Conference Paper

Macroscopic model for on- and off-street parking
Traffic effects

Author(s):
Jakob, Manuel; Menendez, Monica

Publication Date:
2017

Permanent Link:
https://doi.org/10.3929/ethz-b-000119109

Rights / License:
In Copyright - Non-Commercial Use Permitted
MACROSCOPIC MODEL FOR ON- AND OFF-STREET PARKING:

TRAFFIC EFFECTS

Submission Date: 07/28/2016

Manuel Jakob (Corresponding author)
Institute for Transport Planning and Systems (IVT)
ETH Zürich
Office address: HIL F41.3, Stefano-Franscini-Platz 5, 8093 Zurich, Switzerland
Phone: +49 151 108 31 281
Fax: +41 44 633 10 57
Email: manuel.jakob@ivt.baug.ethz.ch

Monica Menendez
Ph.D., Director of Research Group “Traffic Engineering”
Institute for Transport Planning and Systems (IVT)
ETH Zürich
Office address: HIL F37.2, Stefano-Franscini-Platz 5, 8093 Zurich, Switzerland
Phone: +41 44 633 66 95
Fax: +41 44 633 10 57
Email: monica.menendez@ivt.baug.ethz.ch

Paper word Count: 5747 words
Number of tables: 4 tables (1000 words)
Number of figures: 3 figures (750 words)
Final word count: 7497 words
ABSTRACT

On-and off-street parking has been gaining attention in recent research, but its interdependency with searching-for-parking traffic and traffic performance is still unknown. In this paper, we develop a macroscopic formulation to model off-street parking dynamically and integrate it into an urban traffic and on-street parking study to better replicate reality. The parking searchers decide between driving to a parking garage or searching for an on-street parking place in the network.

We analyze the influence of on- and off-street parking on the traffic system with regard to different parking pricing schemes. These pricing scenarios include demand-responsive parking pricing methodologies for both on- and off-street parking. Their effects on cruising-for-parking and traffic performance are evaluated.

This macroscopic pricing model is only based on aggregated data at the network level over time. Hence, it saves on data collection efforts and reduces the computational costs significantly compared to most literature. This easy to implement methodology can be solved with a simple numerical solver.

The model provides a preliminary idea for city councils regarding the interdependency between on- and off-street parking, and their influence on searching-for-parking traffic (cruising), the congestion in the network (traffic performance), the total driven distance (environmental conditions), and the revenue created by on- and off-street parking fees for the city.
1. INTRODUCTION

In nearly all urban areas, there are both on- and off-street parking opportunities that lead to rather complex interdependencies. Both parking possibilities follow diverse policies, which can sometimes lead to significant changes on the performance of a transportation network. The performance of both the urban parking and traffic system can, for example, be influenced by short-term on- and off-street pricing strategies, e.g., parking pricing can affect the parking availability, the congestion and traffic performance, or the traffic composition in the network. Hence, we present a macroscopic off-street parking model and integrate it into the urban traffic and on-street parking study in [8] and [13] to better replicate reality. We analyze the relationship between on- and off-street parking, but also their interdependency on cruising-for-parking traffic and traffic performance with respect to different parking pricing schemes. These pricing scenarios include demand-responsive parking pricing methodologies for both on- and off-street parking.

In the existing literature, there are empirical or modelling approaches used to define on- and off-street parking pricing. Empirical approaches usually focus on collecting data for both on- and off-street parking, e.g., [18] uses its demand-responsive pricing scheme to leave between 20 and 40 percent of on-street parking spaces open on every block, and to have open spaces available in public garages at all times ([16]). Other off-street pricing approaches are based on questionnaires, e.g., [4]; [5]; or they use dynamic information to predict real-time off-street parking availability ([7]). [14] estimates the effect of on-street parking fees on drivers’ choice between on- and off-street parking. [11] analyzes how off-street parking demand is affected by on-street parking regulations. Our macroscopic model provides general results regarding the effects of on- and off-street parking pricing on traffic under generalized conditions without any physical devices or data collections efforts.

For modelling both on- and off-street parking with its associated parking fees, [1] and [12] show that the full price of parking consists of the interaction between garage operators and the cruising costs for on-street parking. They develop a spatial competition model to eliminate cruising by allocating excessive cruising demand to garage parking and focus on social optimum suggestions concerning the relationship between curbside and garage fares. [15] develops a dynamic Stackelberg leader-follower game theory approach to model variable on- and off-street parking prices in real-time for effective parking access and space utilization. Compared to these models that provide a long-term demand management strategy capturing user competition and considering market equilibrium, our models focuses on the short-term effects. [17] models a system optimal parking flow minimization problem that follows a real-time pricing approach for a parking lot based on its occupancy rate. They assume a user equilibrium travel behavior and only focus on off-street parking without analyzing its interdependency to on-street parking in the network. [19] investigates an optimal parking pricing problem in a park-and-ride (P+R) network with multiple origins and one destination. Their objective is to minimize the total travel cost by setting optimal parking fees and only considering P+R terminals. [20] models multi-modal traffic with limited on-street and garage parking and dynamic pricing based on the Macroscopic Fundamental Diagram (MFD). [3] analyzes how much curbside to allocate to parking when the private sector provides garage parking. [2] analyzes parking in a spatially homogeneous downtown area where the drivers chose between on- and off-street parking. Cruising for parking contributes to congestion, such that the full price of the initially cheaper on-street parking is increased until it equals the price of garage parking. Then increasing the on-street parking fee may generate an efficiency gain through reduction of cruising. These papers consider parking pricing but they focus on social optimum and user equilibrium pricing suggestions and do not include demand-responsive garage pricing.
This paper builds on a previous study from [13], in which a macroscopic on-street parking pricing model was developed. It is based on the parking-state-based matrix from [8] providing an approximation of the proportion of cars searching for on-street parking, as well as the time cars spent searching for parking, or travelling through the system. These approximations are now enhanced by including off-street parking and considering various parking pricing schemes, e.g., demand-responsive on- and off-street parking fees over time. Independently of their current traffic state, the drivers can make the decision to use off-street parking, then drive towards the closest parking garage and access it depending on its current capacity. This off-street parking decision is based on several cost factors:

- the drivers’ value of time (VOT) depending on their origin;
- the current on- and off-street parking fees;
- the expected cost of cruising for on-street parking;
- the expected driving cost to the closest possible garage; and
- the walking cost from the off-street parking location to the drivers’ final destination.

By comparing these costs, drivers come to a decision, such that all traffic and parking conditions can be determined over time. We analyze the efficiency of the integrated on- and off-street parking model with respect to its associated pricing scheme.

