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PARKAGENT: An agent-based model of parking in the city

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ABSTRACT

In this paper, we present PARKAGENT, an agent-based, spatially explicit model for parking in the city. Unlike traditional parking models, PARKAGENT simulates the behavior of each driver in a spatially explicit environment and is able to capture the complex self-organizing dynamics of a large collective of parking agents within a non-homogeneous (road) space. The model generates distributions of key values like search time, walking distance, and parking costs over different driver groups. It is developed as an ArcGIS application, and can work with a practically unlimited number of drivers.

The advantages of the model are illustrated using a real-life case from Tel Aviv. Taking detailed data from field surveys, the model is used to study the impact of additional parking supply in a residential area with a shortage of parking places. The PARKAGENT model shows that additional parking supply linearly affects the occurrence of extreme values, but has only a weak impact on the average search time for a parking place or the average walking distance between the parking place and the destination.

1. Introduction

The answer to the question "What is a good parking policy?" depends on the goals and ambitions of politicians and citizens concerning their city. These goals can vary enormously, from guaranteeing optimal accessibility, optimal traffic flow and minimum nuisance from (legally and illegally) parked cars, to maximizing turn-over for shops and minimizing the use of the private car in a city (Marsden, 2006). Parking policy is thus a tool, not a goal in itself. In order to develop a parking policy that can achieve the desired goals, planners and decision-makers need a tool that can help them evaluate the alternatives.

In this paper, we present a spatially explicit, agent-based model of parking in the city (see Benenson and Torrens (2004) for general definitions and a state-of-the art review of agent-based models). The model, called PARKAGENT, is based on a direct representation of every driver, and simulates the whole parking process, including driving towards the destination, searching for parking, and exiting the parking place after a variable period of time.

Traditional approaches to studying parking in the city aggregate individual drivers into an "average driver", who, in turn, reacts to an "average" and non-spatial environment (e.g. D'Acierno, Gallo, & Montella, 2006; Lam, Li, Huang, & Wong, 2006). Our model, in contrast, follows every driver and can thus deal with the variety of parking behaviors resulting from e.g. knowledge of the area, parking habits, or willingness-to-pay for parking. The drivers behave in response to the number of available parking places, with the latter varying in response to the number of drivers entering and leaving the study area. Most importantly, the driver behaves in space, represented by real-world GIS layers.

The disaggregate view of parking is crucial for analyzing how parking policies influence key parameters, like search time and walking time, especially in modern cities with their highly heterogeneous parking supply and demand. We are aware of only one example of a model of similar kind (Thompson & Richardson, 1998). This model, however, focused on simulating the behavior of a single driver within a given constant spatial setting. Our model, in contrast, is able to analyze the collective dynamics of the system of parking drivers in a real-world spatial environment, while simulating the impact on the behavior of each individual driver of the continuously varying parking situation created by the drivers themselves.

The model presented in the paper is employed to study residential parking in the evening hours. In contrast to commuter parking (e.g. Hensher & King, 2001; Martens, 2005; Voith, 1998), this is a relatively neglected topic within the field of parking research. Residential parking differs from e.g. commuter parking in the sense that car-owners have little choice: at the end of each day each car-owner will have to find a parking place, preferably close to his or her place of residence. This contrasts sharply with the situation of commuters or business travelers, who can choose a different mode of transportation to avoid parking problems at the

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destination (see e.g. D'Acierno et al., 2006; Hess, 2001; Kelly & Clinch, 2006). Drivers traveling for recreational or leisure purposes have even more choice options, as they can change both their destination and their mode of transport in response to parking problems at the aimed-for destination (e.g. Shiftan & Burd-Eden, 2001). Drivers returning home at the end of the day do not have these choices: each driver will have to find a place for overnight parking. We use the model to analyze how these resident-parkers respond to different parking situations and policies at the home-end of the trip. The case material is taken from the city of Tel Aviv.

The paper is organized as follows. This introduction is followed by a detailed description of the PARKAGENT model (Section 2). Then, we present the results of a number of surveys carried out to feed the model with empirical data (Section 3). Section 4 reports on the application of PARKAGENT to a case-study area. The paper ends with conclusions, discussing the potential of agent-based models for studying parking behavior.

