OPTIMIZING PARKING PRICES USING AN AGENT BASED APPROACH

Rashid A. Waraich (corresponding author)
Institute for Transport Planning and Systems (IVT)
ETH Zurich, CH-8093 Zurich, Switzerland
phone: +41-44-633 32 79
fax: +41-44-633 10 57
waraich@ivt.baug.ethz.ch

Christoph Dobler
Institute for Transport Planning and Systems (IVT)
ETH Zurich, CH-8093 Zurich, Switzerland
phone: +41-44-633 65 29
fax: +41-44-633 10 57
christoph.dobler@ivt.baug.ethz.ch

Claude Weis
Institute for Transport Planning and Systems (IVT)
ETH Zurich, CH-8093 Zurich, Switzerland
phone: +41-44-633 39 52
fax: +41-44-633 10 57
claude.weis@ivt.baug.ethz.ch

Kay W. Axhausen
Institute for Transport Planning and Systems (IVT)
ETH Zurich, CH-8093 Zurich, Switzerland
phone: +41-44-633 39 43
fax: +41-44-633 10 57
axhausen@ivt.baug.ethz.ch

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ABSTRACT

Many cities around the globe are haunted by limited supply of parking and inefficient fee schedules, which often result in additional traffic by people cruising for parking. Pricing parking in an optimal way both from the municipality’s and user’s perspective in order to balance demand and supply is essential to solve this problem. We propose an agent-based approach to iteratively find such an optimal parking price. A major innovation of our parking model is, that it takes taste heterogeneity of drivers into account. By applying the model to a test scenario in the city of Zurich, we successfully demonstrate, that the model provides key figures, which are essential for supporting decision of policy makers. The paper also discusses some future work, e.g. other applications of the model in the area of parking choice and parking search modeling.
INTRODUCTION

Based on studies conducted in several cities around the globe, it has been estimated that on average one third of city centre traffic is contributed by parking search traffic (1). A main reason for cruising for parking is obviously that parking demand is exceeding its supply. A major instrument that policy makers have to balance supply and demand is adjusting parking price. But the question is, how to get the price for parking right?

Pricing parking correctly is not a new problem: Vickrey suggested already in 1954, that parking should be priced in a way, so that always a parking place is available for those willing to pay for it – he suggested 15% free parking at all times (corresponding to a couple of free parking spaces per block). Furthermore he argued, that there should be no minimal price for parking - if even at price zero a 85% occupancy cannot be reached, parking should be offered for free (2). Shoup developed the ideas of Vickrey further and suggested, that finding the optimal parking price can be solved incrementally by increasing/decreasing the parking price for curb parking, until around 85% parking are occupied at all times (if possible), with possibly different price level at different times of the day (3,4,5).

Exactly such a system has been implemented in 2010 in parts of San Francisco, called SFpark (6), where parking sensors have been installed on 8'200 on street parking spaces. By using parking occupancy data from these sensors the parking rates are adjusted no more than once per month. These rate adjustments are very small, like $0.25 to $0.50 per hour and are also applied to city-owned garages, where often many empty spaces are available. The parking price also varies over the day and between week days and weekends.

Although the SFpark experiment seems to achieve the desired effects in some areas of the city, also some unexpected effects have been observed on some roads, e.g. rising demand with rising prices and falling demand with falling prices (7).

In order to investigate possible effects of such “parking price optimization” in other cities, we describe a parking model in the next section which we use to simulate an application of Shoup’s approach to the city of Zurich. This application demonstrates, that the presented model is able to capture relevant aspects of the problem at hand. After a brief discussion including future work we draw some conclusions.

THE PARKING MODEL

The parking model presented in this paper extends previous work by the authors with regards to agent based modeling of parking choice (8). In (9), a combined parking choice and search model was described, which has been implemented now. In the following, we only present the relevant parts of model for its application within the parking price optimization context.

