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Air pollution hotspots in urban areas – How effective are pricing strategies to comply with the EU limits for NO_2?

Friederike Hülsmann, Benjamin Kickhöfer, Regine Gerike

1 Introduction

When discussing sustainable mobility, one core element is the conservation of natural resources to keep the environment livable for present and future generations. Packages of measures are needed for achieving this ambitious goal (Gehlert et al., 2011; Gerike et al., 2008). These packages combine highly effective measures with low acceptance such as pricing measures and driving bans for trucks and less effective measures with high acceptance such as information and improvements in the transport supply of environmental friendly modes. Significant reductions in the environmental impacts can be achieved with this approach while at the same time getting the acceptance that is the vital pre-condition for the successful implementation of any strategy.

Air pollutant concentration is one of the most important environmental effects of transportation. This topic is constantly under discussion in the European Union (EU) as many cities do not meet the limit values set in the Directive 2008/50/EC on ambient air quality and cleaner air for Europe. High air pollutant concentrations lead to negative effects on human health and the environment (Bickel and Friedrich, 2005). This chapter focuses on pricing measures as a possible strategy for achieving the needed reductions in air pollutant concentrations. However, it should be considered that a pricing measure can only be implemented if it is embedded in a package of strategies to be sustainably effective. By extending a policy sensitive approach of transport and emission modeling by an *air quality module*, this chapter studies the effects of a link-based emission toll on local nitrogen dioxide (NO_2) concentrations in Munich, Germany. The analysis is conducted for NO_2 as it still exceeds the EU limit values in some streets, e.g. along the street “Landshuter Allee” (LFU, 2012). The toll is introduced on all links that are identified as hotspots in a predefined study area. Starting from an emission toll based on emission cost factors provided by Maibach et al. (2008), it is analyzed (i) by how much these cost factors have to be increased to remove a significant number of hotspots, (ii) what the effects on other locations within the study area and on the entire city of Munich are and (iii) whether a link-based emission toll is an effective measure to achieve the limit value for NO_2 concentrations.

The identification of hotspots based on measurements is difficult as only few measurement stations exist in many cities. In the past years, their number has even been reduced mainly for economic reasons. In order to decrease NO_2 concentrations by designing appropriate policies, all hotspots within a city need to be identified. The presented policy sensitive analysis is based on an integrated approach considering the complex interactions between individuals and the environment: the interaction between individual travelers in response to a policy, the impact of changes in travel behavior on NO_2 emissions and concentrations, which vary in time and depend on atmospheric conditions and location. As a result, the presented approach is able to identify all relevant hotspots along every street canyon for different policy scenarios.

In the field of traffic-related emission modeling, different approaches were developed in order to link travel behavior with emission calculations: macroscopic transport models are designed for large scale scenarios and often use MOVES[1], COPERT[2] or

[1] Motor Vehicle Emission Simulator, see www.epa.gov/otaq/models/moves/index.htm.
[2] Computer Program to calculate Emissions from Road Transport, see www.eea.europa.eu/publications/copert-4-2014-estimating-emissions.

aggregated forms of HBEFA[3] as emission models (EPA, 2012, Samaras und Zierock, 2009, INFRAS, 2010). Microscopic traffic flow simulations are suitable for the analysis of a small study area. The emission calculation is often based on detailed models such as VERSIT+[4] or PHEM[5] (Smit et al., 2006, Zallinger et al., 2010). In Hülsmann et al. (2011) and Kickhöfer et al. (2012, in press), the mesoscopic transport model MATSim is linked to the detailed database of HBEFA. This approach combines both, large scale scenarios and detailed emission calculation; it is used in this chapter as input for the NO_2 concentration calculations.

The diversity of air quality models which can be applied to local and urban case studies is large. Typically there are, on the one hand, microscopic models which simulate the dispersion processes in detail with a high spatial resolution, e.g. a few street segments, but they come along with long simulation times. On the other hand, there are urban dispersion models that simulate dispersion processes for an entire urban area, but with a low spatial resolution compared to microscopic approaches (Holmes und Morawska, 2006). One example is the regional and urban dispersion model CALPUFF[6] which is applied by Hatzopoulou and Miller (2010). They use MATSim[7] for the simulation of traffic flows and generate emissions per street segment which are processed in the dispersion model, CALPUFF. The necessary spatial resolution to examine air pollutant concentrations along single street canyons is, however, too low. Street canyon modeling is often based on semi-parametric approaches that can be applied locally. Two examples are the CPBM[8] and the OSPM[9]. In contrast to microscopic models, this approach is not able to consider complex building structures and intersections as well

[3] Handbook on Emission Factors for Road Transport, see www.hbefa.net.
[4] State-of-the art emission model, see www.tno.nl/downloads/lowres_TNO_VERSIT.pdf.
[5] Passenger car and Heavy duty Emission Model.
[6] Advanced non steady-state meteorological and air quality modeling system, see http://www.src.com/calpuff/calpuff1.htm.
[7] Multi-Agent Transport Simulation, see www.matsim.org.
[8] Canyon Plume Box Model.
[9] Operational Street Pollution Model, see http://ospm.dmu.dk/.

as it simplifies the dispersion processes by empirically determined constants. On the contrary, it shows shorter simulation times, less uncertainties and has often been well validated. In order to identify the model, which is appropriate for a specific case study, accuracy and availability of the input data are fundamental preconditions (Vardoulakis et al., 2003).