2. The PARKAGENT model

The PARKAGENT model has been developed according to two principles. First, it is a *spatially explicit model*, which builds on high-resolution urban GIS with layers representing every element of the traffic infrastructure important for investigating the parking process – street segments, on-street parking places, off-street parking places, and buildings. Second, it is an *agent-based model*, which directly represents every driver who drives to the destination, searches for a parking place, parks, and leaves the parking place when her activity has ended.

A key element of any spatially explicit agent-based model is the description of the agents' behavior. The PARKAGENT model contains rules that guide the drivers' driving, parking search, parking and leaving behavior. The rules include a detailed and instantaneous description of each driver's reaction to a lack of parking spaces, differences in pricing, parking enforcement efforts, or the behavior of other drivers, all in relation to the driver's estimate of the distance to the final destination. The stage of 'regular' driving towards the destination is ignored in the model; vehicles "enter" the system close to the actual destination, shortly before the actual search for parking commences.

Real-world drivers behave at a high temporal resolution and reach decisions in seconds or even faster. Hence, the model simulates drivers' behavior and records the system state at a temporal resolution of 0.5 s.

The model is developed as an ArcGIS application, and despite the very high spatial and temporal resolution, it can work with a practically unlimited number of drivers. The model interface contains a set of tools for selecting the area of simulation, establishing model scenarios, and storing the simulation results. The latter is done in Excel format, to facilitate the further analysis of the results.

The main components and features of the model are described below.

2.1. GIS database

The model GIS database consists of high-resolution spatial layers and non-spatial tables. Its main components are as follows: a street network, characterized by driving and parking permissions on each street segment; turn permissions; buildings (foundation polygons), characterized by type of use and capacity; building entrances (points), employed as destinations; and off-street parking lots (polygons), characterized by capacity and price (Fig. 1).

The model tools enable the construction of two additional layers. The layer of *lanes* is constructed in order to represent two-way streets. Each two-way segment of the street network is represented in this layer by two polylines located at both sides of a street centerline and connecting at junctions (Fig. 1). The lane representing a one-way street is itself a street segment.

The on-street *parking places* are represented by a layer of points constructed at both sides of the segment centerline (Fig. 1). The distance between parking places is a model parameter, and currently equals 4 meters as estimated in the Tel Aviv field surveys.

The layer of parking places contains all physically existing places for parking, including places where parking is not allowed, but is technically feasible. The actual legal right to park for vehicles of a specific type, for specific time intervals, as well as the price for each group of drivers (including zero price) are transferred from the road segments.

Private, *off-street*, *parking places* are established on the basis of the layer of houses. For the Tel Aviv case, no detailed GIS information on these parking places (mostly located underneath or behind residential buildings and dedicated to the buildings' residents) was available. Therefore, the fraction of buildings with private parking places and the number of parking places per building were estimated based on a field survey.

2.2. Representation of car advance

The model works in a discrete time and space; at each time-step (iteration) every vehicle can make a move, the size of which is determined by the vehicle's speed. The model's temporal resolution is dictated by the length of a parking place, i.e. 4 m. In what follows, we have set the duration of an iteration at 0.5 s. With this setting, the speed of a vehicle should be 28.8 km/h in order to pass 4 m in one model iteration. In case the length of a parking place or the time-step are changed, all model calculations are automatically adjusted to the new values.

Formally, given the street speed of v_s (km/h), the movement of a single car c in the model is implemented in the following way: c's speed v_s as measured in km/h is recalculated into the speed v_m measured in model parking space lengths per model time-step. The value of v_m is then represented as

$$v_m = v_{m,int} + v_{m,dec}, \tag{1}$$

where $\upsilon_{m,int}$ is the integer part of υ_m and $\upsilon_{m,dec}$ is the decimal part.

To illustrate, if the speed is 15 km/h, the parking place length is 4 m, and the iteration is 0.5 s, then the speed υ_m equals 0.52 park lengths units per time-step, i.e. $\upsilon_m = 0.52$, thus resulting in $\upsilon_{m,int} = 0$, $\upsilon_{m,dec} = 0.52$.

To simulate driving at a "non-integer" speed υ_m, we then generate a random number r from the uniform distribution on (0,1), and assume that the car c advances for a distance of $d_c = \upsilon_{m,int} + 1$ parking-lengths towards the destination in case $\upsilon_{m,dec} > r$ and for only $d_c = \upsilon_{m,int}$ parking-lengths otherwise, that is

$$d_c = \begin{cases} v_{m,int} + 1 & \text{if } v_{m,dec} > \mathrm{r}, \\ v_{m,int} & \text{otherwise}. \end{cases} \tag{2}$$

For the above example, with a speed of 15 km/h, the car advances one 4-m unit in 52% of the model iterations and does not advance in the remaining 48%. The above algorithm is applied separately to each driver.