We have integrated our parking model into the agent based traffic simulation MATSim (10). Figure 1 shows MATSim’s iteration process: Each person in MATSim is modeled as an agent, which has a daily plan of trips and activities, such as going to work, school or shopping. Furthermore each agent has several modes of travel available in order to travel between activity locations, such as car, walk, public transit and bike. MATSim is uses an iterative process, which is based on a co-evolutionary algorithm (11). The iterations start with an initial plan for each agent and the goal of the process is to find an optimal plan for all agents simultaneously. The first step in each iteration is the traffic simulation: The plans of all agents are executed by a micro-simulation, resulting in traffic flow along network links. After this simulation, the execution of the agent’s plan is scored and assigned a utility. For example a person with lower travel time has a higher utility than one, which has a longer
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travel time because of being caught in a traffic jam. Furthermore performing activities, e.g. being at work increases the utility. The goal of each agent is to maximize the utility of its daily plan. During the replanning step, the agent can reselect or adapt a previously executed plan and select it for execution in the next iteration. Plans with a higher utility score have a higher chance of reselection, while plans with bad scores are deleted over time, as only a limited number of plans per agent is kept. This corresponds to the survival of the fittest in a co-evolutionary algorithm. The replanning algorithm has several degrees of freedom, such as changing routes, working time, travel mode or location choice of agents. The execution of all plans, its scoring and replanning is called an iteration. This iterative process approaches a point of rest corresponding to a user equilibrium, called relaxed demand. More details about the conceptual framework and the optimization process of the MATSim toolkit can be found in (10).

![Co-evolutionary simulation process of MATSim](image)

**Figure 1: Co-evolutionary simulation process of MATSim, Source: (12)**

**Utility Function**

An explicit utility function of parking is important for several reasons in our context, although some other agent-based parking models do not use one, e.g. (13): First the parking utility function is needed for comparing different parking places (price, location, price schedule, etc.) to each other. Secondly, the utility function allows the use of personalized taste parameters, which are estimated, e.g. from stated or revealed choice observations. This is clearly important, as people do not only value different components of the parking differently, e.g. search time, walk time and parking cost (14,15), but clearly when it comes to parking policy also the reaction of people is not homogeneous (16). A third reason for using a utility function within the MATSim traffic simulation context is that the parking decision of the agent should influence its other decisions.

The utility function for a specific parking choice for agent $i$ is formulated as in equation (1), where the individual preference of the agent with regards to parking cost, search time and walk time are considered. The $\epsilon_i$ is the random error term.

$$U_{parking,i} = U_{cost,i} + U_{searchTime,i} + U_{walk,i} + \epsilon_i \quad (1)$$

Now, when the agent selects a parking space, its utility is added to the overall utility function in MATSim, which now looks like (2):

$$U_{plan,i} = \sum U_{travelTime,i} + U_{travelCost,i} + U_{performActivity,i} \cdots + \sum U_{parking,i} \quad (2)$$

By doing this, the parking choice impacts the overall utility of the agent and therefore impacts its future choices. E.g. an agent, which gets a bad parking utility score at a certain destination, might change the travel mode for reaching that activity location or even change the activity location, if it is a secondary location, such as shopping.

**Parking Selection**
In order to model the individual selection of parking, we tried to mimic the SFpark scenario. In that scenario, the parking prices can be different per block and based on the time of day. Furthermore, the price can change monthly. It is clear that having lots of different prices on neighboring roads and varying over the day is quite complex. Therefore, it seems reasonable that people don’t search for parking, but instead choose among free parking, e.g., on their mobile device, while taking their preference with regards to walking distance and price tag into account. We have implemented this behavior, i.e., search for parking by smartphone into the agents. The agents have all the information available on free parking at their arrival time together with cost associated with parking, which can depend on the parking duration. Based on this information, the agent assigns a utility to each of the public parking spaces in the surrounding of the destination using its utility function and selects the free space, which gives it the highest utility score. This means, the agent is just trading off between walking distance and parking cost.

**Parking Fee Adaptation**

In order to simulate the change in parking fee and the reaction of agents to this change, two approaches seem possible. The first one would be to run the traffic simulation and let it relax and then change the parking fee before running the traffic simulation again (and repeating this over and over again, until the parking fee convergences). The second approach is to change the price after each iteration. The first approach is slower than the second one. But the second approach has to be applied with care, in order not to put too much change into the system, so that it cannot relax.