The remainder of the present chapter is organized as follows: In section 2, the MATSim simulation framework is presented. The framework generates the necessary input for modeling air pollutant emissions and concentrations. Emissions are computed individually based on time-dependent traffic situations and the traveler's vehicle attributes. The main features of the *air quality module* using the output data of the transport simulation and the emission modeling tool are described. This is followed by an explanation of the identification of hotspots and the emission pricing scheme. In section 3, the large-scale real-world scenario of the Munich metropolitan area, the study area for the identification of hotspots and the simulation approach are described. The goal of decreasing NO_2 concentrations and consequently the number of hotspots is addressed by applying policy scenarios with a parametric variation of the external emission cost factors. In section 4, the effects of these price variations on NO_2 concentration at the hotspots are presented and discussed. The paper ends with a conclusion.

2 Methodology

2.1 MATSim[10]

In the following, we only present general ideas about the transport simulation with MATSim. For in-depth information of the simulation framework, please refer to Raney and Nagel (2006) and the Appendix. 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 that 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 selected plans are simultaneously executed in the simulation of the physical system.
3. **Evaluating plans**: All executed plans are evaluated by a utility function which encodes in this chapter the perception of travel time and monetary costs for the available transport modes.
4. **Learning**: 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. In this chapter, agents adapt their routes only for car trips. Furthermore, they can switch between the modes car and public transit (pt). 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. This is why it is also called learning

[10] Since the methodology remains unaltered, this section is taken from Kickhöfer and Nagel (2012).

mechanism (see Appendix). 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"; we just allow the cycle to continue until the outcome is stable.

2.2 Exhaust Emissions[11]

The emission modeling tool essentially calculates warm and cold-start emissions for private cars and heavy goods vehicles.[12] The former are emitted when the vehicle's engine is already warmed whereas the latter occur during the warm-up phase. Warm emissions differ with respect to road type, driving speed, driving dynamics and vehicle characteristics. Cold-start emissions differ with respect to distance traveled, parking time, and vehicle characteristics. For the majority of air pollutants it is found, that during cold-start conditions in comparison to warm engine conditions more emissions are generated. This is largely relevant for NO_2, but some exceptions of vehicle types exist resulting in lower emissions during the first part of trip. The vehicle characteristics are derived from survey data (see section 3.1) and comprise vehicle type, age, cubic capacity and fuel type. They can, therefore, be used for very differentiated emission calculations. Where no detailed information about the vehicle type is available, fleet averages for Germany are used.

In a first step, MATSim driving dynamics are mapped to two traffic situations of the HBEFA database: free flow and stop&go. The handbook provides emission factors differentiated for the characteristics presented above. In a second step, so-called "emission events" are generated and segmented into warm and cold-start emission events. These events provide information about the person, the time, the street segment (= link), and the absolute emitted values by emission type. The definition of emission events follows the MATSim framework that uses events for storing

[11] Since the methodology remains unaltered, most of this section is taken from Kickhöfer and Nagel (2012).
[12] Public transit is in the present paper assumed to run emission free.

disaggregated information as objects in JAVA and as XML in output files (see Appendix). For the calculation of air pollutant concentration, these emission events are summed up per time period and link, resulting in a line emission source with a time resolution of one hour (see section 2.3). Emission events are also accessed during the simulation in order to assign cost factors to emissions; the monetary value of emissions is then used for hotspot pricing (see section 2.4).

2.3 Air pollutant concentration

This section gives a short introduction to the *air quality module*, which is chosen based on the following criteria:

- Air quality modeling should cover a large scale scenario.
- The spatial resolution of air pollutant concentrations should be directly linked to the spatial resolution of the emissions, which are link based.
- Calculation time should be limited to be able to simulate different policy scenarios in a reasonable timeframe.

The OSPM allows for all three criteria. This street canyon model follows a semi-empirical approach, which is based on a parameterization of the most important dispersion processes close to the street including the influence of the traffic-produced turbulence created by movements of the vehicles, the influence of buildings close to the street on dispersion (street canyon effect) and the chemical transformation between nitrogen monoxide (NO) - ozone (O_3) - NO_2. OSPM has been successfully tested and applied in many places worldwide (Kakosimos et al., 2010) and recently evaluated in connection with an GIS-based procedure allowing calculations for a large number of street segments (Ketzel et al., 2012). The model simulates air pollutant concentration at receptor points which can be located along any street segment. They are not located very close to an intersection as dilution processes and additional emissions of the intersecting street cannot be considered. The following data is processed by the *air quality module* developed for the calculation of NO_2 concentration (see also section 3.1):