During parking search, the velocity of each car is low. As was recorded during trips with drivers, a driver decreases his/her velocity to 20–25 km/h when starting to estimate the state of parking in the area. The speed is further reduced to 10–12 km/h when the driver starts watching parking places ahead with the aim of parking in one of them (Carrese, Negrenti, & Belles, 2004). We thus ignore the possibility of acceleration as employed in, e.g., car following models (Nagel & Schreckenberg, 1992). However, to account for the interaction between parking cars, the model drivers adjust

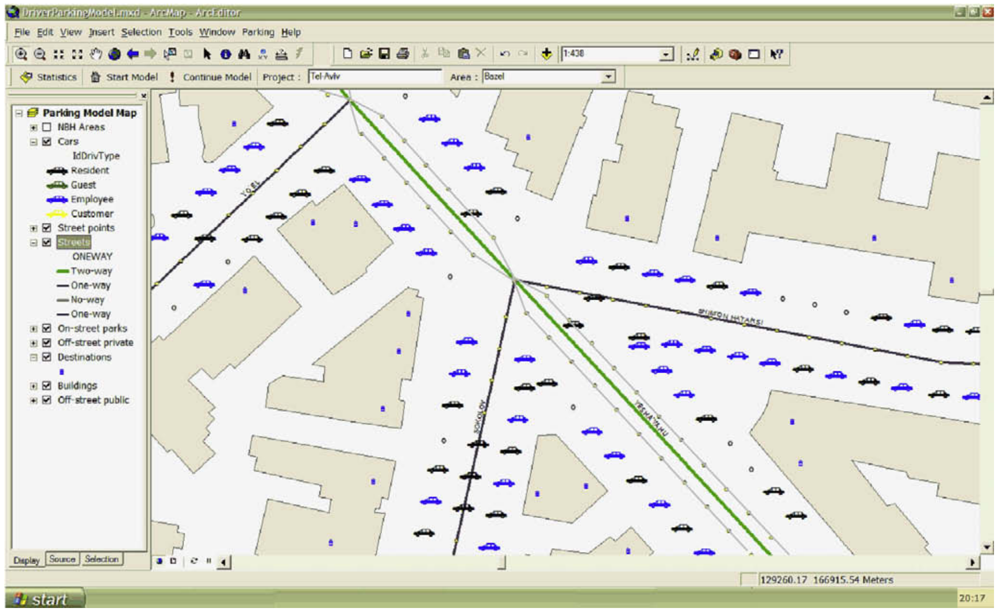

Fig. 1. The basic and derived layers of the PARKAGENT model in the ArcGIS model window.

their movements in response to the car in front of them. Before advancing the d_c parking-length interval, a driver checks whether the interval is free or not; in the latter case, the advancement is interrupted. The order in which the cars advance is established anew at random at every iteration.

2.3. Route choice

When approaching a junction, the driver has to decide which direction to take in order to advance towards the destination. In the model, the driver's decision is based on the comparison of the distance to the destination from the current junction and from all "next" junctions, which are defined as the first junction on the street segments from which the driver can choose.

We assume that the model driver possesses some knowledge of the city street network, and thus selects the segment whose next junction is closest to the destination (Fig. 2). The model thus follows the approach of Bonsall and Palmer (2004) who view route choice as the result of a sequence of decisions, one at each intersection encountered. We have verified the algorithm by driving with several drivers (all Tel Aviv residents) and found that in cases where the destination is a distance of 3–5 street segments from the current junction (typical for driving within the parking search area), the algorithm usually repeats the shortest path to the destination.

The drivers enter the model system at a distance $D_{awareness}$ from the actual destination, the distance at which they become "aware" of the need to start searching for parking. In the current version of the model, this distance is set at 250 m. The set of entrance points for each destination consists of the intersections between the circumference of the circle of radius $D_{awareness}$ around the destination, and the lanes leading towards the destination. To initiate driving, one of these points is randomly selected.