We use the second method, because although the parking choices of agents change, due to the price change in each iteration, this does not have a profound impact on the overall simulation: This does only change traffic pattern close to the destination and impact the parking score. But the change in parking score due to the small parking fee adaptation is not so large, as the simulations show.

**SIMULATIONS**

In order to test our model, we use an existing MATSim implementation of Zurich (8,17) as a starting point. As we are only interested in the city of Zurich for our test experiment, only such agents are part of the simulation which reside or travel within a 8 km radius around a central place in Zurich. As this study does not focus on travel patterns or search related traffic changes, a planning road network of Switzerland with around 60’000 links is used, instead of using a high resolution network. For the initial tests presented here, instead of using a 100% population sample, only a 10% population sample is used for the simulation with around 72’000 agents. In order to account for the population sampling, also the link flow capacities in the network and the parking capacities are adapted to match the population sample size. Although such population sampling may lead to artifacts due to the scaling in the network and especially the parking capacities, for the presented initial experiments such loss in quality is not deemed critical.

The travel modes available in the simulation are car, walk, bike, and public transit. But from these only the car mode is micro-simulated along the roads. The travel times for the other modes are based on simpler models, such as average speed for bike and walk and a fixed travel time matrix for public transport. From iteration to iteration the agents can change travel mode, departure time, activity duration and route. 100 iterations were performed for each simulation, as the demand was then relaxed, as indicated by the small plan changes resp. score difference between best and worst plan.

**Agent’s Preferences**
The household income distribution of agents is based on the census data from the canton of Zurich (18). For modeling the agent’s preferences, response from a previous stated choice survey was used (19). In that survey 1’200 respondents from Switzerland were asked questions to estimate a model for the influence of parking on location and mode choice. Based on that survey, discrete choice models were estimated to determine the respondents’ taste heterogeneity in assessing the various attributes relating to parking (cost, search and walk times). The parameters were estimated using a formulation similar to the one used by (20). Interactions were estimated for income, age, gender and activity duration. The estimated parameters were all significant, and are thus used in the parking utility function of the agents.

**Zurich Parking Supply Data**

For the simulations we use detailed data about parking supply in the city of Zurich. This includes 50’000 on-street parking spaces and over 16’000 parking spaces in more than 100 garage parking around the city. In Zurich there are over 200’000 private parking spaces (in and outside of buildings). These are assigned to buildings and activities in the model. For example, a building might have parking assigned to it which is reserved for a specific purpose, e.g. some parking might be only used by residents and others only by offices or shops, which are located in the same building. For a more detailed description of the private parking model, see (8).

The current fees of on street parking depend on the location of the parking (high tariff zone vs. normal tariff zone). But most of the on street parking in the city are marked blue and are as such usable by people in the following way: Residents can buy a relatively cheap annual ticket for their area and park there without further payment while they park. Visitors can park there also free for one hour using a parking disk. During night and on Sunday the parking is free even without parking disk. The prices for both the public on street and off street parking are based on the data from an earlier study (21).

**Experiments**

The simulation is started with the current prices at all public parking. After each iteration, if a set of parking places had more than 85% occupancy in the previous iteration, its price is incremented by 0.25 CHF (Swiss francs, US$ 0.26 at July 2012 exchange rates). If the occupancy is less than 85%, the rate of the parking deceases by 0.25 CHF. For street parking, 85% occupancy means the occupancy of a group of spaces, e.g. a block/street. For garage parking its original capacity is used for this calculation. The initial parking price for the blue zones is set to zero.

In this experiment, we try to find out, how parking fees could develop, if fees were optimized for all publicly accessible parking in the city, in the above mentioned way. In our experiments we do not distinguish the price in such detail as SFpark does (they have 3 different prices during the day and no fee during the night). We just use one price for the first half of the day and a second price for the second half of the day.

**Scenario Relaxation**

In Figure 2 the score of the agents’ plans are shown after each iteration. The picture clearly shows, that the plan’s scores improve very fast in the beginning and then slow down, as the system relaxes. The picture also shows, that our approach to change the parking price after each iteration did not cause any big changes to the plans of the agents, which would cause the simulation not to relax.
Morning Parking Fee Change

Next we look at the parking fee development in the morning. In Figure 3 (a) the current on street parking price distribution per hour is shown, which is used as initial parking price to the simulation. This clearly shows the high tariff and low tariff fees (0.5 CHF resp. 2.5 CHF). Figure 3 (b) shows the optimized parking fees. On average, the on-street parking price is increased by 29%. Here only prices until 4.5 CHF are shown, although there are a handful of locations with higher fees. The fees at some locations go up to 9 CHF per hour (only 0.3% of the street parking).