The paper is organized as follows. Section 2 presents the overall methodology of the macroscopic off-street parking model. Section 3 reviews the off-street parking decision model by introducing new relevant transition events to the parking-state-based matrix. Section 4 shows a numerical example to explore the use of the concept and the proposed methodology. Section 5 summarizes the findings of this paper.

2. FRAMEWORK

In this research, we develop a macroscopic off-street parking model with an associated pricing scheme. It enhances the on-street parking pricing model in [13] and is incorporated into a traffic system with a parking search model over time to better replicate reality.

The methodology is based on the macroscopic parking-state-based matrix in [8] that estimates the proportion of cars cruising-for-parking and the cruising time, as well as the traffic conditions and parking usage over time. The total time domain is split into small time slices (e.g., 1 minute), and all traffic/parking conditions are assumed steady within each time slice, although they can change over time. In [8] and [13] two types of traffic demands are generated simultaneously in each time slice. The first group of vehicles searches for on-street parking as seen in Fig 1(a) and influences the associated demand-responsive parking fee. The second group of vehicles in Fig 1(b) can be considered as through-traffic and does not search for parking. Accordingly, vehicles go through different transition events, used to update the possible parking-related traffic states in a matrix form (see Table 1). During one single time slice a vehicle may experience at most one transition event. The matrix is then updated iteratively over time.

In this study, all vehicles have in addition the option to decide for garage parking at their current location. This decision can be done anywhere independently of their current traffic state, i.e., the vehicles can decide to use off-street parking in “non-searching” or in “searching”-state. This leads to two new transition event scenarios for garage parking (Fig 1(c) and Fig 1(d)).
(a) First group of vehicles.  
(b) Second group of vehicles.

(c) Third group of vehicles.  
(d) Fourth group of vehicles.

Fig 1. The transition events of urban traffic with on-street parking in (a) and (b) (Source: [9]), and the transition events with off-street parking in (c) and (d).

After the decision for off-street parking the vehicles drive towards the garage and access it depending on its current capacity. If there is no capacity available, the vehicles need to return into the searching-for-parking state.

By including off-street parking, we need to introduce the new traffic states compared to [8], $N_{dp}^I$ that includes all drivers who have decided to use garage parking, and $N_{dp}^f$ that includes the drivers who actually access the garage. These new traffic states and all related transition events are summarized in Table 1.
Table 1. Relevant key variables (including off-street parking related variables) for matrix per time slice.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{ns}$</td>
<td>Number of vehicles in the state “non-searching” at the beginning of time slice $i$ (Non-searching).</td>
</tr>
<tr>
<td>$N_{s}$</td>
<td>Number of vehicles in the state “searching” at the beginning of time slice $i$ (Searching).</td>
</tr>
<tr>
<td>$N_{p}$</td>
<td>Number of vehicles in the state “parking” at the beginning of time slice $i$ (On-street parking).</td>
</tr>
<tr>
<td>$N_{dgp}$</td>
<td>Number of vehicles in the state “decide for garage parking” at the beginning of time slice $i$ (Decide for garage parking).</td>
</tr>
<tr>
<td>$N_{gp}$</td>
<td>Number of vehicles in the state “off-street parking” at the beginning of time slice $i$ (Off-street parking).</td>
</tr>
<tr>
<td>$n_{ns/dgp}$</td>
<td>Number of vehicles that transition from “non-searching” to “decide for garage parking” during time slice $i$ (Go to off-street parking).</td>
</tr>
<tr>
<td>$n_{s/dgp}$</td>
<td>Number of vehicles that transition from “searching” to “decide for garage parking” during time slice $i$ (Switch to off-street parking).</td>
</tr>
<tr>
<td>$n_{dgp/gp}$</td>
<td>Number of vehicles that transition from “decide for garage parking” to “off-street parking” during time slice $i$ (Access off-street parking).</td>
</tr>
<tr>
<td>$n_{dgp/s}$</td>
<td>Number of vehicles that transition from “decide for garage parking” to “parking” during time slice $i$ (Access on-street parking).</td>
</tr>
<tr>
<td>$n_{gp/ns}$</td>
<td>Number of vehicles that leave the area and transition from “non-searching” during time slice $i$ (Leave the area).</td>
</tr>
</tbody>
</table>

Based on Table 1, we adapt all transition state related formulas in [8] between consecutive time slices. By including $n_{ns/dgp}$, $n_{s/dgp}$, $n_{dgp/gp}$, $n_{dgp/s}$ and $n_{gp/ns}$ we get Eq. (1) to (3) that update the number of “non-searching”, “searching”, and “parking” vehicles. Notice that Eq. (3) remains the same.

$$N_{ns}^{i+1} = N_{ns}^{i} + n_{ns}^{i} + n_{p/ns}^{i} + n_{dgp/ns}^{i} - n_{ns/s}^{i} - n_{ns/dgp}^{i} - n_{ns/s}^{i}$$  \(1\)

$$N_{s}^{i+1} = N_{s}^{i} + n_{ns/s}^{i} + n_{dgp/s}^{i} - n_{s/p}^{i} - n_{s/dgp}^{i}$$  \(2\)

$$N_{p}^{i+1} = N_{p}^{i} + n_{s/p}^{i} - n_{p/ns}^{i}$$  \(3\)

Eq. (4) updates the number of vehicles that “decide for garage parking”. Vehicles that decide to use a parking garage during time slice $i$ (i.e., $n_{ns/dgp}^{i}$ and $n_{i/dgp}^{i}$) join this state; vehicles that actually access off-street parking (i.e., $n_{dgp/s}^{i}$) and vehicles that cannot access off-street parking (i.e., $n_{dgp/gp}^{i}$) quit this state. Eq. (5) updates the number of “off-street parking” vehicles. Vehicles that access a garage during time slice $i$ (i.e., $n_{dgp/gp}^{i}$) join this state; vehicles that depart off-street parking (i.e., $n_{gp/ns}^{i}$) quit this state.

$$N_{dgp}^{i+1} = N_{dgp}^{i} + n_{ns/dgp}^{i} + n_{s/dgp}^{i} - n_{dgp/s}^{i} - n_{dgp/gp}^{i}$$  \(4\)

$$N_{gp}^{i+1} = N_{gp}^{i} + n_{dgp/gp}^{i} - n_{gp/ns}^{i}$$  \(5\)

The transition events $n_{ns}$, $n_{ns/s}$, $n_{s/p}$, $n_{p/ns}$ and $n_{ns/s}$ are modeled in [8] and [13]. Here we focus only on the new transition events related to off-street parking, $n_{ns/dgp}^{i}$, $n_{s/dgp}^{i}$, $n_{dgp/gp}^{i}$, $n_{dgp/s}^{i}$ and $n_{gp/ns}^{i}$.
We require the origin $k \in K$ dependent demand $n_{k,ns}^i$ and the transition event $n_{k,ns/s}^i$ to incorporate the VOT influence into our off-street parking decision model. $n_{k,ns}^i$ is an input to the model, such that $n_{i,ns}^i = \sum_{k=1}^{K} n_{k,ns}^i$, whereas $K$ is the total number of origins in the network. $n_{k,ns/s}^i$ is modeled in [13].