2.4. Representation of driver's parking behavior

The rules of agent behavior in the model depend on the stage of the parking process. We distinguish the following behavioral components:

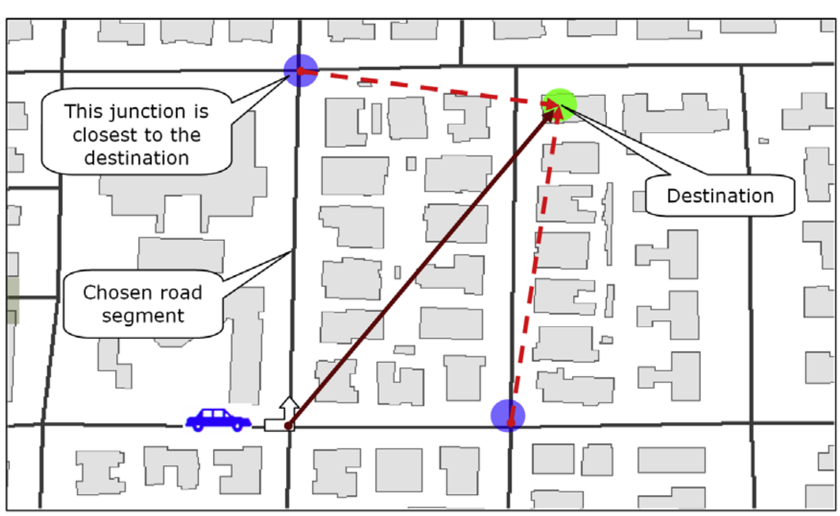

Fig. 2. Schematic presentation of the route choice component of drivers' behavioral algorithm.

1. Driving towards the destination from the distance $D_{awareness}$, estimating the parking supply.
2. Searching for parking and parking before reaching the destination.
3. Searching for parking and parking after passing the destination.
4. Staying at the found parking place.
5. Leaving the parking place and driving out of the system.

Stage 1: Driving towards the destination from the distance $D_{awareness}$
The driver's behavior at this stage includes two subsets of rules:

(a) Decrease speed to 25 km/h and continue driving towards the destination according to rule (2) of driving (see above).
(b) Estimate fraction of unoccupied on-street parking places.

We assume that the estimation is performed when driving between the distances $D_{awareness}$ and $D_{parking}$ (set at 250 and 100 m air distance to destination, respectively). The model driver does this by continuously re-estimating the fraction p_{unoc} of unoccupied parking places:

$$P_{unoc} = N_{unoc}/(N_{unoc} + N_{occ}), \tag{3}$$

where N_{occ} is the number of occupied, and N_{unoc} is the number of unoccupied parking places observed when driving between the distances $D_{awareness}$ and $D_{parking}$. Starting at $D_{awareness}$, the model driver arrives at the $D_{parking}$ distance with an estimate of p_{unoc} (Fig. 3).

Stage 2: Searching for parking and parking before reaching the destination
At the distance $D_{parking}$, the model driver decreases his/her velocity to 12 km/h and implements his/her knowledge regarding the supply of parking by estimating the expected number of free parking places F_{exp} to be found before reaching the destination as

$$F_{exp} = p_{unoc} \times \text{Distance To Destination/Length Of Parking Place}. \tag{4}$$

Intuitively, if the value of F_{exp} is high, say 3–5, then it is worthwhile for the driver to proceed driving towards the destination. In contrast, when the estimate of F_{exp} is low, say 0.5, it is worthwhile to park at the first free space. We represent the probability of the driver deciding to park as dependent upon the value of F_{exp} (Fig. 4). In every iteration of the model, if the driver reaches a free parking space, she decides whether to park or to continue driving.

To guarantee the drivers' reactions to the local parking supply when driving from the distance $D_{parking}$ to the destination, we assume that the model driver continuously re-estimates the parking supply on his/her way. If the driver chooses to drive further and not to park, the values of p_{unoc} and F_{exp} are recalculated on the base of the values for N_{unoc} and N_{occ} accumulated from the moment the car entered the model till the current iteration.

This algorithm results in drivers parking close to the destination in case of a sufficiently high supply of free on-street parking places in the area. In case of "wrong" decisions on the way to the destination or in case of zero supply, the model driver passes her destination without parking and enters the third stage of parking choice.