Figure 3: On-street parking price distribution per hour at iteration 0 (a) and iteration 100 (b)

When we look at the price development of off street parking (Figure 4), we have a totally different picture: The average parking fee at the different parking garages fell by 59%. Initially on average a garage parking space did cost around 8 times more than an on street parking space. After the price optimization a garage parking space only costs 3 times more than an on street space. Due to this
decrease in garage parking price, the usage of garage parking has increased and the usage of street parking decreased a little bit.

![Figure 4: Off-street parking price distribution per hour at iteration 0 (a) and iteration 100 (b)](image)

**Price Difference Morning vs. Afternoon**

The fees reported above are for the morning. The afternoon fees do not have a significantly different distribution than in the morning, but still they are different. For on street parking, 15% of the parking fees are different for the same parking in the afternoon than in the morning. Furthermore in average, the on street parking fee in the afternoon is 18% lower than in the morning.

For the garage parking, there are only 2 garage parking (2%), which have a different price in the morning, than in the evening and therefore the average price does not change significantly.

**Walk Times**

For the walk times between the activity location and the parking, we observed a clear difference between on street and garage parking (Figure 5 and 6). For on street parking, the median walk time is 1.1 min (corresponds to 77 meters) for both the initial and optimized parking price scenario. The maximum walk time is around 13 min (for better visualization, 0.2% of the data is not drawn).
For the garage parking, the initial median walk time is a bit bigger than for on street parking. For the initial case it is 1.5 min, while for the optimal pricing case it was slightly reduced to 1.4 min. The maximum walk time is around 10min (for better visualization, 0.3% of the data is not drawn).

When comparing the initial walk distance for on street and garage parking, one finds, that the on street parking distribution has a thicker tail. One explanation for this phenomenon is that outside the city center often an off street parking alternative is not available and in case of high demand, people have to walk longer distances. On the other side, when we look at the distribution tail of the initial garage parking walk times and those in the optimal case, we find that due to the price decrease of the garage parking the competitiveness of the garage parking increases compared to the on street parking and more people are willing to walk longer distances than initially.

We tried to find out, if there is any correlation between income and walking distance for the initial or the optimized pricing. Because, when one looks at single destination test scenarios (e.g. (21)), one clearly finds such a correlation. We did not find any such correlation, neither in the original pricing nor the optimized pricing case. For the original pricing case one can argue, that due to the flat pricing for on street parking, there is little competitive advantage of higher income. But even for the optimized parking price case, one can argue, that the targets of people are so diverse in our scenario, that income is not directly correlated to walking distance: Even if two persons have the same activity location, the higher income person still might be willing to walk longer, if he wants to park for a longer duration than the other person.
Figure 6: Walk time distribution for garage parking initially and after price optimization (iteration 100)

City Revenue Development

An interesting aspect to look at is, how does the revenue for the city of Zurich develop due to the change in parking fees. Although in reality most of the garage parking of the city are privately owned we assume here, they would belong to the city. While the revenues from on street parking increased, especially due to higher prices for previously free on street parking, the revenue from garage parking shrank - although demand for garage parking increased the fees for garage parking fell. In total this resulted in a 11% decrease in revenue for the city.

DISCUSSION AND FUTURE WORK

We plan to improve and extend our work in several ways.

Improvements of the Experiment

Although, the presented experiment is able to successfully demonstrate the capability of our parking model, it could be improved in the following way:

- For improving the quality of the results, we would require at least a 50% population sample, as due to the scaling of on street and private parking artifacts occur, due to the lower number of parking spaces per street/building compared to that of garage parking. In our test scenario, we probably used a slightly too high supply of street parking due to this problem.
- For the experiments in this paper we just performed one MATSim simulation run. For a real scenario we would need to perform several runs of our simulation, so that we can also report the variance of the simulations.
In the demand used in this paper, cross-border and freight traffic is missing, which would not only increase the traffic on roads, but also the demand for parking. We plan to add such demand to our model.