3. DECISION MODEL FOR OFF-STREET PARKING

This section shows an overview of the assumptions, inputs and outputs of the off-street parking model, and the related transition events.

3.1. Basic information for analytical model

Basic model assumptions, inputs, and expected outputs are briefly described below.

Assumptions:

Basic assumptions from [13] and [8] for the matrix are kept here. They include a simple spatially symmetric urban traffic network where traffic is homogeneously distributed, and the traffic demand over a period of time (e.g., a day), the distribution of parking durations, and the length and general traffic properties of the network are known. All trips are exclusively made by car in this network (i.e., the mode choice has been previously made).

The cruising time and distance depend on drivers’ luck finding an available on-street parking space (based on their own location, that of the available parking spots, and that of the competitors) and on the current traffic conditions. The use of our macroscopic strategy allows us to avoid recording the location of all cars and parking spots throughout the different time slices in the system to specify each vehicles’ driving time and distance, i.e., only average numbers of vehicles during a time slice and total/average times and distances are tracked. The macroscopic model is not influenced by the randomness of vehicles’ location at a specific time slice due to the reset of parking searchers and available parking spaces at the beginning of each time slice. The on-street parking spaces are on average uniformly distributed on the network, i.e., the locations of available parking spaces are assumed as random at the beginning of each time slice. A uniformly distribution of all on-street parking searchers is assumed on the network at the beginning of each time slice, i.e., the traffic demand is guaranteed to be homogeneously generated. This assumption limits the applicability of the model when searchers focus on one street to find parking while parking spots are easily available in other areas of the network. In those cases, the model would likely overestimate the amount of parking spaces being taken in this case.

All parking garages are assumed to be homogeneously distributed within the network and all associated off-street parking capacities are assumed to be equal. The decision for off-street parking can be made anywhere within the “non-searching” or “searching”-state. As soon as this decision is made there is no possibility for the drivers to change it afterwards, unless there is no capacity in the parking garages by the time they get there.

We assume that the VOT is different for individual vehicles depending on their origins. This affects the time-related costs in our off-street parking decision model.
Inputs:

Table 2 shows all the model’s independent variables. The first set corresponds to the travel demand and supply, and can be estimated based on historical data. The second set corresponds to the traffic network, and can be directly measured. The third set corresponds to the initial conditions of the parking-related states, and can be measured, assumed or simulated. The fourth set corresponds to off-street parking specific input parameters, and can be directly measured or estimated based on historical data.

Table 2. Independent variables (inputs to the model).

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K )</td>
<td>Total number of origins for demand input of the network. Each origin might have a different VOT.</td>
</tr>
<tr>
<td>( VOT_k )</td>
<td>VOT for origin ( k \in K ).</td>
</tr>
<tr>
<td>( n_{k,ns}^i )</td>
<td>New arrivals to the network for origin ( k \in K ) during time slice ( i ) (i.e., travel demand per VOT origin).</td>
</tr>
<tr>
<td>( \beta^i )</td>
<td>Proportion of new arrivals during time slice ( i ) that correspond to traffic that is not searching for parking.</td>
</tr>
<tr>
<td>( A )</td>
<td>Total number of existing on-street parking spaces (for public use) in the area.</td>
</tr>
<tr>
<td>( l_{ns/s} )</td>
<td>Distance that must be driven by a vehicle before it starts to search for parking.</td>
</tr>
<tr>
<td>( l_f )</td>
<td>Distance that must be driven by a vehicle before it leaves the area without parking.</td>
</tr>
<tr>
<td>( l_p )</td>
<td>Distance that must be driven by a vehicle before it leaves the area after it has parked.</td>
</tr>
<tr>
<td>( t_d )</td>
<td>Parking duration.</td>
</tr>
<tr>
<td>( L )</td>
<td>Size (length) of the network.</td>
</tr>
<tr>
<td>( b )</td>
<td>Average length of a block in the network.</td>
</tr>
<tr>
<td>( t )</td>
<td>Length of a time slice.</td>
</tr>
<tr>
<td>( v )</td>
<td>Free flow speed, i.e., maximum speed in the network.</td>
</tr>
<tr>
<td>( w )</td>
<td>Walking speed in the network.</td>
</tr>
<tr>
<td>( N_{ss}^0 )</td>
<td>Initial condition for the non-searching state.</td>
</tr>
<tr>
<td>( N_s^0 )</td>
<td>Initial condition for the searching state.</td>
</tr>
<tr>
<td>( N_p^0 )</td>
<td>Initial condition for the parking state.</td>
</tr>
<tr>
<td>( N_{dpp}^0 )</td>
<td>Initial condition for the decision for off-street parking state.</td>
</tr>
<tr>
<td>( N_{opp}^0 )</td>
<td>Initial condition for the off-street parking state.</td>
</tr>
<tr>
<td>( G )</td>
<td>Number of parking garages in the network.</td>
</tr>
<tr>
<td>( R_{tot}^g )</td>
<td>Total capacity of all parking garages, i.e., total number of off-street parking spaces.</td>
</tr>
<tr>
<td>( p_g^0 )</td>
<td>Initial garage parking pricing.</td>
</tr>
<tr>
<td>( \Delta_{max} )</td>
<td>Maximum increase/decrease of garage pricing per time slice.</td>
</tr>
<tr>
<td>( y )</td>
<td>Influence factor of the off-street parking related demand-responsivity during garage parking pricing.</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>Penalty term to reduce circular movements while switching to off-street parking, ( \lambda \in (0,1) ).</td>
</tr>
<tr>
<td>( p_{dist} )</td>
<td>Price per kilometer driven on the network (i.e., external costs as petrol, wear and tear of vehicles).</td>
</tr>
</tbody>
</table>

Outputs:

The model provides, amongst others, the interactions between on- and off-street parking and their influence on the urban traffic system. The short-term effects of parking pricing on traffic conditions can be investigated, i.e., all


distances driven with all related times as well as the effects on city revenue.

Table 3 shows a list of variables we define and use for our methodology. The first set is used to quantify the number of vehicles that experience each transition event in a time slice. The second set corresponds to the off-street parking decision model. The third set is used to compute the costs variables in this decision model.