- number of passenger cars and heavy duty vehicle, vehicle speed
- emissions
- meteorology: wind speed, wind direction, ambient temperature, global solar radiation
- background concentration
- street and building geometry
- receptor points

In a simulation step subsequent to the emission modeling, the information on amount and speed of the vehicles, their emissions and the configuration of the street canyon are passed to OSPM combined with data on wind speed and direction as well as background concentration to determine the pollution concentrations at receptor points at the facade of the buildings. The emissions are aggregated per street cross section because street canyon modeling includes all emissions generated in both directions of a street segment. The OSPM dispersion and chemical processes are transcribed into an *OSPM module* written in JAVA to create an integrated tool that combines the generation of the transport activity, the emissions and air pollutant concentration. For the pollutants, nitrogen oxides (NO_x), carbon monoxide (CO) and particulate matter (PM_{10}), the local contribution from the street is directly proportional to the emission rate. Measured background concentration is added to determine total concentration. Computed total NO_x and measured O_3 background concentration and global radiation are passed to the *OSPM module* on chemical processes to transform NO_x to NO_2 concentrations. For more information about the dispersion and chemical processes of the OSPM see Berkowicz et al. (1997).

2.4 Emission Pricing for "Hotspots"

NO_2 concentrations at each receptor point in the study area (see section 3) are simulated with the integrated approach which has been described in the previous sections. The resulting concentrations are then compared with the EU limit value for annual mean NO_2 concentration of 40 µg/m³ and hourly mean NO_2 concentration of 200 µg/m³ (2008/50/EC). Kickhöfer and Nagel (2012) developed a methodology for the calculation of high-resolution first-best emission tolls with respect to individual vehicle characteristics and time-dependent link-specific traffic situations. The authors price CO_2, NMHC, NO_x, PM, and SO_2 with emission cost factors from Maibach et al. (2008)[13] every time a person produces an emission event, i.e. every time a person leaves a link. For this study, all air pollutant emissions are only priced whenever a person uses one of the links in the network that are defined as hotspots. By applying emission costs to *hotspot links* a direct linkage between polluter and *local* impacts is drawn. In addition, CO_2 costs are not considered. The damage costs of CO_2 emissions appear globally and cannot be attributed to a certain location. In contrast to CO_2, air pollutant concentrations are directly linked to human health of the residents near the hotspot.

Emission type	Cost factor [EUR/ton]
NMHC	1700
NO_x	9600
PM	384500
SO_2	11000

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

[13] Emission cost factors in Maibach et al. (2008) are derived from damage cost approaches.

Following the methodology by Kickhöfer and Nagel (2012), emission events are converted into monetary terms by an *emission cost module* which uses emission cost factors from Table 1 as input. The emission costs for an average passenger car on a local street with a speed limit of 50km/h are 0.75 EURct/km during free flow and 1.87 EURct/km during stop&go. For the evaluation of plans, the monetary equivalent to the emission events is reducing the utility of a traveler if driving on one of the links that were in the base case identified as hotspots. Additionally, the router module, a time-dependent best path algorithm, uses generalized costs (= disutility of traveling) from the last iteration as input for generating new routes for a certain share of agents. In this chapter, generalized costs on hotspots are in addition to travel time and travel costs dependent on individual emission costs which again depend on vehicle characteristics and time-dependent traffic situations. Therefore, the router also has knowledge about this highly disaggregated person-specific information. Outside of hotspots, however, a calculation of the highly differentiated tolls is not necessary which improves the performance of the current setup compared to Kickhöfer and Nagel (2012) enormously (by a factor of 10 for the 1% sample of the scenario described in section 3, since it scales with the number of tolled roads).

3 Scenario

In this section, we first give a short introduction to the large-scale real-world scenario of the Munich metropolitan and the study area as well as the simulation approach, a definition of the available choice dimensions and the utility functions. This is followed by the description of the base and policy cases that aim at reducing the air pollutant concentration for the hotspots under the EU limit values.

3.1 Scenario Setup

Network and Population[14]

The road network consists of 17’888 nodes and 41’942 street segments. It covers the federal state of Bavaria, being more detailed in and around the city of Munich and less detailed further away. Every link is characterized by a maximum speed, a flow capacity, and a number of lanes. This information is stored in the road type which is for the emission calculation always mapped to a corresponding HBEFA road type. In order to obtain a realistic time-dependent travel demand, several data sources have been converted into the MATSim population format. The level of detail of the resulting individual daily plans naturally depends on the information available from either disaggregated stated preference data or aggregated population statistics. Therefore, *three subpopulations* are created, each corresponding to one of the three different data sources:

- Urban population (based on Follmer et al. (2004)): The synthetic population of Munich is created on the base of very detailed survey data provided by the municipality of Munich RSB (2005), named “Mobility in Germany” (MiD 2002). Whole activity chains are taken from the survey data for this population. MiD 2002 also

[14] Since the description of network and population generation remains unaltered, this section is taken from Kickhöfer and Nagel (2012).

provides detailed vehicle information for every household. Linking this data with individuals makes it possible to assign a vehicle to a person's car trip and thus, calculating emissions based on this detailed information. As of now, there is however no vehicle assignment module which models intra-household decision making. It is, therefore, possible that a vehicle is assigned to more than one person at the same time. The synthetic urban population of Munich consists of 1'424'520 individuals.

