Pricing local emission exposure of road traffic: An agent-based approach

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Abstract

This paper proposes a new approach to calculate local air pollution exposure costs in large-scale urban settings by taking the number of exposed agents into consideration. It avoids the need for detailed air pollution concentration calculations and is characterized by little data requirements, reasonable computation times for iterative calculations, and open-source compatibility. It is shown how this approach can be used (i) for deriving marginal time-dependent vehicle-specific exposure tolls, and (ii) for the estimation of exhaust emission cost reductions of transport policy interventions.

1 Introduction

Problem statement Negative externalities in the transport sector are known to lead to market inefficiencies and social welfare losses. The latter exist since individuals base their decisions on marginal private and not on marginal social costs, typically yielding demand levels beyond the economic optimum. To correct for these market failures, Pigou (1920) proposed to internalize the difference between marginal social costs and generalized prices by a toll. Since then, the concept has been studied widely in the transportation economic literature (see, e.g., Lindsey and Verhoef, 2000; Small and Verhoef, 2007; Vickrey, 1969; Arnott et al., 1993; Friesz et al., 2004). However, all these studies focus on congestion costs. Other important contributions to the total external costs are found to be air pollution, accidents, and noise (Maibach et al., 2008; Parry and Small, 2005). Since these environmental externalities have gained more attention over the last decades (OECD, 2006), and some studies find their impact for some regions at the same level as congestion costs (Creutzig and He, 2009), Kickhöfer and Nagel (2013) proposed a new approach to calculate agent-specific time-dependent optimal air pollution tolls. In the literature, other possibilities to correct for these market failures are discussed, e.g. so-called backcasting approaches (Geurs and van Wee, 2004; IWW et al., 1998). The idea is to define threshold values based on medical studies, and then to derive avoidance costs in order to reach the values. The advantage is that avoidance costs are relatively easy to estimate. However, the definition of threshold values remains rather unclear, and exposure or concentration-response relationships could potentially provide more realistic information since they directly estimate damage costs (WHO Europe, 2006). For the European Union (Holland et al., 2005; Hurley et al., 2005) and the US (U.S. EPA, 2011), this exposure approach typically consists of five steps:

- Modeling emission levels and dispersion
- Deriving air quality
- Estimating exposure of individuals to air pollutants with respect to special population groups like pregnant or ill persons, children and elderly
- Applying concentration-response functions yielding numbers of cases for mortality, life years lost, hospital admissions, premature mortality, minor restricted activity days, work loss days, etc.
- Assigning monetary values to each of these cases

Emission exposure models In the literature, a large number of microscopic and macroscopic dispersion models exists. However, as a review paper by Holmes and Morawska (2006) shows, the latter can not provide the spatial resolution that is needed for air pollution concentration modeling within urban-scale scenarios. But also the former are generally characterized by long computing times and are therefore often not applicable to large-scale urban regions. According to Holmes and Morawska (2006), most emission dispersion and air quality modeling tools need geographical and meteorological input data like temperature, altitude, humidity, cloud cover, peak sun, sunrise, terrain elevation data, land cover data, hourly meteorological data, sea and land breezes. This data might not be available for the area of interest.

Despite these data requirements, there exist several attempts to model air quality in urban regions. Hatzopoulou and Miller (2010) use the open-source modeling tool CALPUFF-CALMET to evaluate air quality. Calculation of concentration values for 15'000 areas and 62'500 receptors from link-wise aggregated exhaust emissions initially takes them 190 hours of computing time. The Community Multiscale Air Quality model (CMAQ) and EPA's Modeled Attainment Test Software used by U.S. EPA (2011) have their focus on North American scenarios. When applying the models to European scenarios, Appel et al. (2012) find PM concentration values to be underestimated by 24% to 65%. Holland et al. (2005) use the Cooperative Programme for Monitoring and Evaluation of the Long-range Transmission of Air Pollutants in Europe (EMEP) combined with Regional Air Pollution Information and Simulation (RAINS) on a 50x50 km grid. However, both tools focus on macroscopic long-range dispersion over whole countries. Hülsmann et al. (2013) focus on emission dispersion modeling for street canyons using the Operational Street Pollution Model (OSPM) for a small area of their scenario. Despite the model's complexity and relatively large data requirements, it could be used for deriving emission exposure and for calculating time-dependent agent-specific exposure tolls. Unfortunately, the software is not open-source, and can therefore not be integrated into the iterative loop of MATSim (see Sec. 2.1) for online toll calculations.

