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

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1   **MACROSCOPIC MODEL FOR ON- AND OFF-STREET PARKING:**

2   **TRAFFIC EFFECTS**

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1   **ABSTRACT**

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

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

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

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

1   **1. INTRODUCTION**

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

12   In the existing literature, there are empirical or modelling approaches used to define on- and off-street parking pricing.
13   Empirical approaches usually focus on collecting data for both on- and off-street parking, e.g., [18] uses its demand-
14   responsive pricing scheme to leave between 20 and 40 percent of on-street parking spaces open on every block, and
15   to have open spaces available in public garages at all times ([16]). Other off-street pricing approaches are based on
16   questionnaires, e.g., [4]; [5]; or they use dynamic information to predict real-time off-street parking availability ([7]).
17   [14] estimates the effect of on-street parking fees on drivers' choice between on- and off-street parking. [11] analyzes
18   how off-street parking demand is affected by on-street parking regulations. Our macroscopic model provides general
19   results regarding the effects of on- and off-street parking pricing on traffic under generalized conditions without any
20   physical devices or data collections efforts.

21   For modelling both on- and off-street parking with its associated parking fees, [1] and [12] show that the full price of
22   parking consists of the interaction between garage operators and the cruising costs for on-street parking. They develop
23   a spatial competition model to eliminate cruising by allocating excessive cruising demand to garage parking and focus
24   on social optimum suggestions concerning the relationship between curbside and garage fares. [15] develops a
25   dynamic Stackelberg leader-follower game theory approach to model variable on- and off-street parking prices in real-
26   time for effective parking access and space utilization. Compared to these models that provide a long-term demand
27   management strategy capturing user competition and considering market equilibrium, our models focuses on the short-
28   term effects. [17] models a system optimal parking flow minimization problem that follows a real-time pricing
29   approach for a parking lot based on its occupancy rate. They assume a user equilibrium travel behavior and only focus
30   on off-street parking without analyzing its interdependency to on-street parking in the network. [19] investigates an
31   optimal parking pricing problem in a park-and-ride (P+R) network with multiple origins and one destination. Their
32   objective is to minimize the total travel cost by setting optimal parking fees and only considering P+R terminals. [20]
33   models multi-modal traffic with limited on-street and garage parking and dynamic pricing based on the Macroscopic
34   Fundamental Diagram (MFD). [3] analyzes how much curbside to allocate to parking when the private sector provides
35   garage parking. [2] analyzes parking in a spatially homogeneous downtown area where the drivers chose between on-
36   and off-street parking. Cruising for parking contributes to congestion, such that the full price of the initially cheaper
37   on-street parking is increased until it equals the price of garage parking. Then increasing the on-street parking fee may
38   generate an efficiency gain through reduction of cruising. These papers consider parking pricing but they focus on
39   social optimum and user equilibrium pricing suggestions and do not include demand-responsive garage pricing.

1   This paper builds on a previous study from [13], in which a macroscopic on-street parking pricing model was
2   developed. It is based on the parking-state-based matrix from [8] providing an approximation of the proportion of cars
3   searching for on-street parking, as well as the time cars spent searching for parking, or travelling through the system.
4   These approximations are now enhanced by including off-street parking and considering various parking pricing
5   schemes, e.g., demand-responsive on- and off-street parking fees over time. Independently of their current traffic state,
6   the drivers can make the decision to use off-street parking, then drive towards the closest parking garage and access it
7   depending on its current capacity. This off-street parking decision is based on several cost factors:

8   • the drivers' value of time (VOT) depending on their origin;

9   • the current on- and off-street parking fees;

10   • the expected cost of cruising for on-street parking;

11   • the expected driving cost to the closest possible garage; and

12   • the walking cost from the off-street parking location to the drivers' final destination.