Table 3. Dependent variables.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( n_{ns/s}^k )</td>
<td>Number of vehicles that transition from “non-searching” to “searching” for origin ( k \in K ) during time slice ( i ).</td>
</tr>
<tr>
<td>( A^i )</td>
<td>Number of available parking spots at the beginning of time slice ( i ).</td>
</tr>
<tr>
<td>( v^i )</td>
<td>Average travel speed in time slice ( i ).</td>
</tr>
<tr>
<td>( d^i )</td>
<td>Maximum driven distance of a vehicle in time slice ( i ).</td>
</tr>
<tr>
<td>( R_{tot}^i )</td>
<td>Capacity of all parking garages per time slice.</td>
</tr>
<tr>
<td>( p_{op}^i )</td>
<td>On-street parking fee in time slice ( i ).</td>
</tr>
<tr>
<td>( p_{gp}^i )</td>
<td>Off-street parking fee in time slice ( i ).</td>
</tr>
<tr>
<td>( C_{op}^i )</td>
<td>Average costs of cruising for on-street parking determined in time slice ( i ).</td>
</tr>
<tr>
<td>( C_{gp}^i )</td>
<td>Average costs of garage parking determined in time slice ( i ).</td>
</tr>
<tr>
<td>( C_{drive}^i )</td>
<td>Average costs of driving to the closest off-street parking location in time slice ( i ).</td>
</tr>
<tr>
<td>( C_{walk}^i )</td>
<td>Average costs of walking from the off-street parking to the final destination in time slice ( i ).</td>
</tr>
<tr>
<td>( E_{VOT} )</td>
<td>Expectation value for all VOT costs considering all origins ( k \in K ) and all time slices ( {1, \ldots, i} ).</td>
</tr>
<tr>
<td>( ACD^i )</td>
<td>Average cruising distance for on-street parking in time slice ( i ).</td>
</tr>
<tr>
<td>( ADD )</td>
<td>Average driving distance to the closest off-street parking location.</td>
</tr>
<tr>
<td>( AWD )</td>
<td>Average walking distance from the off-street parking to the final destination.</td>
</tr>
<tr>
<td>( \gamma^i )</td>
<td>Binary variables to model different transition events.</td>
</tr>
</tbody>
</table>

3.2. Model for off-street related transition events

We introduce the following transition events based on the assumption that the urban network is abstracted as one ring road with cars driving in a single direction. This simplifies the model without affecting the model results ([8]). The different costs associated with the parking decisions are formulated in section 3.3.

3.2.1. Transition event: Go to off-street parking

We assume that the vehicles start to search after driving a distance \( l_{ns/s} \) since they enter the area. \( l_{ns/s} \) can be fixed or taken out of a distribution. For simplicity, we assume it is fixed. Besides searching for an on-street parking space, the vehicles have then the option to decide for off-street parking as modelled in Eq. (6); \( n_{ns/gp}^i \) may consist of vehicles entering the network in any former time slice \( i' \in [1, i - 1] \).

\[
\begin{align*}
n_{ns/gp}^i = & \left( \sum_{i' = 1}^{i-1} (1 - \beta^{i'}) \cdot n_{ns/s}^{i'} \cdot \frac{\gamma_{ns/gp}^{i'}}{\text{term 2}} \right) \cdot \frac{\gamma_{ns/gp}^i}{\text{term 3}}
\end{align*}
\]

(6)
where

$$
\gamma_{ns/s}' = \begin{cases} 
1, & \text{if } l_{ns/s} \leq \sum_{j=i}^{i-1} d^j \text{ and } \sum_{j=i}^{i-1} d^j \leq l_{ns/s} + d^{i-1} \\
0, & \text{otherwise}
\end{cases}
$$

(7)

$$
\gamma_{ns/gp}' = \begin{cases} 
1, & \text{if } C_{gp}^i \geq C_{gp}^i \\
0, & \text{otherwise}
\end{cases}
$$

(8)

Term 1 in Eq. (6) represents the portion of the total demand \( n_{ns/s}' \) that needs to park, i.e., all vehicles excluding through traffic. Term 2 indicates whether these vehicles can start to search for parking in time slice \( i \) or need to continue driving (Eq. (7)). The maximum driven distance \( d^i = v^i \cdot t \). Term 3 shows the decision for off-street parking depending on the on- and off-street parking related costs (Eq. (8)). The vehicles decide for garage parking in case the average cruising cost \( C_{gp}^i \) (subsection 3.3.1) to find on-street parking is higher than the associated off-street parking cost \( C_{gp}^i \) (subsection 3.3.2). In case the vehicles do not decide for garage parking, they enter the searching-for-on-street-parking state (see \( n_{ns/s}' \) in [8]). For realistic networks ([10]) the maximum number of vehicles entering a network (see MATSim simulation for the city of Zurich) for a small time slice (\( t = 1 \) min in this paper) is rather small. Thus, we can assume that either all or no vehicles decide for garage parking per time slice.

3.2.2. Transition event: Switch to off-street parking

In this subsection, the transition event \( n_{s/gp}' \) is modelled in Eq. (9) to determine the number of vehicles switching to off-street parking from searching-for-parking state. The drivers can decide to use off-street parking while cruising for on-street parking. Alternatively, the vehicles keep on searching for on-street parking.

$$
n_{s/gp}' = N_s^i \cdot \gamma_{s/gp}' \cdot \gamma_{pen}'
$$

(9)

where:

$$
\gamma_{s/gp}' = \begin{cases} 
1, & \text{if } C_{gp}^i \geq C_{gp}^i \\
0, & \text{otherwise}
\end{cases}
$$

(10)

$$
\gamma_{pen}' = \begin{cases} 
\lambda, & \text{if } n_{s/gp}' > 0 \text{ or } n_{s/gp}' > 0 \\
1, & \text{otherwise}
\end{cases}
$$

(11)

Eq. (10) models the off-street parking decision analogously to Eq. (8). We also introduce an additional penalty term \( \lambda \in (0,1) \) in Eq. (11) to reduce circular movements between \( n_{s/gp}' \) and \( n_{s/gp}' \).