Simplified approach This paper starts from the idea of pricing damage costs to human health. In order to improve the approach by Kickhöfer and Nagel (2013), it proposes how to calculate local air pollution *exposure* in large-scale urban settings by taking the number of exposed agents into consideration. Additionally, the approach is characterized by little data requirements, reasonable computation times, and open-source compatibility. It is composed of the three following steps:

First, the MATSim[1]-HBEFA[2] emission modeling tool is used which has been developed by Hülsmann et al. (2011) and further improved by Kickhöfer et al. (2013). The tool links MATSim's dynamic traffic flows to detailed air pollution emission factors of HBEFA.

In a second step, the resulting vehicle-specific time-dependent exhaust emissions on every link of the network are spatially dispersed using a Gaussian distribution function. For each agent in the simulation who performs an activity inside the dispersion radius, marginal pollution concentration and exposure time are mapped back to the causing agents.

In a third step, a monetary value is assigned to each traveler's contribution to the overall emission exposure. This results in an individual toll. Since the monetary value is assumed to be equal for every agent exposed to a certain emission concentration, the resulting toll captures the effect of population density: driving through a highly populated area results in a higher toll level than driving through a less populated area. Furthermore, the individual toll level at the same location is changing over time of day, since the simulation keeps track of all agents' activity patterns: driving through a highly populated residential area during day time will result in a lower toll than driving through the same area during evening hours. In an iterative process, travelers learn how to adapt their route and mode choice behavior in the presence of this simulated air pollution exposure toll.

After a detailed description of the model in Sec. 2, the implementation is tested in a simple test scenario (Sec. 3.1) and then applied to existing simulation runs of the Munich metropolitan area (Sec. 3.2). The paper ends with a conclusion in Sec. 4.

2 Model

This section gives an overview of the model to calculate exhaust emission exposure and the resulting agent-specific time-dependent toll levels. The section starts with a short introduction to the agent-based transport simulation MATSim, followed by a description of the emission modeling tool which calculates vehicle-specific warm and cold-start emissions. The emissions are then converted into monetary terms using average cost factors from Maibach et al. (2008). Subsequently, the exhaust emission cost dispersion model is presented. Finally, the idea of using the activity-based demand model for calculating population exposure to air pollution is described. Since, in the present approach, emission costs and not emissions are dispersed, this last step gives the marginal cost factors, and thus the individual toll levels.

[1] 'Multi-Agent Transport Simulation', see `www.matsim.org`
[2] 'Handbook Emission Factors for Road Transport', version 3.1, see `www.hbefa.net`

2.1 MATSim

In the following, only general ideas about the transport simulation with MATSim are presented. For in-depth information of the simulation framework, please refer to Raney and Nagel (2006). In MATSim, each traveler of the real system is modeled as an individual agent. The approach consists of an iterative loop that is characterized by the following steps:

1. **Plans generation:** All agents independently generate daily plans from survey data. These plans encode among other things their desired activities during a typical day as well as the transport mode for every intervening trip.

2. **Traffic flow simulation:** All plans are simultaneously executed in the simulation of the physical environment. In the *car traffic flow simulation*, agents interact on the roads which are simulated as first-in first-out queues with flow and storage capacity restrictions (Gawron, 1998; Cetin et al., 2003).

3. **Evaluating plans:** All executed plans are evaluated by a utility function with the following functional form:

$$V_p = \sum_{i=1}^{n} \left(V_{perf,i} + V_{tr,i} \right) \,, \tag{1}$$

   where V_p is the total utility for a given plan; n is the number of activities; $V_{perf,i}$ is the (positive) utility earned for performing activity i; and $V_{tr,i}$ is the (usually negative) utility earned for traveling during trip i. Activities are assumed to wrap around the 24-hours-period, that is, the first and the last activity are stitched together. In consequence, there are as many trips between activities as there are activities.

4. **Learning mechanism:** Some agents obtain new plans for the next iteration by modifying copies of existing plans. This modification is done by several strategy modules that correspond to the available choice dimensions. The choice between plans is performed within a multinomial logit model.