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

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

20   **2. FRAMEWORK**

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

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

33   In this study, all vehicles have in addition the option to decide for garage parking at their current location. This decision
34   can be done anywhere independently of their current traffic state, i.e., the vehicles can decide to use off-street parking
35   in "non-searching" or in "searching"-state. This leads to two new transition event scenarios for garage parking (Fig
36   1(c) and Fig 1(d)).
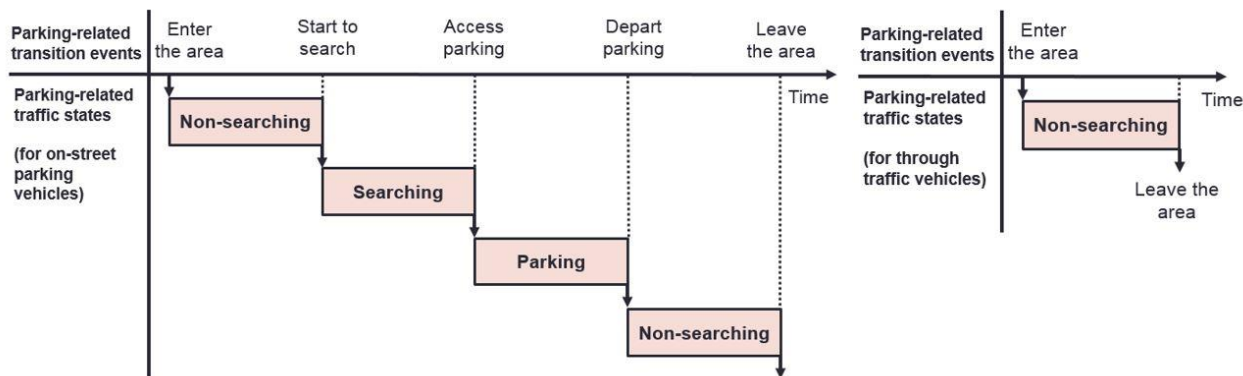
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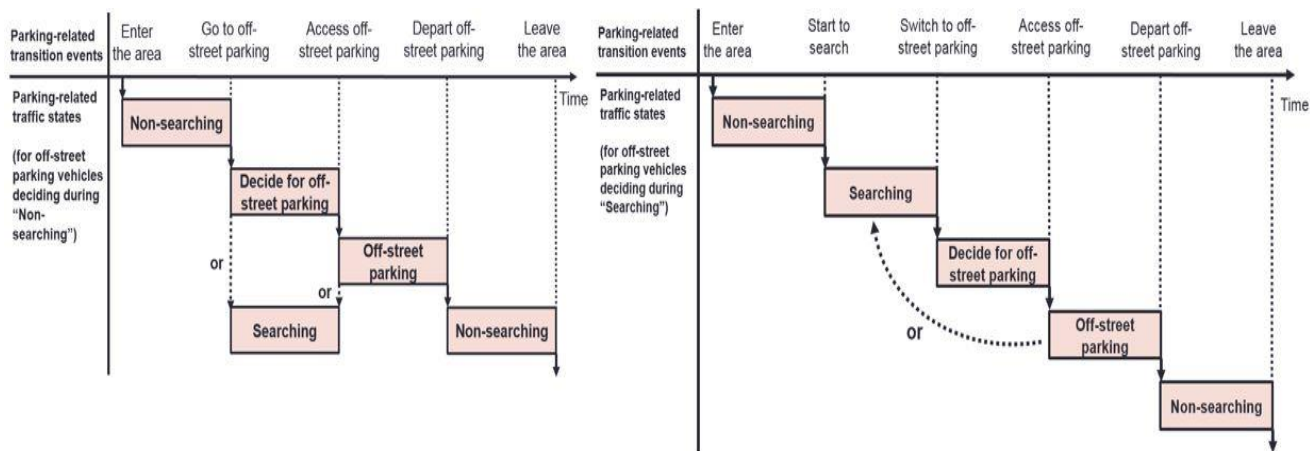2   (a) First group of vehicles.   (b) Second group of vehicles.

3

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

7   After the decision for off-street parking the vehicles drive towards the garage and access it depending on its current

8   capacity. If there is no capacity available, the vehicles need to return into the searching-for-parking state.

9   By including off-street parking, we need to introduce the new traffic states compared to [8], N_{dgp}^i that includes all

10   drivers who have decided to use garage parking, and N_{gp}^i that includes the drivers who actually access the garage.

11   These new traffic states and all related transition events are summarized in Table 1.

1   Table 1. Relevant key variables (including off-street parking related variables) for matrix per time slice.

Notation	Definition
N_{ns}^i	Number of vehicles in the state "non-searching" at the beginning of time slice i (Non-searching).
N_s^i	Number of vehicles in the state "searching" at the beginning of time slice i (Searching).
N_p^i	Number of vehicles in the state "parking" at the beginning of time slice i (On-street parking).
N_{dgp}^i	Number of vehicles in the state "decide for garage parking" at the beginning of time slice i (Decide for garage parking).
N_{gp}^i	Number of vehicles in the state "off-street parking" at the beginning of time slice i (Off-street parking).
$n_{/ns}^i$	Number of vehicles that enter the area and transition to "non-searching" during time slice i (Enter the area).
$n_{ns/s}^i$	Number of vehicles that transition from "non-searching" to "searching" during time slice i (Start to search).
$n_{s/p}^i$	Number of vehicles that transition from "searching" to "parking" during time slice i (Access on-street parking).
$n_{p/ns}^i$	Number of vehicles that transition from "parking" to "non-searching" during time slice i (Depart on-street parking).
$n_{ns/}^i$	Number of vehicles that leave the area and transition from "non-searching" during time slice i (Leave the area).
$n_{ns/dgp}^i$	Number of vehicles that transition from "non-searching" to "decide for garage parking" during time slice i (Go to off-street parking).
$n_{s/dgp}^i$	Number of vehicles that transition from "searching" to "decide for garage parking" during time slice i (Switch to off-street parking).
$n_{dgp/gp}^i$	Number of vehicles that transition from "decide for garage parking" to "off-street parking" during time slice i (Access off-street parking).
$n_{dgp/s}^i$	Number of vehicles that transition from "decide for garage parking" to "searching" during time slice i (Not access off-street parking).
$n_{gp/ns}^i$	Number of vehicles that transition from "off-street parking" to "non-searching" during time slice i (Depart off-street parking).