3.2.3. Transition event: Access off-street parking

The transition event \( n_{gp/gp}' \) (Eq. (12)) describes the process of accessing a parking garage. After the vehicles have decided to use off-street parking, they drive towards the parking garage where they realize whether it is possible for them to access it depending on the available capacity.

$$
n_{gp/gp}' = \min \left( \sum_{i=1}^{i-1} (n_{ns/gp}' + n_{s/gp}') \cdot \gamma_{ADD}' \cdot R_{tot}' \right)
$$

(12)
where

\[
\gamma_{ADD} = \begin{cases} 
1, & \text{if } ADD \leq \sum_{j=i-1}^{j=i'-1} d_j \text{ and } \sum_{j=i'}^{j=i-1} d_j \leq ADD + d^{i-1} \\
0, & \text{otherwise}
\end{cases}
\]  

(13)

Term 1 in Eq. (12) shows the sum of all vehicles (from section 3.2.1 and 3.2.2) that have decided to use garage parking in any former time slice \( i' \in [1, i - 1] \). Term 2 (Eq. (13)) indicates whether these vehicles have arrived at the garage after reaching the average driving distance \( ADD \) (subsection 0). Here two conditions must be satisfied: the vehicles have driven enough distance to arrive at an off-street parking after having decided for it, and they have not accessed a garage in a former time slice. The number of vehicles that can access parking at the end is the minimum of the total capacity available and the number of vehicles that want to park.

3.2.4. Transition event: Not access off-street parking

This transition event describes the case when the vehicles cannot access off-street parking due to capacity limitations. In this situation, these vehicles \( n^i_{dgp/s} \) in Eq. (14) return back to searching-for-parking state.

\[
n^i_{dgp/s} = \max\{n^i_{dgp/gp} - R^i_{tot}; 0\} 
\]  

(14)

In case \( n^i_{dgp/gp} \) surpasses \( R^i_{tot} \), the remaining vehicles need to return to searching-for-parking state; otherwise all vehicles can successfully enter a garage.

3.2.5. Transition event: Depart off-street parking

The transition event \( n^i_{gp/ns} \) is modeled analogously to \( n^i_{p/ns} \) in [8]. As we know the number of vehicles having decided to use off-street parking in all former time slices, we can find \( n^i_{gp/ns} \) based on the distribution of parking durations (an input to the model). Eq. (15) shows the number of vehicles to depart off-street parking in time slice \( i \).

\[
n^i_{gp/ns} = \sum_{i'=1}^{i-1} n^{i'}_{dgp/gp} \cdot \int_{(i-1)' \cdot t}^{(i+1)' \cdot t} f(t_d) dt_d 
\]  

(15)

\( n^i_{gp/ns} \) may consist of vehicles \( n^{i'}_{dgp/gp} \) having accessed off-street parking in any former time slice \( i' \in [1, i - 1] \). The probability that these vehicles depart off-street parking in time slice \( i \) equals to the probability of the parking duration between \( (i - i') \cdot t \) and \( (i + 1 - i') \cdot t \), i.e., \( \int_{(i-1)' \cdot t}^{(i+1)' \cdot t} f(t_d) dt_d \).

After vehicles access or depart from off-street parking, the total capacity is updated in Eq. (16).

\[
R^{i+1}_{tot} = R^i_{tot} + n^i_{gp/ns} - n^i_{dgp/gp} 
\]  

(16)

3.2.6. Transition event: Leave the area

The vehicles leave the area after having driven for a given distance. Here \( n^i_{ns/f} \) needs to be modified in Eq. (17) to include \( n^{i'}_{gp/ns} \).
where

\[
\gamma'_i = \begin{cases} 
1, & \text{if } l_i \leq \sum_{j=i}^{j=i-1} d_j \text{ and } \sum_{j=i}^{j=i-1} d_j \leq l_i + d_i^{-1} \\
0, & \text{otherwise} 
\end{cases}
\]

\[
\gamma'_{p_i} = \begin{cases} 
1, & \text{if } l_{p_i} \leq \sum_{j=i}^{j=i-1} d_j \text{ and } \sum_{j=i}^{j=i-1} d_j \leq l_{p_i} + d_i^{-1} \\
0, & \text{otherwise} 
\end{cases}
\]

Further details can be found in [8].

### 3.3. Off-street parking decision related costs

In subsections 3.2.1 and 3.2.2, we have introduced the costs \(C_{op}^i\) and \(C_{gp}^i\) that are required to model the off-street parking related decisions. In the following subsections, we mathematically derive these cost terms.

#### 3.3.1. Cost of cruising for on-street parking

We determine \(C_{op}^i\) in Eq. (18). This cost is only related to on-street parking searchers as there is no cruising cost assumed for finding off-street parking. Term 1 represents the on-street parking fee which can be constant or demand-responsive ([13]). Term 2 represents the average cruising distance expressed in distance price units. Term 3 represents the average cruising time expressed in VOT price units. We differentiate between computations considering \(n_{ns/dgp}^i\) (subsection 3.2.1) and \(n_{s/dgp}^i\) (subsection 3.2.2). \(E_{VOT}^i\) in Eq. (19) shows the expectation value for VOT in time slice \(i\), whereas \(VOT_k^i\) are input parameters showing the actual VOT costs for all origins \(k \in K\) (more details on the derivation are shown in [13]).

\[
C_{op}^i = p_{op}^i \cdot \text{term } 1 + p_{dist} \cdot ACD^i \cdot \text{term } 2 + E_{VOT}^i \cdot ACD^i \cdot \text{term } 3
\]

where

\[
E_{VOT}^i = \begin{cases} 
\frac{1}{K} \sum_{k=1}^{K} \sum_{i=1}^{i} \frac{n_{k,ns}^i}{n_{ns}^i} \cdot VOT_k^i, & \text{for } n_{ns/dgp}^i \\
\frac{1}{i} \sum_{k=1}^{K} \sum_{i=1}^{i} \frac{n_{k,ns}^i}{n_{ns}^i} \cdot VOT_k^i, & \text{for } n_{s/dgp}^i 
\end{cases}
\]

The average cruising distance \(ACD^i\) is determined as in [13].
3.3.2. Cost of garage parking

The costs \( C_{gp}^i \) in Eq. (20) consist of the off-street parking fee \( p_{gp}^i \) (subsection 0), the average driving cost to the closest off-street parking location \( C_{drive}^i \) (subsection 0) and the average walking cost to the final destination \( C_{walk}^i \) (subsection 0).

\[
C_{gp}^i = p_{gp}^i + C_{drive}^i + C_{walk}^i
\]  

(20)

3.3.2.1 Off-street parking fee. In general, the off-street parking fee \( p_{gp}^i \) can be considered as a constant input or as a demand-responsive pricing variable. The demand-responsive fee \( p_{gp}^i \) in Eq. (21) is modelled analogously to the on-street parking model in [13].