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. The iteration cycle continues until the system has reached a relaxed state. At this point, there is no quantitative measure of when the system is "relaxed"; the cycle is simply continued until the outcome is stable.

2.2 Emission Calculation and Monetization

The emission modeling tool was developed and tested by Hülsmann et al. (2011) and was further improved by Kickhöfer et al. (2013).

The tool links MATSim's traffic flows to the HBEFA database, and essentially calculates warm and cold-start emissions for private cars and freight vehicles. The former emissions are emitted when the vehicle's engine is already warmed whereas the latter occur during the warm-up phase. In the present model, warm emissions differ with respect to vehicle characteristics, traffic state, and road type. Cold-start emissions differ with respect to vehicle characteristics, accumulated distance, and parking duration.

Table 1: Emission cost factors by emission type (Maibach et al., 2008)

Emission type	Cost factor [EUR/ton]
CO_2	70
$NMHC$	1’700
NO_x	9’600
PM	384’500
SO_2	11’000

In a first step, vehicle characteristics are obtained from survey data and typically comprise vehicle type, age, cubic capacity and fuel type. They are then used for very differentiated emission calculations. Where no detailed vehicle information is available, fleet averages for Germany are used. For the calculation of warm emissions, MATSim traffic dynamics are mapped to two HBEFA traffic states: free flow and stop&go. In order to identify road types, information from network data is mapped to HBEFA road types, such as motorway, trunk road, distributor road, or tertiary road. For the calculation of cold-start emissions, parking duration and accumulated distance are monitored in the simulation. The handbook then provides emission factors for all relevant pollutants differentiated among the characteristics presented above.

In a second step, so-called ‘emission events’ are generated based on these warm and cold emission factors. The events provide information about person, time, link, and absolute emitted values by emission type. The definition of emission events follows the MATSim framework that uses events for storing disaggregated information as objects in JAVA programming language and as XML in output files. Emission event objects can be accessed during the simulation or generated later on in a post-processing of the standard MATSim events.

External cost factors for CO_2, $NMHC$, NO_x, PM, and SO_2 are taken from Maibach et al. (2008) (see Tab. 1). These values are average estimates for urban regions in Germany with a population greater than 500’000. We assume these being correct for the average population density of the respective scenario. This becomes important when calculating the emission exposure toll (see later in Sec. 2.4).

2.3 Emission (Cost) Dispersion

For emission dispersion of single point sources and long time intervals, Stern et al. (1984) proposed a model with a simple Gaussian distribution function (*plume model*, see Eq. 2). For multiple and area sources and for emission concentration calculations in urban areas, those authors suggest the *box model*, a discretization in grid cells as in Fig. 1 (Stern et al., 1984, Chapter 18). Presumably, both models only work for larger numbers of agents and appropriate time intervals. They cannot simulate the dispersion of a single agent or car realistically.

In this paper, the plume model is combined with the box model. Thus, following the plume model, the emission dispersion is modeled by multiplying the emission cost value of every emission event by

$$\frac{1}{\sqrt{2\pi\sigma^2}}exp(-\frac{(x)^2}{2\sigma^2}) \tag{2}$$

where x is the distance between the emitting car to the locations of the exposed persons. The variance σ is set to the cell length. Applying this to the box model, emission costs are distributed to the nearby cells in such a way that the factors add up to one. The generated distribution factors from the Gaussian distribution function with a variance of 1 divided by the cell length give the average cost factor in the receptor cell, depending on the distance between source and receptor cell. To keep computational time within reasonable limits only cells within a maximal distance of four are considered. For cells further away the distribution factor values fall below 0.0001. This yields a discrete distribution of emission costs into 25 cells (see Fig. 1).

0.000 €	0.000 €	0.000 €	0.002 €	0.000 €	0.000 €	0.000 €
0.000 €	0.000 €	0.002 €	0.029 €	0.002 €	0.000 €	0.000 €
0.000 €	0.002 €	0.029 €	0.132 €	0.029 €	0.002 €	0.000 €
0.002 €	0.029 €	0.132 €	0.216 €	0.132 €	0.029 €	0.002 €
0.000 €	0.002 €	0.029 €	0.132 €	0.029 €	0.002 €	0.000 €
0.000 €	0.000 €	0.002 €	0.029 €	0.002 €	0.000 €	0.000 €
0.000 €	0.000 €	0.000 €	0.002 €	0.000 €	0.000 €	0.000 €

Figure 1: Distribution of 1 EUR of emission costs emitted in the center cell marked with grey background color). Cells beyond the shown area are assumed to ave a distribution factor of 0.000.