2

3   Based on Table 1, we adapt all transition state related formulas in [8] between consecutive time slices. By including

4    $n_{ns/dgp}^i$, $n_{s/dgp}^i$, $n_{dgp/gp}^i$, $n_{dgp/s}^i$ and $n_{gp/ns}^i$ we get Eq. (1) to (3) that update the number of "non-searching",

5   "searching", and "parking" vehicles. Notice that Eq. (3) remains the same.

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

$$N_s^{i+1} = N_s^i + n_{ns/s}^i + n_{dgp/s}^i - n_{s/p}^i - n_{s/dgp}^i \tag{2}$$

$$N_p^{i+1} = N_p^i + n_{s/p}^i - n_{p/ns}^i \tag{3}$$

6   Eq. (4) updates the number of vehicles that "decide for garage parking". Vehicles that decide to use a parking garage

7   during time slice i (i.e., $n_{ns/dgp}^i$ and $n_{s/dgp}^i$) join this state; vehicles that actually access off-street parking (i.e.,

8    $n_{dgp/\mathrm{gp}}^i$) and vehicles that cannot access off-street parking (i.e., $n_{dgp/s}^i$) quit this state. Eq. (5) updates the number of

9   "off-street parking" vehicles. Vehicles that access a garage during time slice i (i.e., $n_{dgp/gp}^i$) join this state; vehicles

10   that depart off-street parking (i.e., $n_{gp/ns}^i$) quit this state.

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

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

11   The transition events $n_{/ns}^i$, $n_{ns/s}^i$, $n_{s/p}^i$, $n_{p/ns}^i$ and $n_{ns/}^i$ are modeled in [8] and [13]. Here we focus only on the new

12   transition events related to off-street parking, $n_{ns/dgp}^i$, $n_{s/dgp}^i$, $n_{dgp/gp}^i$, $n_{dgp/s}^i$ and $n_{gp/ns}^i$.

1 We require the origin $k \in K$ dependent demand $n^i_{k,/ns}$ and the transition event $n^i_{k,ns/s}$ to incorporate the VOT
2 influence into our off-street parking decision model. $n^i_{k,/ns}$ is an input to the model, such that $n^i_{/ns} = \sum_{k=1}^K n^i_{k,/ns}$,
3 whereas K is the total number of origins in the network. $n^i_{k,ns/s}$ is modeled in [13].

3. DECISION MODEL FOR OFF-STREET PARKING

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

3.1. Basic information for analytical model

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

9 *Assumptions:*

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

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

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

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

1   *Inputs:*

2   Table 2 shows all the model's independent variables. The first set corresponds to the travel demand and supply, and

3   can be estimated based on historical data. The second set corresponds to the traffic network, and can be directly

4   measured. The third set corresponds to the initial conditions of the parking-related states, and can be measured,

5   assumed or simulated. The fourth set corresponds to off-street parking specific input parameters, and can be directly

6   measured or estimated based on historical data.

