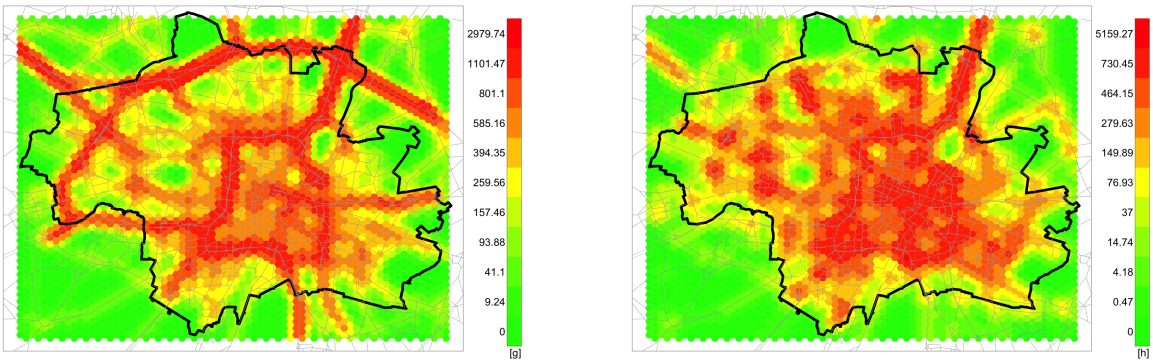
Strategies	BAU	EI	CI	ECI
Change in emission costs	–	-0.57%	-1.94%	-2.48%
Change in congestion costs	–	-3.26%	-42.83%	-43.32%
Modal split (car : non-car)	32.47 : 67.53	32.21 : 67.64	30.90 : 69.10	30.76 : 69.12
Avg. trip travel time car (*min*)	60.32	59.68	47.80	47.75
Avg. trip travel time non-car (*min*)	16.95	17.06	18.09	18.22
Avg. trip travel time car to non-car (*min*)	20.71	22.72	36.19	38.24

Table 1 shows the comparison of all strategies with respect to BAU. When pricing emissions only (EI), the reduction in emission and congestion costs are 0.57% and 3.26%, respectively. Similarly, pricing congestion reduces emission and congestion costs by 1.94% and 42.83%, respectively[2]. Thus, in accordance to the literature, pricing one externality has a positive impact on other and consequently, they prove to be positively correlated.[3,9,22,5,20,2]

However, pricing only one externality does not achieve the same increase in car system efficiency as the combined pricing scheme (ECI): The latter strategy reduces emission and congestion costs caused in the car mode by 2.48% and

[2] Compared to the changes in emission costs, the change in congestion costs seems rather high. This is, however, due to the fact that delays can actually be avoided (e.g. by shifting enough individuals to PT), whereas emission costs can only be avoided by shifting *all* individuals to PT, or by changing completely to zero emission vehicles which is not considered in this study.

43.32%, respectively. That is, the combined approach yields the highest efficiency gains of the presented strategies for the car transport system. This is supported by the decrease in average trip travel time for car[3] in Table 1. For non-car users, this average trip travel time increases for the different pricing strategies which implies that especially longer trips are shifting to the non-car mode. This indicates that the above efficiency gain in the car transport system needs to be compared with the increased travel times for individuals who switch from car to non-car mode. For them, it can observed that the average trip travel time increases for all pricing strategies. However, given that the users remaining in the car mode by far outnumber the mode switchers (see change in modal split), the pricing strategies still yield efficiency gains for the whole transport system.



(a) Absolute NO_2 emissions **(b)** Absolute delays

Fig. 1: Absolute NO_2 emissions and absolute delays for BAU

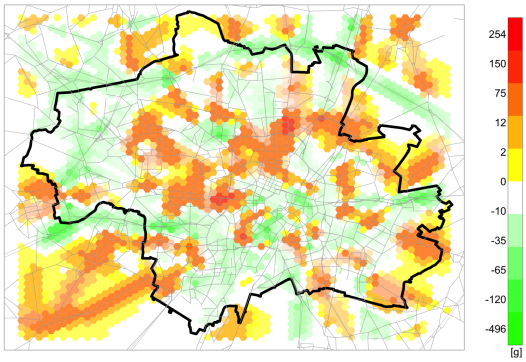
Furthermore, in order to understand the agent's behavior under different pricing strategies, spatial plots are used. Gaussian distance weighing function is used to smooth emissions and delays throughout the area of Munich and surroundings, using uniform hexagonal cells with a smoothing radius of 500 m. Fig. 1 and Fig. 2 show a variety of spatial plots. Absolute NO_2 emissions for BAU are presented in Fig. 1a as a reference.[4] One can observe that absolute emissions are most important on primary roads (inner and middle ring road, main arterials, and the tangential motorway in the north-west of Munich). In contrast, congestion is evident on almost all major roads inside the city area, but not as important on the tangential motorway (see Fig. 1b).