2.4 Population Exposure

Emission exposure depends on the number of persons experiencing a certain concentration level for a certain period of time. Dispersed emission (cost) levels are, thus, multiplied by a factor which represents the respective local population exposure times. To calculate these required exposure times, the simulation time is split into isochronous one hour time bins. For each of these bins the amount of time spent by the agents is recoded for each grid cell. The result is a three dimensional data structure consisting of time bin, horizontal and vertical position, and the aggregated durations of agent's presence in the cell (in person seconds Ps).

To give an example: Consider an area with 160 times 120 cells and time bins that correspond to full hours. If an agent arrives at a location in cell (25,32) at 8:30 and leaves at 10:15, then 1800 Ps are added to the array at ($x = 25$, $y = 32$, $time =$ 8:00–9:00), another 3600 Ps are added to ($x = 25$, $y = 32$, $time =$ 9:00–10:00), and 900 Ps are added to ($x = 25$, $y = 32$, $time =$ 10:00–11:00).

In the next step, emission (cost) levels after dispersion in every cell (see Sec. 2.3) are multiplied by the aggregated Ps in the corresponding cell. This gives a product of exposure times and emission (cost) levels for each grid cell and each time bin. For illustration purposes, consider 2 g of SO_2 emitted in a cell at 9:15. Also consider that 15 people are present in a neighboring cell from 9:00 to 10:00. This neighboring cell has $15 \cdot 3600$ aggregated Ps of time spent from 9:00 to 10:00. Following the dispersion approach from

Sec. 2.3, $0.132 \cdot 2g$ are dispersed to the considered cell with the 15 agents. This yields $15P \cdot 3600s \cdot 0.132 \cdot 2g = 14256gPs$ of experienced exposure.

Please note at this point, that the approach presented in this paper does not distribute emission levels, but already monetized emissions in EUR.[3] This simplification assumes (i) that all pollutants are dispersed in the same manner, (ii) that the external effects of all pollutants depend on the population density in the same way, and (iii) that the average cost factors from Sec. 2.2 are correct for the average exposure time in the scenario. That is, for the illustration from above and an assumed average exposure time over all cells of 5000 Ps between 9:00 and 10:00, the cell with the 15 agents yields external exposure costs of

$$\frac{14256gPs}{5000Ps} \cdot 0.011\frac{\text{EUR}}{g} = 0.00319572 \text{ EUR} \tag{3}$$

Actual exposure times of each cell are calculated for every time bin. The correction factor of $\frac{1}{5000Ps}$ scales the actual exposure time of the cell to the average exposure time of all cells, which is calculated in every iteration of the simulation. The ratio between actual exposure times and average exposure time is non-negative and the average of all ratios is adds up to one. This highlights the design of the exposure calculation: it is computed in such way that a uniform distribution of the actual exposure times over all cells would result in equality between the sum of *marginal* external emission costs and the sum of emissions multiplied by the *average* emission costs values from Sec. 2.2.

3 Experiments

This sections introduces the first two experiments where the the new emission exposure model is applied. First, a test scenario is set up for calculating a marginal emission exposure toll, and analyzing the behavioral reactions of agents. Second, the emission cost differences for two policy cases in Kickhöfer and Nagel (2013) are recalculated with respect to emission exposure.

3.1 Test Scenario

Kickhöfer and Nagel (2013) implemented an approach to calculate high-resolution air pollution tolls and priced all agents with their marginal emission costs with respect to congestion levels and vehicle attributes. However, the calculated tolls did not reflect marginal costs with respect to damage to human health, i.e. population exposure. To extend the approach by Kickhöfer and Nagel (2013) by the new method of of calculating emission exposure, a small test scenario is set up in order to investigate the plausibility and correctness of the new approach.