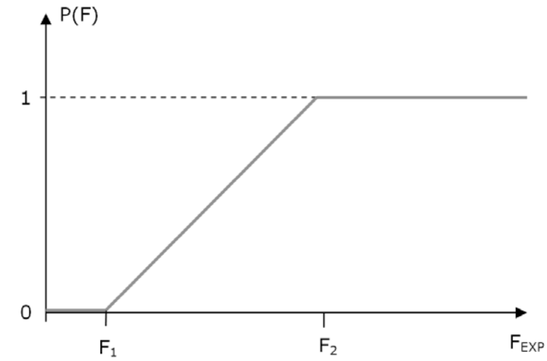

Fig. 4. The probability to continue driving as a function of the expected number of unoccupied parking places between the current location and the destination. In the current application of the model, the values of $F_1 = 1$ and $F_2 = 3$ are used.

Stage 3: Searching for parking and parking after passing the destination
At this stage, the decision to park does not depend on estimates of F_{exp} any more. Rather, we assume that a driver will park at any free parking place as long as it is not too far from the destination. Since what counts as "too far" will depend at least in part on the time a driver has already spent on the parking search, we furthermore assume that the driver's perception of "closeness" to the destination becomes more and more flexible. We express this in the model by a linear increase in the $D_{parking}$ distance, starting from 100 m and increasing at a rate of 30 m/min until reaching the value of 400 m.

In reality, at this stage, the driver takes two more factors into account. First, she watches the accumulated search time. Second, she considers the possibility of paid parking, which becomes more and more attractive with time. At the current stage of model development, we account for the first factor only, and in the simplest possible way. Namely, we establish the maximal possible time T_{search} for the parking search (10 min in the current version), and assume that the driver whose accumulated search time exceeds T_{search} will simply park at the paid parking lot closest to the destination. We follow the observed reality in Tel Aviv and assume that an off-street paid parking place is always available.

Stage 4: Leave the parking place and the system
The driver parks for the time interval that is attributed to each driver according to the exogenous distribution of parking time. After this given parking duration, she disappears from the system.

2.5. Groups of drivers

In the model we distinguish between four groups of drivers, which may differ in parameters of their behavior and are marked by different colors in the model window (Fig. 1). The most important difference between the drivers is in their destination, arrival time and duration of parking. For example, the destinations of *Res-*

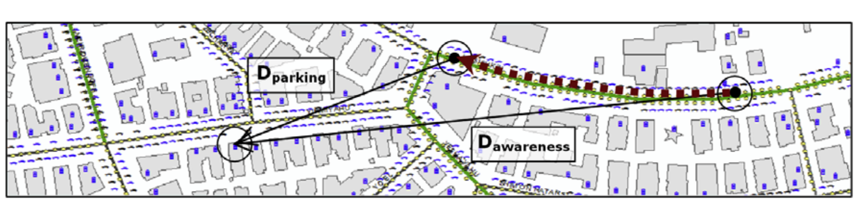

Fig. 3. Schematic presentation of the "Driving towards destination from $D_{awareness}$ distance" component of drivers' behavioral algorithm.

idents and *Guests* are residential buildings, and those of *Employees* and *Customers* are offices and public places.

2.6. Model output

The PARKAGENT model can generate results from the perspective of either the driver or the policy maker. In the case-study below, we focus on the driver's perspective of the parking situation and, given the area and period under investigation, we assume that a driver wants:

- To find a parking place as close as possible to the destination.
- To find a parking place as quickly as possible.
- To pay as little as possible.

The agent-based model makes it possible to record the life-path of every model driver; on this basis we construct three key *distributions*: one of parking search time, one of the air distance to destination, and one of paid parking fees, each for drivers who enter the system during selected time interval(s) and whose destination belongs to selected area(s).

Each of these distributions demands some specification. First, if the driver finds a parking place on the *way to the destination*, we consider his/her search time as zero. Otherwise, we register as the search time the interval from the moment the driver passes the location on the road closest to the destination, until the moment she finds a parking place. Second, in the case of Tel Aviv, the actual walking distance between two points at a distance of several hundred meters is 1.3–1.4 times larger than the air distance between these points. Third, we do not consider the payment distribution further in this paper, as we focus on resident parking, and local residents can park for free on-street in Tel Aviv.

The model output also includes several global characteristics of the parking process, such as the number of free parking places and the number of drivers searching for a parking place at every iteration of the model.

The drivers' life-paths could be processed in many other ways in order to estimate, for instance, the relationship between the duration of the parking search and the distance between the parking place and the destination.