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

Notation	Definition
K	Total number of origins for demand input of the network. Each origin might have a different VOT.
VOT_k	VOT for origin $k \in K$.
$n^i_{k,/ns}$	New arrivals to the network for origin $k \in K$ during time slice i (i.e., travel demand per VOT origin)
β^i	Proportion of new arrivals during time slice i that correspond to traffic that is not searching for parking.
A	Total number of existing on-street parking spaces (for public use) in the area.
$l_{ns/s}$	Distance that must be driven by a vehicle before it starts to search for parking.
$l_/$	Distance that must be driven by a vehicle before it leaves the area without parking.
$l_{p/}$	Distance that must be driven by a vehicle before it leaves the area after it has parked.
t_d	Parking duration.
L	Size (length) of the network.
b	Average length of a block in the network.
t	Length of a time slice.
v	Free flow speed, i.e., maximum speed in the network.
w	Walking speed in the network.
N^0_{ns}	Initial condition for the non-searching state.
N^0_s	Initial condition for the searching state.
N^0_p	Initial condition for the parking state.
N^0_{dgp}	Initial condition for the decision for off-street parking state.
N^0_{gp}	Initial condition for the off-street parking state.
G	Number of parking garages in the network.
R^0_{tot}	Total capacity of all parking garages, i.e., total number of off-street parking spaces.
p^0_{gp}	Initial garage parking pricing.
Δ_{max}	Maximum increase/decrease of garage pricing per time slice.
y	Influence factor of the off-street parking related demand-responsivity during garage parking pricing.
λ	Penalty term to reduce circular movements while switching to off-street parking, $\lambda \in (0,1)$.
p_{dist}	Price per kilometer driven on the network (i.e., external costs as petrol, wear and tear of vehicles).

8

9   *Outputs:*

10   The model provides, amongst others, the interactions between on- and off-street parking and their influence on the

11   urban traffic system. The short-term effects of parking pricing on traffic conditions can be investigated, i.e., all

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

2   Table 3 shows a list of variables we define and use for our methodology. The first set is used to quantify the number

3   of vehicles that experience each transition event in a time slice. The second set corresponds to the off-street parking

4   decision model. The third set is used to compute the costs variables in this decision model.

5   Table 3. Dependent variables.

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

6

7   **3.2.   Model for off-street related transition events**

8   We introduce the following transition events based on the assumption that the urban network is abstracted as one ring

9   road with cars driving in a single direction. This simplifies the model without affecting the model results ([8]). The

10   different costs associated with the parking decisions are formulated in section 3.3.

11   *3.2.1.   Transition event: Go to off-street parking*

12   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

13   or taken out of a distribution. For simplicity, we assume it is fixed. Besides searching for an on-street parking space,

14   the vehicles have then the option to decide for off-street parking as modelled in Eq. (6); $n_{ns/dgp}^i$ may consist of

15   vehicles entering the network in any former time slice $i' \in [1, i-1]$.

$$n_{ns/dgp}^i = \left[\sum_{i'=1}^{i-1} \underbrace{\left(1 - \beta^{i'}\right) \cdot n_{/ns}^{i'}}_{\text{term 1}} \cdot \underbrace{\gamma_{ns/s}^{i'}}_{\text{term 2}} \right] \cdot \underbrace{\gamma_{ns/dgp}^i}_{\text{term 3}} \tag{6}$$

1   where

$$\gamma_{ns/s}^{i'} = \begin{cases} 1, & \text{if } l_{ns/s} \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq l_{ns/s} + d^{i-1} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

$$\gamma_{ns/dgp}^{i} = \begin{cases} 1, & \text{if } C_{op}^i \geq C_{gp}^i \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

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

11   *3.2.2. Transition event: Switch to off-street parking*

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

$$n_{s/dgp}^i = N_s^i \cdot \gamma_{s/dgp}^i \cdot \gamma_{pen}^i \tag{9}$$

15   where:

$$\gamma_{s/dgp}^{i} = \begin{cases} 1, & \text{if } C_{op}^i \geq C_{gp}^i \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

$$\gamma_{pen}^{i} = \begin{cases} \lambda, & \text{if } n_{s/dgp}^{i-1} > 0 \text{ or } n_{s/dgp}^{i-2} > 0 \\ 1, & \text{otherwise} \end{cases} \tag{11}$$

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

18   *3.2.3. Transition event: Access off-street parking*

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

$$n_{dgp/gp}^i = \min\left\{ \sum_{i'=1}^{i-1} \underbrace{(n_{ns/dgp}^{i'} + n_{s/dgp}^{i'})}_{\text{term 1}} \cdot \underbrace{\gamma_{ADD}^{i'}}_{\text{term 2}} ; R_{tot}^i \right\} \tag{12}$$

1 where

$$\gamma_{ADD}^{i'} = \begin{cases} 1, & \text{if } ADD \leq \sum_{j=i'}^{j=i-1} d^j \text{ and } \sum_{j=i'}^{j=i-1} d^j \leq ADD + d^{i-1} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

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

8 *3.2.4. Transition event: Not access off-street parking*

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

$$n_{dgp/s}^i = \max\{n_{dgp/gp}^i - R_{tot}^i; 0\} \tag{14}$$

11 In case $n_{dgp/gp}^i$ surpasses R_{tot}^i, the remaining vehicles need to return to searching-for-parking state; otherwise all
12 vehicles can successfully enter a garage.