The simulation setup consists of one *active agent* with one plan, a simple network and 36 *inactive agents* (see Fig. 2). The active agent's plan is to leave the home location A at 8:00 a.m. to drive to the work location B and to go back at 4:00 pm. Typical durations for 'home' is set to 12 h, and for work to 8 h. The is no opening or closing time restriction for either activity. The network allows two different routes from A to B, both described by the same link parameters. However, the area around the southern route is populated by the inactive agents.

[3] This is done because of computational performance reasons.

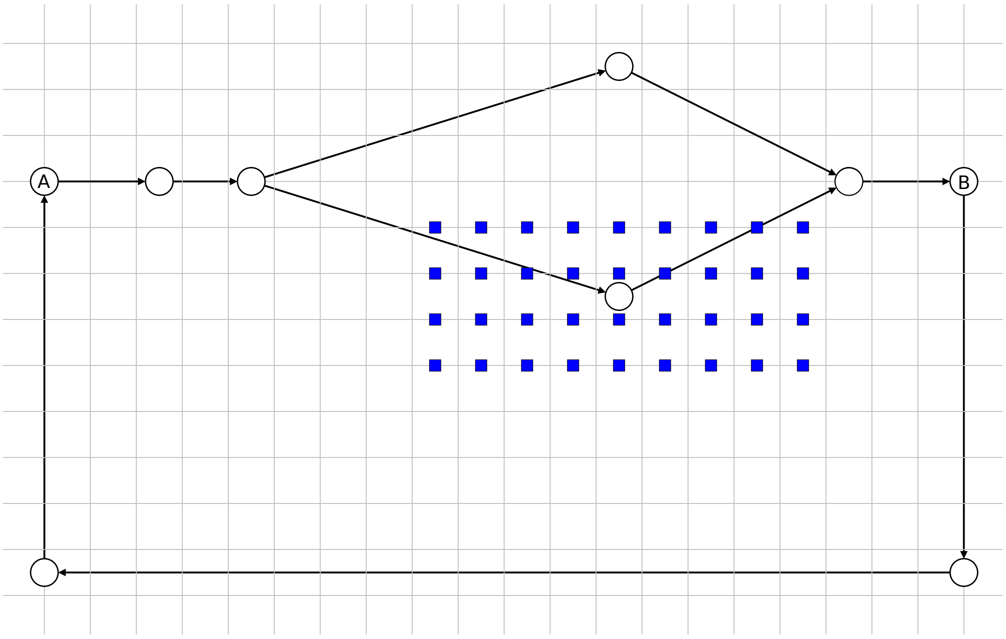


Figure 2: One agent drives from home location A to work location B and back to A. Both routes have the same length and travel time. The links of the network are one-way roads allowing the agent to choose one route for the work trip but leaving no choice for the way back home. The blue boxes depict the inactive agents' locations. Grey lines mark the boundaries of each cell.

For the first iteration in the simulation, the agent is expected to choose one of the routes randomly since both routes are equal in terms of generalized prices. At this point, no exposure times are calculated for the routing. It does therefore not depend on the expected emission costs. The active agent is forced to re-route in every iteration and to store the route with the according score in his memory. The score of the executed plan containing the specified route is calculated at the end of the respective iteration, following the standard MATSim scoring function (see Eq. 1). The travel related part $V_{tr,i}$ is in this paper as follows:[4]

$$V_{tr,i} = \beta_{tr} \cdot t_i + \beta_c \cdot c_i \tag{4}$$

where t_i is the travel time of a trip to activity i and c_i is the monetary cost corresponding to the individual emission exposure toll. After ten iterations the agent is only allowed to switch between his existing plans.

Running the test scenario yields the expected results: The agent generates five plans which include the northern route and another five plans with the southern route. The score of the plans containing the southern route is 130.21 *utils*, the score of the plans containing the northern route is 137.85 *utils*. This implies exposure emission costs on the southern route of 7.64 *utils* (here $utils = EUR$). Thus, the agent finally chooses the northern route to go to work. In consequence, the plausibility test can be regarded as successful: Emission exposure costs influence the decision making of the agent during the simulation.

[4] The behavioral parameters are the standard parameters from Charypar and Nagel (2005): $\beta_{tr} = -6.00\ utils/h$, and $\beta_c = -1.00\ utils/EUR$, and $\beta_{perf} = +6.00\ utils/h$.