- Commuter population (based on Böhme and Eigenmüller (2006)): Unfortunately, the detailed data for the municipality of Munich does neither contain information about commuters living outside of Munich and working in Munich nor about people living in Munich and working outside of Munich. The data analyzed by Böhme and Eigenmüller (2006) provides information about workers that are subject to the social insurance contribution with the base year 2004. With this information, a total of 510'150 synthetic commuters are created from which 306'160 people have their place of employment in Munich. All commuters perform a daily plan that only encodes two trips: from their home location to work and back.
- Freight population (based on ITP/BVU (2005)): Commercial traffic is based on a study published on behalf of the German Ministry of Transport by ITP/BVU (2005). It provides origin-destination commodity flows throughout Germany differentiated by mode and ten groups of commodities. After converting flows that are relevant for the study area into flows of trucks, this population consists of 158'860 agents with one single commercial traffic trip.

Overall, the synthetic population now consists of 2'093'530 agents. To speed up computations, a 1% sample is used in the subsequent simulations. For commuters and freight, no detailed vehicle information is available. Emissions are, therefore, calculated based on fleet averages for cars and trucks from HBEFA.

Study Area for Air pollutant concentration

For the identification of hotspots, an area of approximately 3x3 km² is chosen. The area is located around “Maxvorstadt”, a district north of the Munich city centre (see Figure 1). It shows links of different road types, different street orientation and building structure.

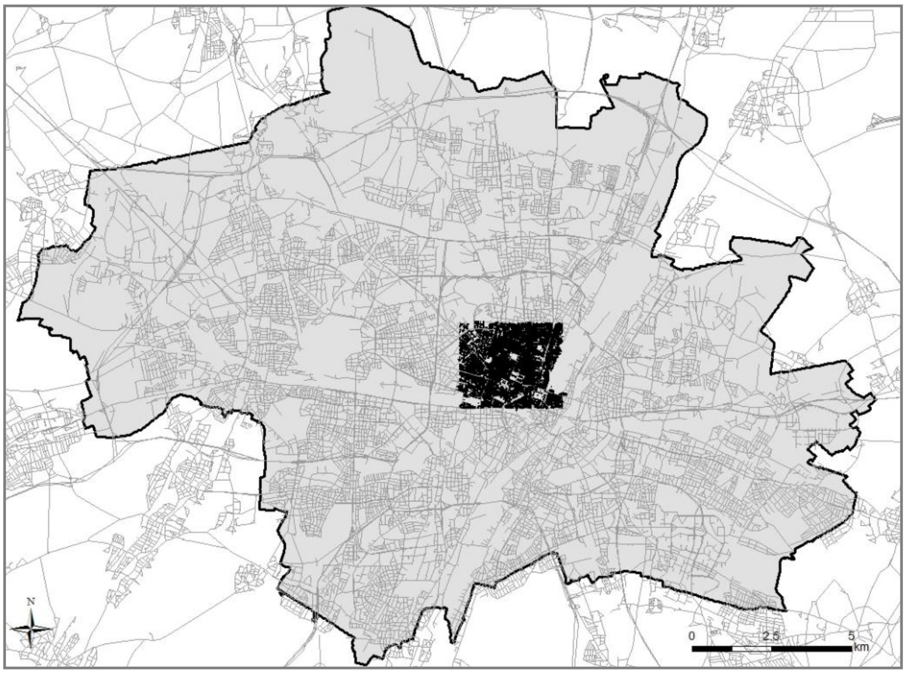

Figure 1: Munich city and study area (black area).

As mentioned above, the *air quality module* combines information of the transport model, the emission modeling tool, the data on street and building geometry and meteorological data. The data on street and building geometry is provided by the municipality of Munich (RGU, 2006). For this chapter, receptor points are placed at the facade of the buildings along street canyons in the study area. Several receptor points are distributed within each street canyon on both sides resulting in a total of 447 receptor points. Intersections and areas with a large proportion of open space are not included as they show more complex dispersion processes, which cannot be captured with this approach. The following attributes are extracted from the given data and used in the *OSPM module*: From the position of a receptor the street orientation, the street width, the building height and all gaps in the building structure including the respective height are calculated. With an extension of ArcGIS, the AirGIS, three shapefiles – street, building and receptor points – are joined and the attributes are calculated (Jensen et al., 2001). An air quality monitoring station, located in the northeast of Munich and operated by the Bavarian Environment Agency, is measuring hourly background concentrations of NO, NO_2 and O_3 (LFU, 2008). In addition, hourly meteorological data including wind speed and direction, temperature and relative humidity are measured at one location in Munich at and by the German meteorological service (DWD, 2008). Data on global radiation are available per month for a grid cell of 1 km (DWD, 2008). All this data is available for the year 2008.