2.7. Initial and boundary conditions

We begin the model run by establishing the time interval and the area of the simulation. The initial numbers of drivers of every type in the study area are parameters of the model run, and their parking places are assigned randomly from the total set of parking places in the area. The parking durations are assigned in relation to the type of driver, and are usually distributed uniformly between the minimum and maximum parking times for that group.

The numbers of drivers of every type who arrive in the area are also parameters of the model, as are the distributions of arrival times for every type of drivers. To generate the destination for an arriving driver of a given type, we consider the entire set of destinations in the area relevant for this type of driver, and exclude the destinations already assigned to those who previously entered the system. Each resident driver entering the model area is randomly assigned a destination from the resulting set.

3. Surveys

Two main surveys were carried out during 2005–2006 in the case-study area (the Basel neighborhood in Tel Aviv) in order to gain a better understanding of drivers' behavior in terms of parking time, location, and parking preferences, and to establish the initial and boundary conditions of the simulations. Below, we report the main findings of each survey.

3.1. Survey of parking space use during daytime and overnight

A survey of parking space use during the daytime was performed in the Basel neighborhood every working day during two consecutive weeks, on the same street segments, with 1500 m total length of parking spaces. About 350 feasible – illegal and legal – parking places were repeatedly surveyed between 14:00 and 16:00 h during the first week and between 12:00 and 14:00 h during the second week. The plate number and area parking tag of every parked car, as well as the location of every parked car and of every free place, were marked on a GIS layer. In addition, the number of private off-street parking places belonging to the residents was recorded, as well as the number of occupied off-street parking places.

The results repeat themselves during the 2 weeks and all 10 survey days. Close to 60% of on-street parking places, 61.8% and 58.1% in the first and second weeks, respectively, were occupied by owners of a local area tag. Half of the remaining 40% of parking places (17.4% and 19.9%) were occupied by visitors, and half (20.8% and 22.0%) were not occupied. Note that these figures relate to all *feasible* on-street parking places, both legal and illegal. The fraction of occupied private off-street parking places was slightly below the on-street fraction, 56.2% and 59.4%. In what follows, we employ estimate of 60% for the residents' on- and off-street parking use during the day.

The amount of private off-street parking places was estimated at about six places per residential building, with about one-third of the buildings having these places. In what follows, we use an average of two private off-street parking places per residential building.

The survey of parking space use overnight was performed once, between 23:00 and 4:00 h. During this period, all feasible parking places – both legal and illegal – are occupied. The high level of illegal parking is a consequence of the fact that parking regulations are only enforced between 6:30 and 21:30 h. The fraction of cars lacking a local area tag recorded in the night survey was close to 5%.

3.2. Survey of distance between parking place and residence

The distance between overnight parking places and residents' home locations was surveyed over two consecutive nights, between 23:00 and 01:00 h. The plate number and location of each car were recorded and compared with the database of the Israel Central Bureau of Statistics (ICBS), which contains the home address of the owner. The results of the comparison show that 59% of drivers park within 350 m of their location of residence. The remaining 41% are distributed almost uniformly over an area ranging from 350 m to 6 km from the location of residence (Fig. 5). Based on these results, we assumed that the drivers who parked further than 350 m from their registered residences do not actually live there.

4. Application of the PARKAGENT model

The PARKAGENT model has been developed as a tool for analyzing and comparing parking policy and management alternatives aimed at improving the existing parking situation. The disaggregate nature of the model enables the direct estimation of the consequences of policy alternatives from both the driver's and the policy-maker's point of view. Thus, it can generate an unambiguous understanding of the parking situation and the effectiveness of proposed alternatives for a *certain area*, during a *certain time-period* and for *certain groups of drivers*.

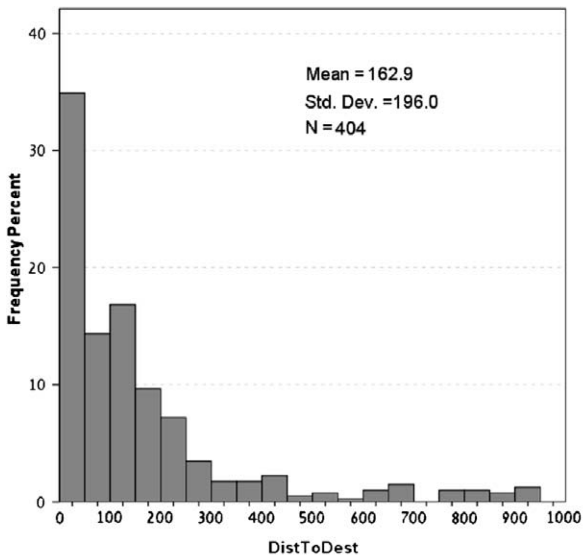

Fig. 5. The distance between the place of overnight parking and the driver's address as registered in the ICBS database (distances below 1 km account for 67.2% of total population). Note that the percentage of cars registered at a distance below 50 m is overestimated, as it includes drivers with disabilities who receive a reserved parking place from the Tel Aviv Municipality as close as possible to their home address.