3.2 Munich

In the following, simulation output of Kickhöfer and Nagel (2013) is used in order to quantify the impact of the emission exposure cost calculation on the reduction of external emission costs *given* the behavioral reactions of the agents to two policy measures:[5] (i) a speed limitation in the inner city of Munich to 30 km/h (Zone 30), and (ii) a high-resolution exhaust emission toll on the complete network (Internalization).

In order to recalculate the resulting external emission costs for the two cases from above, the area of Munich is partitioned into 19'200 cells. The area measures approximately 40 km in west-east direction and 30 km in north-south direction. Dividing the horizontal distance into 160 and the vertical distance into 120 segments yields almost quadratic cells with a cell length of 250 m.

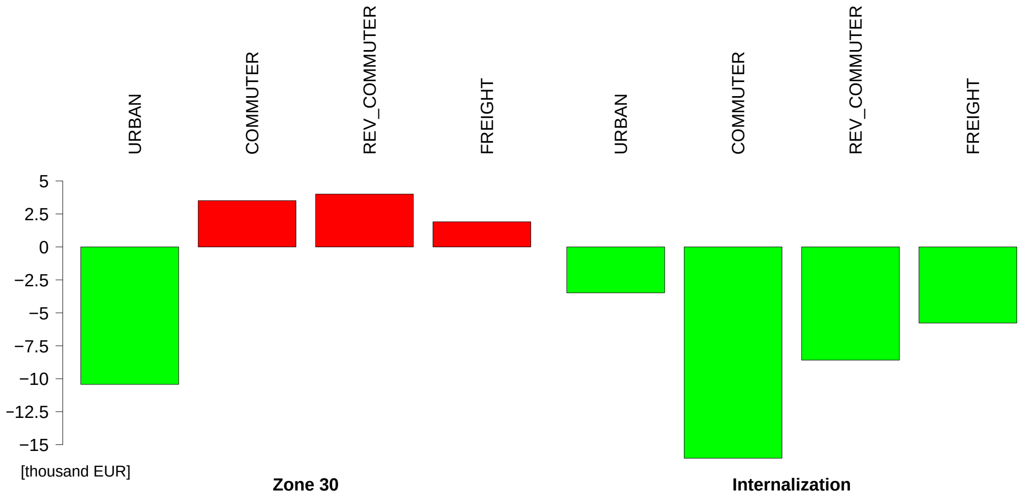
Fig. 3 compares changes in external emission costs between the regulatory Zone 30 policy and the Internalization approach. Fig. 3(a) is taken from Kickhöfer and Nagel (2013), and shows this comparison when monetizing the absolute emission differences with the average cost factors from Sec. 2.2. For the Zone 30, emission costs for society even increase due to higher emissions levels by commuters, reverse commuters and freight. Only the behavior of urban travelers mitigates emission costs. Compared to the Internalization policy, their emission level is even reduced beyond the economic optimum. For the Internalization policy, all user groups contribute to a reduction in emission costs by changing their route and/or mode choice behavior (the latter was not allowed for freight transport).

Fig. 3(b) shows the same comparison for the emission exposure approach developed in this paper. Intuitively, both policies lead for urban travelers to a more important reduction of external emission costs when considering population exposure: their car trips simply affect more individuals and therefore the change to another transport mode has a huge impact on emission exposure. Interestingly, for the Zone 30, commuters and freight now also reduce emission costs despite the higher emission levels that they produce due to re-route effects around the zone. That is, overall emissions increase for these user groups, but they are emitted in less populated areas. The latter effect on emission costs dominates the first. The Internalization policy on the right now yields a less prominent reduction in emission costs for commuters, reverse commuters, and freight. This is due to the fact that their car trips generally affect less people since they drive outside of build-up areas for long distances. That is, the Internalization policy has less impact on the reduction of emission costs when considering emission exposure. However, to re-iterate: The toll level, and therefore the behavioral model, did not include emission exposure. For this reason, it seems necessary to run the Internalization policy again with the corrected individual toll levels.