3.2 Simulation

Utility-based Approach

For the mental layer within MATSim, which describes the behavioral learning of agents, a simple utility based approach is used in this chapter. When choosing between different options with respect to a multinomial logit model, agents are allowed to adjust their behavior among two choice dimensions: route choice and mode choice. The former allows individuals to adapt their routes on the road network when going by car. The latter makes it possible to change the transport mode for a sub-tour (see Appendix) within the agent's daily plan. Only a switch from car to public transit or the other way around is possible. Trips that are initially done by any other mode remain fixed within the learning cycle. From a research point of view, this approach can be seen as defining a system where public transit is a placeholder for all substitutes of the car mode. The following utility functions are used for car and public transit, representing the travel related part of utility[15] (see equation (3) in the Appendix):

$$V_{car,i,j} = -0.96 \cdot t_{i,car} - 0.07949 \cdot c_{i,car} \tag{1}$$

$$V_{pt,i,j} = -0.75 - 1.14 \cdot t_{i,pt} - 0.07949 \cdot c_{i,pt}, \tag{2}$$

where t_i is the travel time of a trip to activity *i* and c_i is the corresponding monetary cost. Travel times and monetary costs are mode dependent, indicated by the indices. The utilities $V_{car,i,j}$ and $V_{pt,i,j}$ for person *j* are computed in "utils". Due to a lack of behavioral parameters for the municipality of Munich, these are taken from an Australian study by Tirachini et al. (2012) and adjusted in order to meet the MATSim framework (Kickhöfer and Nagel, 2012).

Simulation Procedure

In each of the first 800 iterations, 15% of the agents are forced to discover new routes, 15% change the transport mode for a car or public transit sub-tour in their daily plan, and 70% switch between their existing plans. Between iteration 801 and 1000, route and mode choice is switched off; in consequence, agents only switch between existing options. The output of iteration 1000 is then used for the identification of hotspots, where all receptor points with a NO_2 concentration higher than EU limits[16] are selected.

It is also used as input for the simulation of the following cases:

- **Base case**: no external cost pricing with unchanged cost structure

[15] Please note that the following formulas include opportunity costs of time β_{perf}; the effective Values of Travel Time Savings (VTTS) are therefore 12.08 EUR/h for car and 14.34 EUR/h for public transit. Additionally, the alternative specific constant for public transit was calibrated in order to replicate the modal split in Munich.

[16] In this chapter, the emissions are simulated for a representative weekday whereas the EU limit value considers concentrations over an entire year including weekdays and the weekend. In order to reduce this discrepancy, the limit value is modified by the following calculation: based on measured NO2 concentrations over the entire focus year the relative difference between NO2 concentrations including every day of the week and weekday concentrations were calculated. With the help of this difference, the limit value was then approximated.

- **Policy cases**: external cost pricing using the methodology from section 2.4. In order to capture the impacts of price changes on hotspots, emission cost factors from table 1 are multiplied by constants of 1.0, 10.0, 20.0, 30.0, 40.0, 100.0 and 200.0[17]; this parametric procedure results in seven different policy cases.

User costs[18] for car are always fixed to 30 EURct/km. For the policy cases, additional costs apply (see above). User costs for public transit are assumed to be constant at 18 EURct/km. All simulations are continued for another 500 iterations. Again, during the first 400 iterations 15% of the agents perform route adaption while another 15% of agents choose between car and public transit for one of their sub-tours. The remaining agents switch between existing plans. For the final 100 iterations only a fixed choice set is available for all agents. When evaluating the impact of the two policy measures, the final iteration 1500 of every policy case is compared to iteration 1500 of the base case.

[17] The highest constant results in emission costs for an average passenger car on a local street with a speed limit of 50km/h of 1.5 EUR/km during free flow and of 3.74 EUR/km during stop&go, according to Maibach et al. (2008).

[18] The term "user costs" is referred to as out-of-pocket costs for the users.

4 Results and discussion

For the base case, 34 hotspots of the 447 receptor points are identified within the study area. They exceed the annual mean NO_2 concentration limit value. The hotspots are mainly located on north-south oriented streets. This is due to the traffic volume, which is generally higher along those axes, and due to the dominating west wind, which leads to a better dilution of air pollution within west-east-oriented street canyons (see Figure 2).