Fig. 2a to 2c present the change in NO_2 emissions and the change in delays by color scale and opacity, respectively. Yellow to red colors indicate an increase, green colors a decrease in NO_2 emissions. Transparent colors denote a decrease in delays whereas opaque colors exhibit an increase in delays.

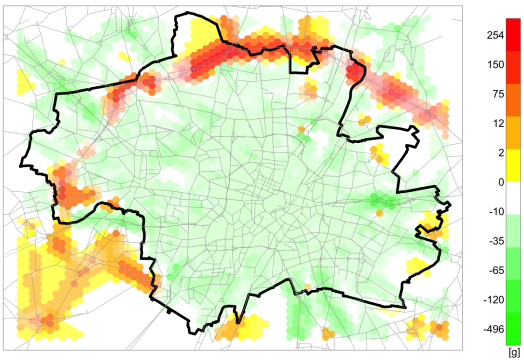
When pricing emissions only, re-routing steers most of the agents to shorter distance routes (see Fig. 2a) and some of the agents to shift to non-car travel modes (see Table 1). As a result, an increase in NO_2 emissions (orange and yellow hexagons) *and* an increase in congestion (opaque) can be identified mainly in the north of the inner city, whereas a decrease in emissions and delays is observed on the longer distance routes. From Fig. 2b it can be noticed that pricing congestion only reduces NO_2 emissions and congestion in urban areas of Munich significantly (transparent green hexagons). On the other hand, this strategy increases emission (red hexagons) on the tangential motorway in the north-west of Munich where the intensity of NO_2 emissions was already high in the BAU case (see Fig. 1a). Clearly, congestion pricing redirects agents to less congested routes (see Fig. 2b) and to non-car travel modes (see Table 1). The effects of simultaneous pricing are shown in Fig. 2c. Since congestion costs in BAU are by a factor of 3.4 higher than emission costs, the agent's behavior is dominated by the congestion toll. Fig. 2c therefore looks rather similar to Fig. 2b. However, as shown in Fig. 2c, the orange and red hexagons are a lot less than in congestion pricing. This

[3] The average car travel times seem rather high compared to PT. This is due to the fact that freight, commuters and reverse commuters (mainly) use car and drive long distances.

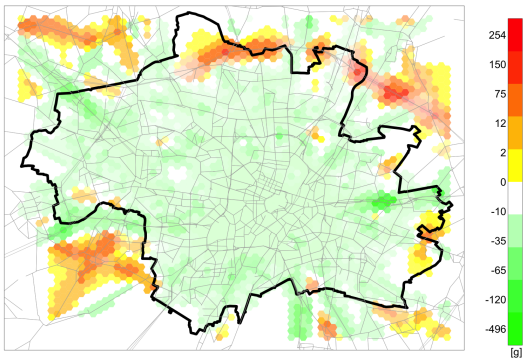
[4] All important pollutants are considered for pricing. For illustration purposes, the emission plots only show NO_2 values.



(a) Change in NO_2 emissions for EI



(b) Change in NO_2 emissions for CI



(c) Change in NO_2 emissions for ECI

Fig. 2: Change in NO_2 emissions for the different pricing strategies with respect to BAU. Additionally, transparent colors denote a reduction in congestion whereas opaque colors show an increase in congestion.

again shows the need for investigating the effects of combined pricing approaches that incorporate more than one externality.

4. Conclusion and Outlook

This study examined the impact of congestion pricing on emission levels and vice versa. Both externalities are found to be positively correlated since introducing a correction term in the form of a toll for one externality also reduced the other externality. Furthermore, it was demonstrated that a combined pricing strategy increases the car system efficiency most importantly yielding lowest congestion and emission costs. Additionally, agents' behavior for both pricing strategies was investigated with help of spatial plots. It was found that pricing emissions pushes users on routes with shorter distances, whereas pricing congestion steers users on routes with shorter travel times, and potentially longer distance. That is, for congested areas, the two regimes influence route choice behavior by tendency into opposite directions.

Finally, it can be concluded that with the methodology developed in this paper, efficient prices for negative externalities in large-scale urban areas can be derived and can be used as benchmarks when evaluating the effects of real-world policies. Beside the external costs considered here, the approach can also be applied to other external costs such as noise or accidents. In future studies, the authors aim at evaluating the proposed strategies economically

on a more dis-aggregated level, and incorporate emission exposure to gain most out of the underlying activity-based demand.

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