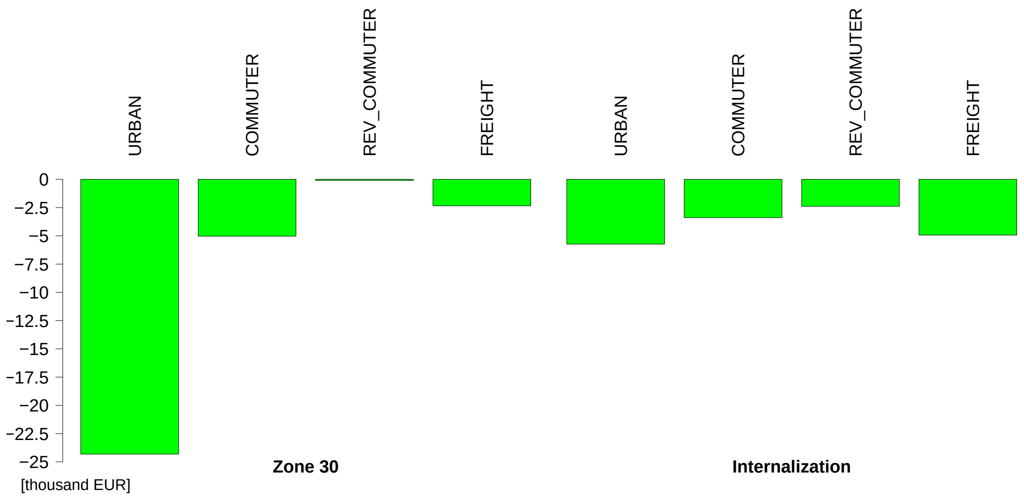
4 Conclusion

This paper proposed a new simplistic approach to calculate local air pollution exposure in large-scale urban settings by taking the exposure time derived from the agent-based transport simulation MATSim into consideration. The approach is characterized by little

[5] Please note, that the behavioral reactions of agents to the policy measures do not take the newly developed exposure toll into account. This would require new simulation runs similar to those in Sec. 3.1. The focus here is rather the recalculation of the resulting external emission costs.



(a) Kickhöfer and Nagel (2013)



(b) Emission exposure approach

Figure 3: Absolute changes in external emission costs by subpopulation.

data requirements, reasonable computation times, and open-source compatibility. For emission modeling, the MATSim-HBEFA tool developed by Hülsmann et al. (2011) was used which calculates warm and cold-start exhaust emissions every time a traveler leaves a road segment. Emission values were monetized using average cost factors from Maibach et al. (2008). Subsequently, the resulting costs were dispersed by a simple Gaussian distribution function applied to discrete cells, and exposure times of affected agents were calculated. Finally, the resulting exposure costs were calculated by scaling the actual exposure times in every cell with the average exposure time of the scenario. Hence, the approach considers population density in the external cost calculations.

The main advantage of the presented approach is that average cost factors can be used to derive marginal emission costs and map these back to the responsible person. Additionally, there is no need for expensive emission concentration calculations. However, the idea is based on the assumptions that all pollutants are dispersed in the same manner, that the external effects depend on the population density in the same way, and that the average cost factors from the literature are correct for the average exposure time in the scenario.

The implementation was then tested in a simple test scenario where a marginal exposure toll was calculated. It was proven that the implementation influences route choice behavior of agents in the expected way. In order to show the applicability for large-scale real-world scenarios, the approach was then used to recalculate emission cost differences for two policy cases from Kickhöfer and Nagel (2013) who internalized emissions directly with average cost factors without accounting for population exposure. The comparison showed that the higher emission levels resulting from the speed limitation in the inner city are not any more reflected by higher emission costs for society. That is, despite higher emission levels are overcompensated by the effect of less affected individuals. The Internalization policy from Kickhöfer and Nagel (2013) now yields a less prominent reduction in emission costs, urban travelers being an exception. That is, the Internalization policy has less impact on the reduction of emission costs when considering emission exposure. However, for future studies, the toll calculation of the test scenario needs to be applied to the large-scale scenario in order to see the correct behavioral reactions to such a toll. Until then, the figures presented in this paper remain preliminary.

Overall, it can be stated that the emission exposure calculation proposed in this paper improves the evaluation of policies that aim at reducing environmental costs in urban settings. The eventual goal is to combine the exposure toll with the internalization of other external costs, such as congestion or noise.

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