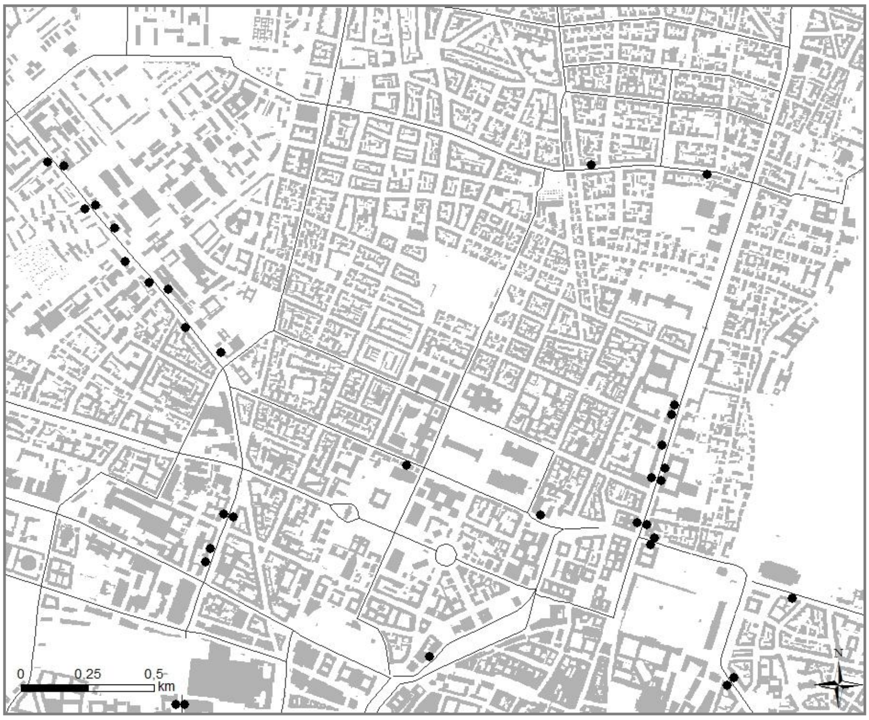

Figure 2: Hotspots in the base case, study area.

The EU limit value of 200 µg/m³ for hourly mean NO_2 concentrations is not exceeded within the study area. This can be explained by several reasons. Emissions are calculated for one representative weekday averaging out any peak emissions that may occur due to certain circumstances such as congestion, accidents. The area shows only a few large street segments, but does not include parts of the middle ring road where exceedances were measured. Therefore, the following discussion refers only to the annual mean NO_2 concentration. Figures 3 and 4 show the expected effect of different emission cost levels on the number of hotspots and on average annual NO_2 concentration: besides a few exceptions, average annual NO_2 concentrations and consequently the number of hotspots decrease with increasing emission costs at the hotspots. Policy case 30[19] shows that the removal of some hotspots can produce new hotspots, which can be mainly explained by an increased choice of routes with no emission costs within the study area to avoid the costly hotspots. However, it should be noted that such an effect can partly result from model related stochastics.

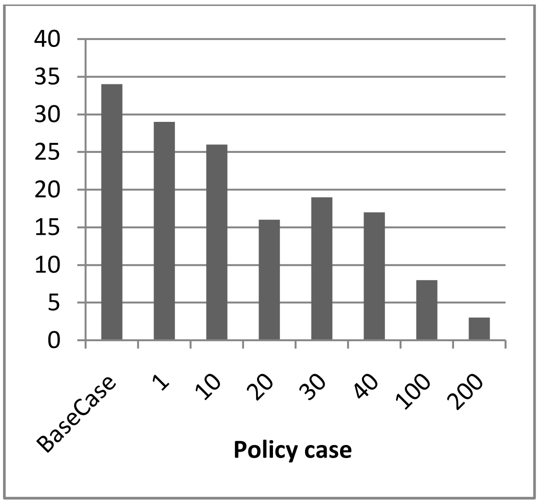

Figure 3: Number of hotspots for each policy scenario.

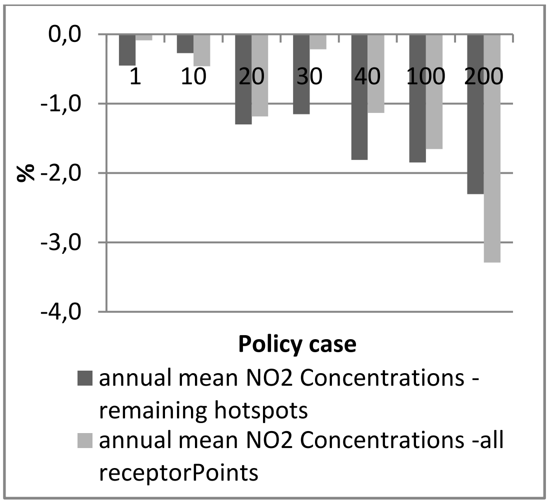

Figure 4: Relative change in annual mean NO_2 concentration between policy and base case for the hotspots and for all receptor points.

The reaction of the users to policy cases 100 and 200 show a significant decrease in the number of hotspots. Comparing the annual mean NO_2 concentration of all remaining hotspots with the concentration at all receptor points captures the impacts of increasing emission costs on the whole study area (see Figure 4). The price increase shows a decreasing trend in NO_2 concentration at both the remaining hotspots and at all receptor points.

[19] A policy case 30 implies a scenario with emissions costs multiplied by a constant of 30.

The effect of different pricing schemes on total NO_2 emissions in the metropolitan area of Munich is presented in Figure 5. Policy cases 20, 30 and 100 show an increase in the emission level compared to the base case which is due to longer car distances travelled. The relatively low emission level of policy cases 1 and 10 can be explained by shorter distances travelled by car and a lower share of car trips in the total number of trips. The fluctuations in the relative change of total NO_2 emissions - travelers shifting from car to pt and back - with increasing costs result presumably from the changes in traffic demand and, therefore, travel time.