\[
p_{gp}^i = \begin{cases} 
  p_{gp}^{i-1} + \min\{\Delta p_{gp}^i, \Delta_{max}\}, & \text{if } \Delta \frac{N_{gp}^i}{R_{tot}^i} > 0 \\
  p_{gp}^{i-1}, & \text{if } \Delta \frac{N_{gp}^i}{R_{tot}^i} = 0 \\
  p_{gp}^{i-1} - \min\{\Delta p_{gp}^i, \Delta_{max}\}, & \text{if } \Delta \frac{N_{gp}^i}{R_{tot}^i} < 0 
\end{cases}
\]  

(21)

where

\[
\Delta \frac{N_{gp}^i}{R_{tot}^i} = \frac{N_{gp}^i}{R_{tot}^i} - \frac{N_{gp}^{i-1}}{R_{tot}^{i-1}}
\]  

(22)

\[
\Delta p_{gp}^i = p_{gp}^0 \left( \left( \Delta \frac{N_{gp}^i}{R_{tot}^i} \right) \right)^{\frac{1}{\gamma}}
\]  

(23)

The ratio concerning \( N_{gp}^i \) and \( R_{tot}^i \) varies between consecutive time slices (Eq. (22)). Depending on \( \Delta \frac{N_{gp}^i}{R_{tot}^i} \) the garage fee \( p_{gp}^i \) in Eq. (21) increases or decreases per time slice. The actual change of the off-street parking pricing is modelled in Eq. (23), where term 1 represents the initial fee \( p_{gp}^0 \) and term 2 the demand-responsive impact to \( \Delta p_{gp}^i \). Within term 2, \( \gamma \) is the influence factor of the demand-responsivity. It changes the level of influence of \( \Delta \frac{N_{gp}^i}{R_{tot}^i} \) to the delta pricing value \( \Delta p_{gp}^i \). For further studies in this paper, we assume a square root dependency and set \( \gamma = 2 \).

To avoid drastic price fluctuations in Eq. (21) a maximum pricing increase/decrease input variable \( \Delta_{max} \) is used per time slice ([13]).

3.3.2.2 Cost of driving from current vehicle location to closest off-street parking. The driving cost \( C_{drive}^i \) from the actual vehicle decision location to the closest garage is modelled in Eq. (24). It contains the average distance to the closest off-street parking expressed in distance price units (term 1) and the average time expressed in VOT price units that is needed to get there (term 2).

\[
C_{drive}^i = p_{dist}^{\text{term 1}} \cdot ADD + E_{VOT}^{\text{term 2}} \cdot \frac{ADD}{\gamma^i}
\]  

(24)
Both terms include $ADD$ (determined in Eq. (25)). The computation is based on the assumption that vehicles and garages are uniformly distributed over the network and that the relationship between on- and off-street parking locations is random, i.e., the locations could be close or far away from each other.

$$ADD = \frac{L}{2 \cdot G}$$

(25)

Fig. 2(a) shows a simple example of four on-street parking spaces and two uniformly distributed parking garages to illustrate Eq. (25).

(a) Average driving distance from current location to closest garage. (b) Average walking distance from garage to destination.

Fig. 2. Simple example of uniformly distributed on- and off-street parking to illustrate Eq. (25) and Eq. (27).

3.3.2.3 Cost of walking from off-street parking to destination. Assuming that drivers choose on-street parking close to their destination, there is no need to consider walking costs for on-street parking. Garages could be further away from the drivers’ destination. Thus, the associated walking cost $C_{walk}^i$ in Eq. (26) consists of the average walking distance from the garage to the destination expressed in distance price units (term 1), and its associated average walking time cost expressed in VOT price units (term 2). The walking speed $w$ is assumed to be a constant input.

$$C_{walk}^i = p_{dist} \cdot AWD_{\text{term 1}} + E_{VOT}^i \cdot \frac{AWD}{w} \quad \text{term 2}$$

(26)

We may assume without loss of generality that the network is a square grid, whereas the average length of a block $b$ in the network is known. This network is then visualized as a ring network by joining all blocks together. We take the surface of this total square $\left[ b \cdot \left( -\frac{1}{2} + \frac{1}{4} + \frac{L}{2n} \right) \right]^2$ and divide it by $G$. We move this partial surface into a circle where we assume that its radius is the average walking distance $AWD$ to the drivers’ destination described in Eq. (27).
\[ AWD = \frac{b}{\sqrt{\pi \cdot G}} \left[ -\frac{1}{2} + \frac{1}{4} \sqrt{\frac{L}{b}} \right] \] (27)

Fig. 2(b) shows a simple example with uniformly distributed garages to illustrate the model in Eq. (27).

4. APPLICATIONS

Here a numerical example is provided to illustrate the influences of on- and off-street parking on the traffic system. We present the results obtained from multiple simulation runs and discuss the findings regarding the average/total searching time and distance in the network.

4.1. Numerical example

There is a total travel demand of 160 trips spread between three different origins (30/50/80 trips) in the network associated to different VOTs \( VOT_1 = 14 \) CHF/h; \( VOT_2 = 18 \) CHF/h; \( VOT_3 = 16 \) CHF/h). A Poisson distribution is used to define the entry time of the vehicles to the area, where the average arrival rate is 20 vehicles per hour. We consider time slices of 1 min, i.e., \( t = 1 \) min. Due to space constraints and for simplicity, no through-traffic (i.e., \( \beta_i = 0, \forall i \)) is assumed. The price per distance driven is assumed as \( p_{\text{dist}} = 0.3 \) CHF/km and the walking speed is set to \( w = 5 \) km/h ([6]). The number of garages is \( G = 3 \) with a total capacity of \( R_{t,o}^0 = 27 \). The penalty term \( \lambda \) should be calibrated, but for simplicity we assume \( \lambda = 0.5 \). Other inputs include: \( L = 1 \) km; \( b = 83.3 \) m; \( A = 23 \) on-street parking spaces, and \( v = 30 \) km/h. All further input parameters to the general macroscopic model can be found in the numerical example in [13].

4.2. Impacts of on- and off-street parking pricing

The focus of this paper is on the influence of on- and off-street parking to the traffic system with regard to different parking pricing schemes. We consider the following pricing scenarios:

- Scenario (a): Without parking pricing
- Scenario (b): \( p_{op}^i \) and \( p_{gp}^i \) constant
- Scenario (c): \( p_{op}^i \) demand-responsive, \( p_{gp}^i \) constant
- Scenario (d): \( p_{op}^i \) constant, \( p_{gp}^i \) demand-responsive
- Scenario (e): \( p_{op}^i \) and \( p_{gp}^i \) demand-responsive

All constant and initial parking fees in all scenarios are set to \( p_{op}^0 = 2.50 \) CHF for all on-street and to \( p_{gp}^0 = 6 \) CHF for all off-street parking spots. We consider the pricing fees grouped over 5 consecutive time slices, i.e., the parking price is updated every 5 minutes, and it is rounded to the next 0.5 CHF value to simplify the pricing structure.