13 *3.2.5. Transition event: Depart off-street parking*

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

$$n_{gp/ns}^i = \sum_{i'=1}^{i-1} n_{dgp/gp}^{i'} \cdot \int_{(i-i')\cdot t}^{(i+1-i')\cdot t} f(t_d)\, dt_d \tag{15}$$

17 $n_{gp/ns}^i$ may consist of vehicles $n_{dgp/gp}^{i'}$ having accessed off-street parking in any former time slice $i' \in [1, i-1]$.
18 The probability that these vehicles depart off-street parking in time slice i equals to the probability of the parking

19 duration between $(i-i') \cdot t$ and $(i+1-i') \cdot t$, i.e., $\int_{(i-i')\cdot t}^{(i+1-i')\cdot t} f(t_d)\, dt_d$.

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

$$R_{tot}^{i+1} = R_{tot}^i + n_{gp/ns}^i - n_{dgp/gp}^i \tag{16}$$

21 *3.2.6. Transition event: Leave the area*

22 The vehicles leave the area after having driven for a given distance. Here $n_{ns/}^i$ needs to be modified in Eq. (17) to
23 include $n_{gp/ns}^{i'}$.

$$n_{ns/}^i = \sum_{i'=1}^{i-1}\left(\beta^{i'}\cdot n_{/ns}^{i'}\cdot\gamma_{/}^{i'} + \left(n_{p/ns}^{i'} + n_{gp/ns}^{i'}\right)\cdot\gamma_{p/}^{i'}\right)$$

(17)

1   where

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

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

2   Further details can be found in [8].

3   **3.3. Off-street parking decision related costs**

4   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
5   parking related decisions. In the following subsections, we mathematically derive these cost terms.

6   *3.3.1. Cost of cruising for on-street parking*

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

$$C_{op}^i = \underbrace{p_{op}^i}_{term\ 1} + \underbrace{p_{dist}\cdot ACD^i}_{term\ 2} + \underbrace{E_{VOT}^i\cdot\frac{ACD^i}{v^i}}_{term\ 3}$$

(18)

14   where

$$E_{VOT}^i = \begin{cases} \dfrac{1}{i}\sum_{k=1}^{K}\sum_{t=1}^{i}\dfrac{n_{k,/ns}^t}{n_{/ns}^t}\cdot VOT_k, & \text{for } n_{ns/dgp}^i \\[3mm] \dfrac{1}{i}\sum_{k=1}^{K}\sum_{t=1}^{i}\dfrac{n_{k,ns/s}^t}{n_{ns/s}^t}\cdot VOT_k, & \text{for } n_{s/dgp}^i \end{cases}$$

(19)

15   The average cruising distance ACD^i is determined as in [13].

1   *3.3.2. Cost of garage parking*

2   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

3   closest off-street parking location C_{drive}^i (subsection 0) and the average walking cost to the final destination C_{walk}^i

4   (subsection 0).

$$C_{op}^i = p_{gp}^i + C_{drive}^i + C_{walk}^i \tag{20}$$

5   **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

6   as a demand-responsive pricing variable. The demand-responsive fee p_{gp}^i in Eq. (21) is modelled analogously to the

7   on-street parking pricing model in [13].

$$p_{gp}^i = \begin{cases} p_{gp}^{i-1} + min\{\Delta p_{gp}^i, \Delta_{max}\}, & \text{if } \Delta \dfrac{N_{dgp}^i}{R_{tot}^i} > 0 \\[2ex] p_{gp}^{i-1}, & \text{if } \Delta \dfrac{N_{dgp}^i}{R_{tot}^i} = 0 \\[2ex] p_{gp}^{i-1} - min\{\Delta p_{gp}^i, \Delta_{max}\}, & \text{if } \Delta \dfrac{N_{dgp}^i}{R_{tot}^i} < 0 \end{cases} \tag{21}$$

8   where

$$\Delta \frac{N_{dgp}^i}{R_{tot}^i} = \frac{N_{dgp}^i}{R_{tot}^i} - \frac{N_{dgp}^{i-1}}{R_{tot}^{i-1}} \tag{22}$$

$$\Delta p_{gp}^i = \underbrace{p_{gp}^0}_{\text{term } 1} \cdot \underbrace{\left(\left| \Delta \frac{N_{dgp}^i}{R_{tot}^i} \right| \right)^{\frac{1}{y}}}_{\text{term } 2} \tag{23}$$

9   The ratio concerning N_{dgp}^i and R_{tot}^i varies between consecutive time slices (Eq. (22)). Depending on $\Delta \frac{N_{dgp}^i}{R_{tot}^i}$ the

10   garage fee p_{gp}^i in Eq. (21) increases or decreases per time slice. The actual change of the off-street parking pricing

11   is modelled in Eq. (23), where term 1 represents the initial fee p_{gp}^0 and term 2 the demand-responsive impact to

12   Δp_{gp}^i. Within term 2, y is the influence factor of the demand-responsivity. It changes the level of influence of $\Delta \frac{N_{dgp}^i}{R_{tot}^i}$

13   to the delta pricing value Δp_{gp}^i. For further studies in this paper, we assume a square root dependency and set $y = 2$.