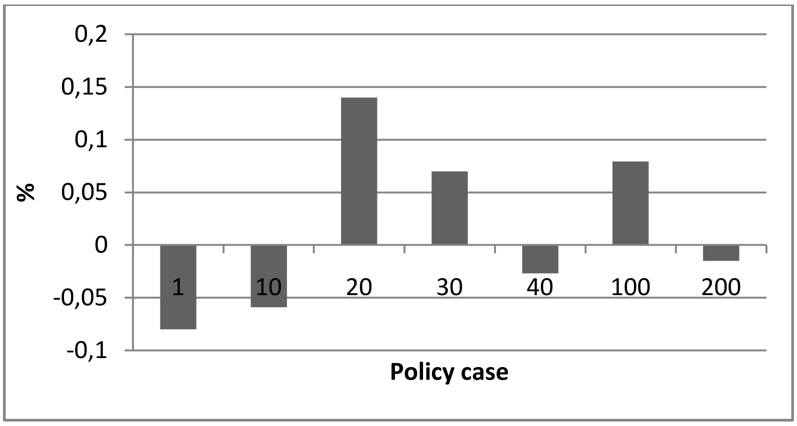

Figure 5: Relative change in total NO_2 emissions for each policy case compared to the base case, Munich metropolitan area.

The most effective policy case 200 removes almost all hotspots, decreases total NO_2 emissions by a small amount, but involves a multiple of the emission costs proposed in the literature. This implies an enormous discrepancy between the two approaches of (i) pricing and (ii) the definition of limit values. Different reasons can be given for the mentioned discrepancy: This study only sets internalization prices on links with a hotspot. The chosen cost factors from Maibach et al. (2008) are intended to be set on the entire network of links. As a result, in the simulation car by travel is in general more attractive than with a full emission cost internalization strategy (see Kickhöfer and Nagel, 2012). Maibach et al. (2008) calculate the emission costs based on the impact pathway approach. This study determines internalization prices based on these emission costs. The impact pathway approach comprises the calculation of air pollutant emissions, the cumulative exposure from the increased concentrations, the damage from this and the monetary valuation (Bickel and Friedrich, 2005). Therefore, the simulated air pollutant concentrations would provide a better basis for the approximation of the actual damage costs to be internalized. This issue will be addressed in future studies.

Another reason for the high emission costs that are needed to eliminate hotspots may be the uncertainty and possibly the underestimation of damage costs in the literature. Health impacts of air pollution are difficult to determine and some effects are likely to be not included in the cost estimation. The exposure response functions are widely derived by epidemiological studies, which reveal several uncertainties, especially for NO_x. Long term studies of exposure to air pollution are time-consuming and costly (Bickel and Friedrich, 2005). Such long term studies, e.g. cohort studies, often identify higher estimates of health impacts than short term studies (Künzli et al., 2001). The exposure response functions give an indication of the health impacts, but the translation to the willingness to pay for clean air is nontrivial. The determination of health and environmental impacts is not only relevant for an effective pricing strategy. Limit values are calculated based on such impacts to avoid, prevent or reduce harmful effects on human health and/or the environment (Directive 2008/50/EC). As any µg of NO_2 will harm human health to some extent[20], limit values can never be too strict if any harm to human health is to be avoided.

[20] Voss, U. and Pfäfflin, F. (2012). Ermittlung und Quantifizierung gesundheitlicher Wirkungen von PM2,5 und NO2, Presentation to the 4. Freiburger Workshop „Luftreinhaltung und Modelle“ – 2012. IVU Umwelt GmbH, Freiburg.

5 Conclusions

This chapter extends a transport and emission modeling approach by an *air quality module.* Applying this integrated approach, pricing strategies are evaluated with respect to their mitigation potential in removing NO_2 hotspots, which show higher concentrations than EU limit values. Overall, it is shown that the effect of increasing emission costs on the number of hotpots shows a decreasing trend. NO_2 concentrations in the study area are reduced and the impact on the entire urban area in terms of total emissions is small. In order to eliminate NO_2 hotspots in an urban context, internalizing prices from the literature need to be multiplied by a large number when only being applied on links that exceed the limit values. Uncertainties remain with respect to the exact cost factor. Having completed the analysis of a singular measure the following can be concluded: A pricing strategy can be effective, but its efficiency may be questioned as user costs increase considerably based on the assumptions of this chapter. The cause and effect relationship between pricing of external effects and compliance with the environmental limit values is complex. This relation needs to be further investigated, e.g. the calculation of external costs based on concentrations and abatement costs or the comparison with a full emission cost internalization strategy.

In order to sustain the effects of an internalization strategy and make it effective in the long term, additional measures need to be in place. An adequate mixture of measures is necessary with the pricing strategy as one effective policy. The current approach allows for the modeling of a package of measures which include driving bans, speed limits, technological changes and others. The integrated modeling approach can be projected on the entire city of Munich and on other cities given the required data are available.