In order to explore the benefits of the model in practice, it has been employed to analyze the parking situation in the Basel neighborhood of Tel Aviv. The Basel neighborhood is considered by the municipality to be suffering from a substantial imbalance between the existing supply of, and demand for, residential parking. The results of the surveys confirm the municipality's view that the problems are most notable in the evening hours, when local residents have problems finding a parking place to park their vehicle overnight. The solution proposed by the municipality is the extension of a planned underground parking garage underneath a yet-to-be-built residential building and the sale of the additional parking places to residents living nearby. This new residential building is located in the center of the Basel neighborhood (Fig. 6, blue[1] circle).

For the analysis presented below, we limited the study area to a block of 1.2 by 1.1 km around the planned parking garage (Fig. 6). The study area, which we will refer to as the Basel neighborhood, contains a total of 1562 buildings and 291, mostly one-way, street segments. We expect no impact from the additional parking facility on the parking situation outside this area.

In what follows, we estimate the total demand and supply for on-street residential parking in the neighborhood. We then turn to the demand and supply for parking during the period 17.00–21.00 h, when resident drivers return home from work or other errands. Finally, we analyze the possible impact of the additional parking supply, both from a resident's and a policy maker's perspective.

4.1. Estimate of demand for on-street parking in the Basel neighborhood

The estimate of total parking demand in the Basel neighborhood is based on the number of apartments and registered businesses per building, and on the number of parking tags issued to the residents in the area, both available as part of Tel Aviv Municipal GIS. The first dataset shows that 93% of all buildings in the area contain

[1] For interpretation of color in Fig. 6, the reader is referred to the web version of this article.

Fig. 6. The two concentric rings employed for estimating the effects of a new parking lot in the Basel neighborhood.

at least one apartment and that the average number of apartments per residential building equals 10.17, while the average number of parking tags per residential building equals 9.79. Based on this, we assume that the average number of cars per residential building is 10, and the demand for on-street parking per building equals 8 (since, as mentioned above, each residential building has, on average, two off-street parking places). Based on these results, we estimate that:

$$\text{Residents' demand for on-street parking} = 0.93 \times \text{number of buildings} \times 8. \quad (5)$$

The number of buildings in the area is 1562, so by applying (5), we estimate the residents' on-street parking demand in the area as $0.93 \times 1562 \times 8 = 11{,}621$ cars (Table 1).

4.2. Estimate of on-street parking supply in the Basel neighborhood

The estimate of the supply of public on-street parking is based on the actual use of space, rather than on the number of legal parking places. During the night hours, virtually every space where a car can park without being an immediate disturbance to traffic, regardless of whether parking in that spot is prohibited or not, is used for parking. The only places that remain free are entrances to parking lots and short street sections around junctions. To estimate, we reduced the total number of feasible parking places on a

Table 1
Residents' overnight (O) and end-of-day (E) demand for, and supply of, on-street parking places within two areas: NBH1, and NBH2 excluding NBH1.

Characteristic	Basel neighborhood
Area (km^2)	1.378
Number of buildings	1562
Number of street segments	291
Total street length (m)	25,138
O: [a]On-street supply of parking places	10,340
O: On-street parking demand	11,621
O: [a]On-street demand/supply	1.12
E: [a]On-street supply between 17:00 and 21:00 h	3809
E: On-street parking demand between 17:00 and 21:00 h	5091
E: [a]On-street demand/supply between 17:00 and 21:00 h	1.34

[a] The calculation of the *residents'* overnight on-street parking supply encompasses 95% of the total amount of on-street parking places, as the survey results have shown that 5% of all on-street parking places are used by overnight visitors.