14   To avoid drastic price fluctuations in Eq. (21) a maximum pricing increase/decrease input variable Δ_{max} is used per

15   time slice ([13]).

16   **3.3.2.2 Cost of driving from current vehicle location to closest off-street parking.**   The driving cost C_{drive}^i from

17   the actual vehicle decision location to the closest garage is modelled in Eq. (24). It contains the average distance to

18   the closest off-street parking expressed in distance price units (term 1) and the average time expressed in VOT price

19   units that is needed to get there (term 2).

$$C_{drive}^i = \underbrace{p_{dist} \cdot ADD}_{\text{term } 1} + \underbrace{E_{VOT}^i \cdot \frac{ADD}{v^i}}_{\text{term } 2} \tag{24}$$

1   Both terms include ADD (determined in Eq. (25)). The computation is based on the assumption that vehicles and

2   garages are uniformly distributed over the network and that the relationship between on- and off-street parking

3   locations is random, i.e., the locations could be close or far away from each other.

$$ADD = \frac{L}{2 \cdot G} \tag{25}$$

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

5   illustrate Eq. (25).
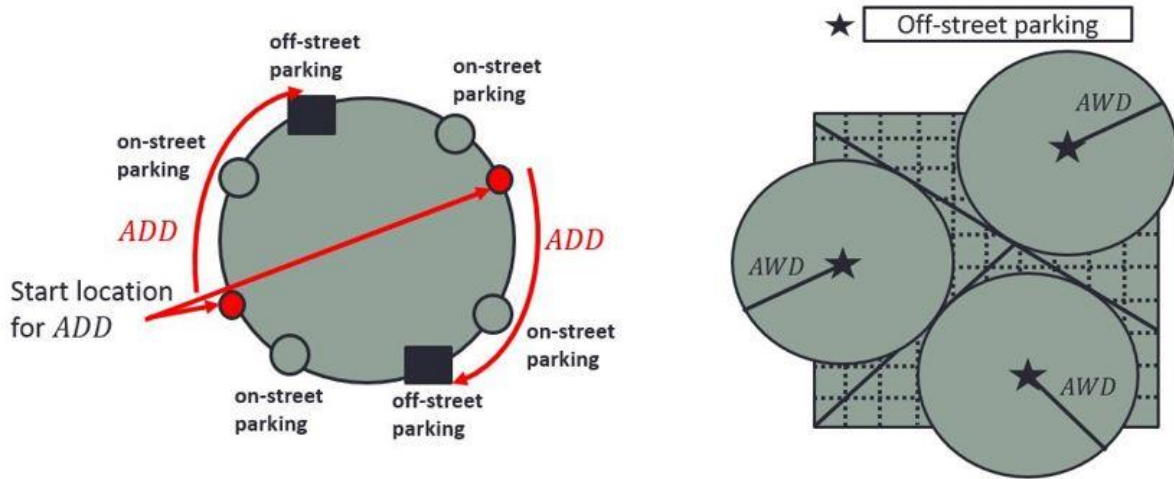
6

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

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

9   **3.3.2.3 Cost of walking from off-street parking to destination.**   Assuming that drivers choose on-street parking

10 close to their destination, there is no need to consider walking costs for on-street parking. Garages could be further

11 away from the drivers' destination. Thus, the associated walking cost C_{walk}^i in Eq. (26) consists of the average

12 walking distance from the garage to the destination expressed in distance price units (term 1), and its associated

13 average walking time cost expressed in VOT price units (term 2). The walking speed w is assumed to be a constant

14 input.

$$C_{walk}^i = \underbrace{p_{dist} \cdot AWD}_{\text{term 1}} + \underbrace{E_{VOT}^i \cdot \frac{AWD}{w}}_{\text{term 2}} \tag{26}$$

15 We may assume without loss of generality that the network is a square grid, whereas the average length of a block b

16 in the network is known. This network is then visualized as a ring network by joining all blocks together. We take the

17 surface of this total square $\left[b \cdot \left(-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}} \right) \right]^2$ and divide it by G. We move this partial surface into a circle

18 where we assume that its radius is the average walking distance AWD to the drivers' destination described in Eq.