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Appendix[21]

The following paragraphs are meant to present more information about the MATSim simulation approach that is used in this chapter. Every step of the iterative loop in section 2.1 is now illustrated in more detail.

Plans Generation

An agent's daily plan contains information about his planned activity types and locations, about duration and other time constraints of every activity, as well as the mode, route, the desired departure time and the expected travel time of every intervening trip (= leg). Initial plans are usually generated based on microcensus information and/or other surveys. The plan that was reported by an individual is in the first step marked as "selected".

Traffic Flow Simulation

The traffic flow simulation executes all selected plans simultaneously in the physical environment and provides output describing what happened to each individual agent during the execution of its plan. The car traffic flow simulation is implemented as a queue simulation, where each road (= link) is represented as a first-in first-out queue with two restrictions (Gawron, 1998, Cetin et al., 2003): First, each agent has to remain for a certain time on the link, corresponding to the free speed travel time. Second, a link storage capacity is defined which limits the number of agents on the link; if it is filled up, no more agents can enter this link. The public transport simulation simply teleports agents between two activity locations. The distance is defined by a factor of 1.3 times the beeline distance between the locations. Travel speed can be configured and is set in this chapter to 25 km/h. Public transit is assumed to run continuously and

[21] Since the methodology remains unaltered, this section is taken from Kickhöfer and Nagel (2012).

without capacity restrictions (Grether et al., 2009, Rieser et al., 2009). All other modes are modeled similar to public transport: travel times are calculated based on mode specific travel speed and the distance estimated for public transport. However, the attributes of these modes are not relevant for this chapter since agents are only allowed to switch from car to public transport and the other way around. Trips from the survey that are not car or public transport trips, remain fixed during the learning cycle. Output of the traffic flow simulation is a list that describes for every agent different events, e.g. entering or leaving a link, arriving or leaving an activity. These events are written in XML-format and include agent ID, time and location (link or node ID). It is, therefore, quite straightforward to use this disaggregated information for the calculation of link travel times or costs (which is used by the router module), trip travel times, trip lengths, and many more.

Evaluating Plans

In order to compare plans, it is necessary to assign a quantitative measure to the performance of each plan. In this work, a simple utility-based approach is used. The elements of our approach are as follows:

- The total utility of a plan is computed as the sum of individual contributions:

$$V_p = \sum_{i=1}^{n} \left(V_{perf,i} + V_{tr,i} \right), \quad (3)$$

  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.

- A logarithmic form is used for the positive utility earned by performing an activity (see e.g. Charypar and Nagel, 2005, Kickhöfer et al., 2011):

$$V_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln\left(\frac{t_{perf,i}}{t_{0,i}}\right) \tag{4}$$

  where t_{perf} is the actual performed duration of the activity, $t_{*,i}$ is the "typical" duration of activity *i*, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is the same for all activities, since in equilibrium all activities at their typical duration need to have the same marginal utility. $t_{0,i}$ is a scaling parameter that is related both to the minimum duration and to the importance of an activity. As long as dropping activities from the plan is not allowed, $t_{0,i}$ has essentially no effect.

- The disutility of traveling used for simulations is taken from Tirachini et al. (2012). More details are given in section 3.2.

In principle, arriving early or late could also be punished. For this chapter, there is, however, no need to do so, since agents are not allowed to reschedule their day by changing departure times. Arriving early is already implicitly punished by foregoing the reward that could be accumulated by doing an activity instead (opportunity cost). In consequence, the effective (dis)utility of waiting is already $-\beta_{perf}\, t_{*,i} / t_{perf,i} \approx -\beta_{perf}$. Similarly, this opportunity cost has to be added to the time spent traveling.

Learning

After evaluating daily plans in every iteration, a certain number of randomly chosen agents is forced to re-plan their day for the next iteration. This learning process is, in this chapter, done by two modules corresponding to the two choice dimension available: a module called *router* for choosing new routes on the road network and a module called *sub-tour mode choice* for choosing a new transport mode for a car or public transport trip. The router module bases its decision for new routes on the output of the car traffic flow simulation and the knowledge of congestion in the network. In the policy cases, it also uses the knowledge about expected emission costs on hotspots (see section 2.4). The router is implemented as a time-dependent best path algorithm Lefebvre and Balmer (2007), using generalized costs (= disutility of traveling) as input. The sub-tour mode choice module changes the transport mode of a car sub-tour to public transport or from a public transport sub-tour to car. A sub-tour is basically a sequence of trips between activity locations. However, the simulation needs to make sure that a car can only be used if it is parked at the current activity location. Thus, a sub-tour is defined as a sequence of trips where the transport mode can be changed while still being consistent with the rest of the trips. It is e.g. assured that a car which is used to go from home to work in the morning needs to be back at the home location in the evening. If the car remains e.g. at the work location in order to use it to go for lunch, then the whole sub-tour of going to work and back needs to be changed to public transport.