We concentrate on short-term effects such as the financial benefits of on- and off-street parking fees which can lead to the following revenues for the city.

- Scenario (b): Total revenue: 475 CHF (347 CHF on-street, 128 CHF off-street)
- Scenario (c): Total revenue: 718 CHF (416 CHF on-street, 365 CHF off-street)
• Scenario (d): Total revenue: 475 CHF (347 CHF on-street, 128 CHF off-street)
• Scenario (e): Total revenue: 900 CHF (418 CHF on-street, 482 CHF off-street)

All effects on cruising-for-parking and traffic performance are evaluated in Table 4 with respect to the results of scenario (a).

Fig. 3(a) and (b) show the influence of ratio \( \frac{p_{op}^i}{p_{gp}^i} \) on \( C_{op}^i \) (see section 3.3.1 for \( n_{ns/dgp}^i \)) and \( C_{gp}^i \) in scenario (c) and (e). We used a quadratic regression approach based on aggregated data that shows an increasing \( C_{op}^i \) (red continuous line) and a constant/increasing \( C_{gp}^i \) (blue dashed line) for an increasing ratio \( \frac{p_{op}^i}{p_{gp}^i} \).

(a) \( p_{op}^i \) demand-responsive and \( p_{gp}^i \) constant (scenario (c))  
(b) \( p_{op}^i \) and \( p_{gp}^i \) demand-responsive (scenario (e))

Fig. 3. Demand-responsive on- and off-street parking pricing and its influence on the cost of cruising and garage parking.

By introducing demand-responsive on- and off-street parking pricing in scenario (e), \( C_{op}^i \) and \( C_{gp}^i \) increase until both are equal at approximately \( p_{op}^i = p_{gp}^i \). The system balances out \( C_{op}^i \) and \( C_{gp}^i \) depending on the traffic situation by using demand-responsive \( p_{op}^i \) and \( p_{gp}^i \). This leads to significant time (distance) improvements across all states in scenario (e) (Table 4). These improvements come along with financial revenues such as a total revenue of 900 CHF for city councils or private agencies in the area. Scenario (c) uses a constant \( p_{gp}^i \) and thus, has less flexibility to adapt \( C_{gp}^i \) on the traffic situation. These traffic effects lead to less time (distance) improvements across all states in scenario (c) compared to scenario (e). Scenario (b) and (d) lead to a worse traffic performance with respect to scenario (a) and a relatively small numbers of vehicles deciding for garage parking. Due to the gap between \( p_{op}^i = 2.50 \) CHF and \( p_{gp}^i = 6 \) CHF vehicles will only consider to drive to a garage in case the average cruising time and distance are high. Therefore, congestion with high cruising cost already exists before the vehicles consider this garage parking decision.
Table 4. Average/Total time and driven distance for vehicles in relevant traffic states. Value within parenthesis represents percentage change with respect to the scenario (a) without parking pricing.

<table>
<thead>
<tr>
<th>State</th>
<th>Average travel time per vehicle (min/veh)</th>
<th>Total travel time (min)</th>
<th>Total time costs (converted through VOT)</th>
<th>Average driven distance (km/veh)</th>
<th>Total driven distance (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Without parking pricing</td>
<td>3.214</td>
<td>514.186</td>
<td>139.242</td>
<td>1.128</td>
<td>180.48</td>
</tr>
<tr>
<td>(b) $p_{ip}$ and $p_{ip}$ constant</td>
<td>4.664 (+ 45.1 %)</td>
<td>746.166 (+ 45.1 %)</td>
<td>202.062 (+ 45.1 %)</td>
<td>1.197 (+ 6.1 %)</td>
<td>191.569 (+ 6.1 %)</td>
</tr>
<tr>
<td>(c) $p_{ip}$ demand-responsive, $p_{ip}$ constant</td>
<td>2.864 (- 10.9 %)</td>
<td>458.287 (- 10.9 %)</td>
<td>124.105 (- 10.9 %)</td>
<td>1.073 (- 4.9 %)</td>
<td>171.733 (- 4.9 %)</td>
</tr>
<tr>
<td>(d) $p_{ip}$ constant, $p_{ip}$ demand-responsive</td>
<td>4.664 (+ 45.1 %)</td>
<td>746.166 (+ 45.1 %)</td>
<td>202.062 (+ 45.1 %)</td>
<td>1.197 (+ 6.1 %)</td>
<td>191.569 (+ 6.1 %)</td>
</tr>
<tr>
<td>(e) $p_{ip}$ and $p_{ip}$ demand-responsive</td>
<td>2.889 (- 10.1 %)</td>
<td>462.233 (- 10.1 %)</td>
<td>125.173 (- 10.1 %)</td>
<td>1.111 (- 1.5 %)</td>
<td>177.735 (- 1.5 %)</td>
</tr>
<tr>
<td>(a) Without parking pricing</td>
<td>8.644</td>
<td>1383</td>
<td>374.516</td>
<td>3.107</td>
<td>497.12</td>
</tr>
<tr>
<td>(b) $p_{ip}$ and $p_{ip}$ constant</td>
<td>25.355 (+ 193.3 %)</td>
<td>4056.7 (+ 193.3 %)</td>
<td>1098.554 (+ 105 %)</td>
<td>6.37 (+ 105 %)</td>
<td>1019.2 (+ 105 %)</td>
</tr>
<tr>
<td>(c) $p_{ip}$ demand-responsive, $p_{ip}$ constant</td>
<td>9.17 (+ 6.1 %)</td>
<td>1467.2 (+ 6.1 %)</td>
<td>397.316 (+ 5.7 %)</td>
<td>3.283 (+ 5.7 %)</td>
<td>525.339 (+ 5.7 %)</td>
</tr>
<tr>
<td>(d) $p_{ip}$ constant, $p_{ip}$ demand-responsive</td>
<td>25.355 (+ 193.3 %)</td>
<td>4056.7 (+ 193.3 %)</td>
<td>1098.554 (+ 105 %)</td>
<td>6.37 (+ 105 %)</td>
<td>1019.2 (+ 105 %)</td>
</tr>
<tr>
<td>(e) $p_{ip}$ and $p_{ip}$ demand-responsive</td>
<td>6.745 (- 22 %)</td>
<td>1080.8 (- 22 %)</td>
<td>292.247 (- 19.9 %)</td>
<td>2.489 (- 19.9 %)</td>
<td>398.235 (- 19.9 %)</td>
</tr>
<tr>
<td>(a) Without parking pricing</td>
<td>3.983</td>
<td>637.194</td>
<td>172.552</td>
<td>1.32</td>
<td>211.129</td>
</tr>
<tr>
<td>(b) $p_{ip}$ and $p_{ip}$ constant</td>
<td>0.133 (- 96.7 %)</td>
<td>21.326 (- 96.7 %)</td>
<td>5.775 (- 95 %)</td>
<td>0.067 (- 95 %)</td>
<td>10.663 (- 95 %)</td>
</tr>
<tr>
<td>(c) $p_{ip}$ demand-responsive, $p_{ip}$ constant</td>
<td>1.761 (- 55.8 %)</td>
<td>281.757 (- 55.8 %)</td>
<td>76.3 (- 52.1 %)</td>
<td>0.632 (- 52.1 %)</td>
<td>101.148 (- 52.1 %)</td>
</tr>
<tr>
<td>(d) $p_{ip}$ constant, $p_{ip}$ demand-responsive</td>
<td>0.133 (- 96.7 %)</td>
<td>21.326 (- 96.7 %)</td>
<td>5.775 (- 95 %)</td>
<td>0.067 (- 95 %)</td>
<td>10.663 (- 95 %)</td>
</tr>
<tr>
<td>(e) $p_{ip}$ and $p_{ip}$ demand-responsive</td>
<td>2.731 (- 31.4 %)</td>
<td>436.852 (- 31.4 %)</td>
<td>118.299 (- 26.6 %)</td>
<td>0.969 (- 26.6 %)</td>
<td>155.075 (- 26.6 %)</td>
</tr>
<tr>
<td>(a) Without parking pricing</td>
<td>15.841</td>
<td>2534.38</td>
<td>686.31</td>
<td>5.555</td>
<td>888.729</td>
</tr>
<tr>
<td>(b) $p_{ip}$ and $p_{ip}$ constant</td>
<td>30.152 (+ 90.3 %)</td>
<td>4824.192 (+ 90.3 %)</td>
<td>1306.391 (+ 37.4 %)</td>
<td>7.634 (+ 37.4 %)</td>
<td>1221.432 (+ 37.4 %)</td>
</tr>
<tr>
<td>(c) $p_{ip}$ demand-responsive, $p_{ip}$ constant</td>
<td>13.795 (- 12.9 %)</td>
<td>2207.244 (- 12.9 %)</td>
<td>597.721 (- 10.2 %)</td>
<td>4.988 (- 10.2 %)</td>
<td>798.22 (- 10.2 %)</td>
</tr>
<tr>
<td>(d) $p_{ip}$ constant, $p_{ip}$ demand-responsive</td>
<td>30.152 (+ 90.3 %)</td>
<td>4824.192 (+ 90.3 %)</td>
<td>1306.391 (+ 37.4 %)</td>
<td>7.634 (+ 37.4 %)</td>
<td>1221.432 (+ 37.4 %)</td>
</tr>
<tr>
<td>(e) $p_{ip}$ and $p_{ip}$ demand-responsive</td>
<td>12.365 (- 21.9 %)</td>
<td>1979.885 (- 21.9 %)</td>
<td>535.719 (- 17.7 %)</td>
<td>4.569 (- 17.7 %)</td>
<td>731.045 (- 17.7 %)</td>
</tr>
</tbody>
</table>