It is unclear, if for a larger population sample, the price could be adapted after each iteration of the traffic simulation or should it be adapted less frequently. As mentioned above, in our test scenario, we probably had too high supply of street parking. Therefore for a real/tighter parking supply the parking price could rise much faster than agents in the traffic simulation would be able to adapt to such price change, e.g. by changing the travel mode. Therefore in order to keep the system stable, one would probably need to reduce the frequency at which parking price is adapted in such a simulation, e.g. each 5th iteration instead of each iteration.

Next steps
We plan to work on the follows things in future:

- Although rising parking fees might force some people to change their travel mode, other non-car traveler might be attracted towards usage of car due to the improved parking situation. Although in our simulation, mode choice was an option for the agents, we did not observe any significant change in car mode travel. Probably due to the slight oversupply of parking, there was little incentive for people to change their travel mode to a non-car mode. Clearly we are interested to investigate this in detail for an improved Zurich scenario.

- In our experiments we did not look at detailed parking fee changes over the day. We would like to investigate, what effects smaller time slots, e.g. of one hour duration might have.

- In our scenario, the city lost 11% due to the parking fee changes. We are interested to find out, how we could change the price optimization to maximize the usage of parking and also the income for the city. Especially it seems to be an important goal to maximize the revenues for the city from parking, if such revenues are allocated as suggested by Shoup to improve the situation of communities located close to the parking or used to support alternative modes of travel (3). In the SFpark a minimum fee is proposed, but we would like to investigate, if there are other ways to raise the revenue for the city, without going against the suggestion of Vikrey, that if 85% parking is not occupied for a low fee, one should offer it for free.

- We also need to work on the performance of our simulation. Although MATSim itself is capable of simulating millions of agents on high resolution networks (17,22), parking choice and search models pose additional computational burden, so clearly this is something we need to focus on for being able to simulate larger scenarios.

- In this paper, we increased resp. decreased the price, if the occupancy was below resp. above 85%. In the SFpark pricing scheme, the hourly rate is raised by $0.25 if occupancy is above 80%, not changed if occupancy is 60 to 80% and reduced by $0.25, if occupancy is 30 to 60%. Furthermore the fee is even lowered by $0.5, if occupancy is less than 30% (with minimum price at $0.25). Although with this price changing scheme the fees do change less often than with the pricing scheme we used, it is unclear what such difference in price schemes can have on the overall performance of the system. Therefore we are clearly interested to investigate this.

- In this paper we did not describe the full capability of our parking model, especially its parking choice and parking search capabilities. We intend to work in this direction also in the near future.

- Another aspect of parking, which we need to look further into is, the use of the random error term within the utility function. One possible and efficient implementation of this for location choice has been proposed in (23). This might especially be useful during calibration, e.g. when
Another thing, which we did not look in detail in this paper, is how fast prices converge. This would also be useful for cities to know, how many iterations they can expect before a possible stabilization of the price. Furthermore we also intend to experiment with different initial parking fees to see, if they converge towards the same parking fee in the end.

CONCLUSIONS

In this paper, we applied parts of an agent-based parking model, which has recently been proposed, to demonstrate that the model is capable of application to real-world parking policy scenarios and price optimization as suggested by Shoup. The model successfully captures relevant aspects of parking preferences and trade-off by people, e.g. parking cost and walk time. Furthermore the parking model has direct influence on other choices of the agent, e.g. mode or location choice.

As highlighted in the future work section, there are many aspects of the price optimization approach, which need to be further investigated and where the proposed model could be used. Furthermore this paper also lays the foundation for related work, that the authors are pursuing in (12), where the electricity demand by electric vehicles is modeled. Modeling parking decisions of electric vehicles is more complex than for gasoline vehicles, as additionally the availability of a charging plug and state of charge of the vehicle’s battery is part of the parking decision. The agent-based aspect of our model seems to be an powerful approach, when modeling such complex decisions of drivers.

Although we only looked at optimal pricing in this paper, we also want to use our parking model to further our understanding of parking search traffic so that effective parking policies can be designed.

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REFERENCES