19 (27).

$$AWD = \frac{b}{\sqrt{\pi \cdot G}} \left[-\frac{1}{2} + \sqrt{\frac{1}{4} + \frac{L}{2b}} \right] \tag{27}$$

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

2   **4. APPLICATIONS**

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

6   **4.1. Numerical example**

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

16   **4.2. Impacts of on- and off-street parking pricing**

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

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

24   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
25   for all off-street parking spots. We consider the pricing fees grouped over 5 consecutive time slices, i.e., the parking
26   price is updated every 5 minutes, and it is rounded to the next 0.5 CHF value to simplify the pricing structure.

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

29   - Scenario (b): Total revenue: 475 CHF (347 CHF on-street, 128 CHF off-street)
30   - Scenario (c): Total revenue: 718 CHF (416 CHF on-street, 365 CHF off-street)

1 • Scenario (d): Total revenue: 475 CHF (347 CHF on-street, 128 CHF off-street)

2 • Scenario (e): Total revenue: 900 CHF (418 CHF on-street, 482 CHF off-street)

3 All effects on cruising-for-parking and traffic performance are evaluated in Table 4 with respect to the results of

4 scenario (a).

5 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 $n_{ns/\mathrm{d}gp}^i$) and C_{gp}^i in scenario (c) and

6 (e). We used a quadratic regression approach based on aggregated data that shows an increasing C_{op}^i (red continuous

7 line) and a constant/increasing C_{gp}^i (blue dashed line) for an increasing ratio $\frac{p_{op}^i}{p_{gp}^i}$.
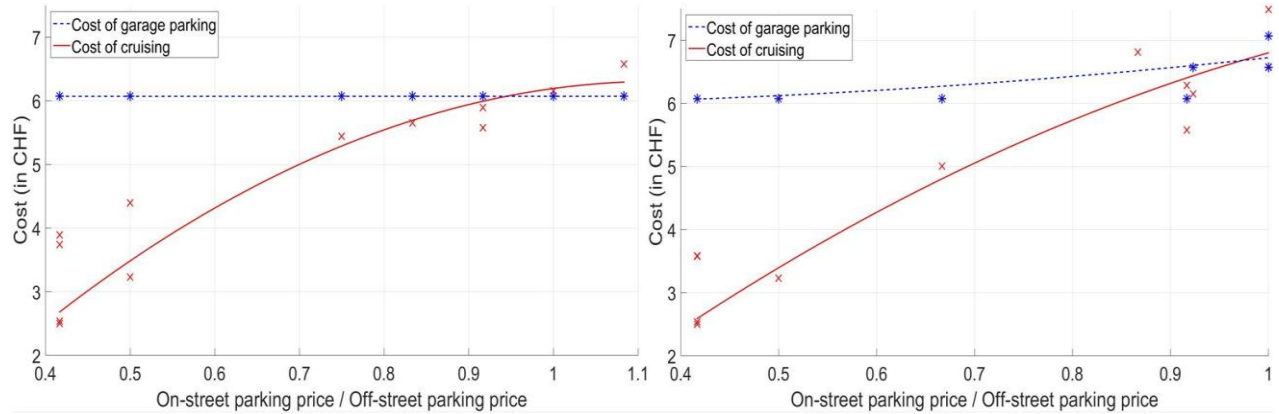
9   (a) p_{op}^i demand-responsive and p_{gp}^i constant (scenario (c))   (b) p_{op}^i and p_{gp}^i demand-responsive (scenario (e))

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

11 By introducing demand-responsive on- and off-street parking pricing in scenario (e), C_{op}^i and C_{gp}^i increase until

12 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

13 by using demand-responsive p_{op}^i and p_{gp}^i. This leads to significant time (distance) improvements across all states in

14 scenario (e) (Table 4). These improvements come along with financial revenues such as a total revenue of 900 CHF

15 for city councils or private agencies in the area. Scenario (c) uses a constant p_{gp}^i and thus, has less flexibility to adapt

16 C_{gp}^i on the traffic situation. These traffic effects lead to less time (distance) improvements across all states in scenario

17 (c) compared to scenario (e). Scenario (b) and (d) lead to a worse traffic performance with respect to scenario (a) and

18 a relatively small numbers of vehicles deciding for garage parking. Due to the gap between $p_{op}^0 = 2.50$ CHF and

19 $p_{gp}^0 = 6$ CHF vehicles will only consider to drive to a garage in case the average cruising time and distance are high.

20 Therefore, congestion with high cruising cost already exists before the vehicles consider this garage parking decision.

1   Table 4. Average/Total time and driven distance for vehicles in relevant traffic states. Value within parenthesis represents
2   percentage change with respect to the scenario (a) without parking pricing.