Demand-responsive on- and off-street parking pricing (scenario (e)) not only leads to high financial revenues, it also leads to significant cruising, environmental and traffic performance improvements across all states. However, the usage of the model is not limited to these specific results. It can be used to optimize on- and off-street parking for different object criteria (e.g., minimize cruising traffic, minimize travel distance, and maximize revenues) in the
network.

5. CONCLUSIONS

In this study, we develop a dynamic macroscopic off-street parking model and integrate it into the urban traffic and on-street parking study in [8] and [13] to better replicate reality. We analyze the influence of on- and off-street parking on searching-for-parking traffic and traffic performance based on different parking pricing schemes.

The main contributions of this paper are:

- We model off-street parking macroscopically, including the parking searcher’s decision between driving to a parking garage or searching for an on-street parking place in the network.
- We formulate pricing scenarios including demand-responsive parking pricing methodologies as introduced in [13] for both on- and off-street parking. Scenarios include both constant and demand-responsive pricing policies. By evaluating their effects on the traffic system in all scenarios, we show that the demand-responsive on- and off-street parking pricing scenario leads to significant cruising and environmental improvements. In addition, a relationship between on- and off-street parking pricing and the costs of cruising and garage parking are analyzed in this paper. The model provides a preliminary idea for city councils regarding the on- and off-street parking influence on searching-for-parking traffic (cruising), the congestion in the network (traffic performance), the total driven distance (environmental conditions), and the revenue created by on- and off-street parking fees for the city. In the long-term, drivers might avoid paying high on- or off-street parking fees and quit their journeys. This could affect the demand, but long-term effects are out-of-scope of this paper.

The general framework provides an easy to implement methodology to macroscopically model on- and off-street parking. All methods are based on very limited data inputs, including travel demand, VOT, number of garages with their capacity, the traffic network, and initial parking specifications. Only aggregated data at the network level over time is required such that there is no need for individual parking data. This macroscopic approach saves on data collection efforts and reduces the computational costs significantly compared to existing literature. Additionally, there is no requirement of complex simulation software and the model can be easily solved with a simple numerical solver.

Overall, the usage of the model is far beyond the illustration in the numerical example. The relation between through traffic, i.e., vehicles that are not searching for parking, on- and off-street parking and traffic conditions can be analyzed. Due to simplification purposes through-traffic was assumed to be zero in this paper. For simplicity we have additionally assumed that all individual on- and off-street parking spaces have the same initial parking price and all garages have equal capacities. The influence of individual parking prices and individual off-street capacities on the traffic system can be analyzed in future studies. In reality, vehicles often prefer parking possibilities in a central street or area of the network. Parking in non-homogenous environments can be included in future research. We can also include a traffic demand split with a fixed (low subsidized) parking fee for all on- and/or off-street parking spaces. All remaining portions of demand could be treated demand responsively, reflecting the external costs for parking. This approach can be motivated by, e.g., the subsidy by a company or a city for their residents.

In summary, the model can be used to efficiently analyze the influence of on- and off-street parking on the traffic
system, despite its simplicity in data requirements. Based on scarce aggregated data, this model can be used to analyze how on- and off-street parking can affect cruising-for-parking traffic; and how cruising vehicles can affect the decision to use on- or off-street parking. It is hoped that the knowledge and methodology obtained in this research can later be transferred and used in urban areas. A validation with real data will, evidently, be required.
REFERENCES