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

3

4   Demand-responsive on-and off-street parking pricing (scenario (e)) not only leads to high financial revenues, it also

5   leads to significant cruising, environmental and traffic performance improvements across all states. However, the

6   usage of the model is not limited to these specific results. It can be used to optimize on- and off-street parking for

7   different object criteria (e.g., minimize cruising traffic, minimize travel distance, and maximize revenues) in the

1   network.

2   **5. CONCLUSIONS**

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

6   The main contributions of this paper are:

7   • We model off-street parking macroscopically, including the parking searcher's decision between driving to
8   a parking garage or searching for an on-street parking place in the network.

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

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

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

36 In summary, the model can be used to efficiently analyze the influence of on- and off-street parking on the traffic

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

1   **REFERENCES**

2   [1] Arnott, R. (2006). Spatial competition between parking garages and downtown parking policy, Transp. Policy 13, pp. 458-469.

3   [2] Arnott, R. and Rowse, J. (2009). Downtown parking in auto city, Regional Science and Urban Economics 39 (1), pp. 1-14.

4   [3] Arnott, R., Inci, E., Rowse, J. (2015). Downtown curbside parking capacity, J. Urban Econ. 86, pp. 83-97.

5   [4] Auchincloss, A.H., Weinberger, R., Aytur, S., Namba, A., Ricchezza, A. (2015). Public Parking Fees and Fines: A Survey of U.S. Cities. Public
6   Works Management & Policy, Vol. 20 (1), pp. 49–59.

7   [5] Bianco, M. (2000). Effective Transportation Demand Management: The Results of Combining Parking Pricing, Transit Incentives, and
8   Transportation Management in a Commercial District of Portland, Oregon, Transportation Research Board - 79th Annual Meeting, Washington,
9   D.C.

10   [6] Browning, R. C., Baker, E. A., Herron, J. A. and Kram, R. (2006). Effects of obesity and sex on the energetic cost and preferred speed of walking,
11   Journal of Applied Physiology 100 (2), pp. 390-398.

12   [7] Caicedo, F., Blazquez, C., Miranda, P. (2012). Prediction of parking space availability in real time, Expert Systems with Applications, 39 (8),
13   pp. 7281-7290.

14   [8] Cao, J., Menendez, M. (2015a). System dynamics of urban traffic based on its parking-related-states, Transportation Research B, 81 (3), pp.
15   718-736.

16   [9] Cao, J., Menendez, M. (2015b). Cruising for parking: causes, effects, and control strategies, SVT Working Paper, 103, IVT, ETH Zurich, Zurich.

17   [10] Cao, J. (2016). How parking affects traffic performance on urban networks, Presentation at the World Parking Symposium, Vancouver, June
18   2016.

19   [11] Gragera, A., Albalate, D. (2016). The impact of curbside parking regulation on garage demand, Transport Policy 47, pp. 160-168.

20   [12] Inci, E., Lindsey, R. (2015). Garage and curbside parking competition with search congestion, Reg. Sci. Urban Econ. 54, pp. 49-59.

21   [13] Jakob, M., Menendez, M., Cao, J. (2015). A dynamic macroscopic parking pricing model, Submitted to the World Conference on Transport
22   Research - WCTR 2016 Shanghai.

23   [14] Kobus, M., Gutierrez-Puigarnau, E., Rietveld, P., van Ommeren, J. (2013). The on-street parking premium and car drivers' choice between
24   street and garage parking, Reg. Sci. Urban Econ. 43 (2), pp. 395–403.

25   [15] Mackowski, D., Bai, Y., Ouyang, Y. (2015). Parking Space Management via Dynamic Performance-Based Pricing, Transportation Research
26   Procedia, Volume 7, pp. 170-191.

27   [16] Pierce, G., Willson, H., Shoup, D. (2015). Optimizing the use of public garages: Pricing parking by demand, Transport Policy 44, pp. 89-95.

28   [17] Qian, Z., Rajagopala, R. (2013). Optimal parking pricing in general networks with provision of occupancy information, Procedia-Social and
29   Behavioral Sciences, 80, pp. 1-26.

30   [18]   SFpark,   San   Francisco   County   Transportation   Authority   (2009).   SF-CHAMP   Base   OD.   Available   at:
31   http://www.sfcta.org/downloads/ServiceBureau/. Accessed on June 20, 2016.

32   [19] Wang, H., Meng, Q., Zhang, X. (2015). Optimal Parking Pricing in Many-to-One Park-and-Ride Network with Parking Space Constraints,
33   Transportation Research Record Journal of the Transportation Research Board 2498.

1   [20] Zheng, N., Geroliminis, N. (2016). Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing,

2   Transportation Research Part B 83, pp. 36–58.