segment to four parking places directly adjacent to junctions (two places on each side of the street), with one place for each entrance to off-street private parking facilities, which exist in one-third of the buildings. Hence,

$$\begin{aligned}&\text{Maximal on-street parking capacity for local residents}\\&\quad = (\text{overall street length in meters}/4) \times 2 - 4\\&\qquad \times \text{number of street segments}\\&\qquad - \text{number of buildings}/3. \qquad (6)\end{aligned}$$

Estimating the parameters of (6) on the base of GIS layers of streets and houses, we obtain 10,884 on-street parking places. Since 5% of the parking places are used by visitors overnight, only 95% of the available on-street parking supply, i.e. 10,340 places, is available for the residents overnight. The overall demand/supply ratio is thus $11{,}621/10{,}884 \approx 1.07$ when ignoring overnight visitors, and $11{,}621/10{,}340 \approx 1.12$ when accounting for them (Table 1).

A number of paid parking lots and garages located in the Basel neighborhood provide a *de facto* over-capacity of public off-street parking. During the evening, the parking facilities are primarily used by local residents. One parking lot provides several hundred free parking places to residents with a subscription, between 19.00 and 07.00 h. Most other parking lots can be used by local residents for overnight parking for a relatively low fee. These latter lots serve as a 'fall-back' option for residents who fail to find an on-street parking place at the end of the day.

4.3. Estimate of parking demand versus supply at end of the day

The parking demand of residents at the end of the day includes only those cars that return home at the end of the day from work or other activities. In other words, the end-of-day demand consists of total demand for resident parking in the Basel neighborhood, minus those residents' cars that did not leave the area during the day or that returned before 17.00 h. Based on the above survey results, which show an occupation rate of about 60% for on-street private parking, we can estimate the number of parking places available for residents and visitors arriving after 17:00 h: 10,884 (total on-street parking supply for residents) $\times$ 40% $\approx$ 4354 on-street parking places. Note that overnight visitors occupy 5% of these parking places, so that $4354 \times 95\% \approx 3809$ parking places are available for residents returning home. Residents' demand for these on-street parking places can be calculated as follows: 11,621 (total on-street residents' demand) $-$ 10,881 (on-street parking supply) $\times$ 60% $\approx$ 5090 residents' cars looking for on-street parking in the evening. The residents who return home at the end of the day thus experience a demand/supply ratio of $5090/3809 \approx 1.34$ (Table 1).

Note that 20% of all feasible parking places in the Basel neighborhood are unoccupied during the day, while daytime visitors occupy another 20% of the parking places. In the model application, we have assumed that 3/4 of these daytime visitors leave uniformly during the period 17.00–21.00 h. The remaining 1/4 remain in the area and occupy 5% of all the on-street parking places during the night period.

We assume that in such a situation, with a parking demand/supply ratio well above one, resident drivers who do not have a dedicated private or public off-street parking place have a tendency to cruise for parking in order to find free on-street parking (see also Shoup, 2006). Given a *de facto* shortage in the parking supply, some of the residents eventually end up at the paid parking lots in the neighborhood. However, according to the survey results, the residents revert there only when they do not find a free parking place within a reasonable time period or at a reasonable distance from their location of residence.

5. Estimating the effects of a new parking facility

The question is now whether the addition of off-street parking places to the existing parking stock can improve the parking situation of the local residents. In line with the proposed policy of the Tel Aviv Municipality, we assume that the additional off-street parking spaces will be purchased or rented by local residents. The additional parking places thus reduce the number of drivers looking for on-street parking, assuming that these places have no impact on the motorization rate of local residents.

Given the preference of residents to park as close as possible to home, the impact of the additional parking capacity will not be uniform over the entire Basel neighborhood. In order to reflect this, we consider an internal polygonal around the new parking facility of about 700×700 m (NBH1), and an outer concentric ring (NBH2). Together, NBH1 and NBH2 comprise the entire Basel neighborhood (Fig. 6).

The effects of the new parking garage are estimated for NBH1 and NBH2 separately. Intuitively, one would expect stronger effects to occur within NBH1, and weaker effects in NBH2. In what follows we provide the corresponding quantitative estimates.

Note that the area *surrounding* the Basel neighborhood also influences the demand/supply ratio in the Basel neighborhood, as residents from that area may search for parking within the Basel neighborhood, and vice versa. Since the parking situation in the surrounding area is largely comparable with that in the Basel neighborhood, we assume that there is no negative or positive effect.

5.1. Initial and boundary conditions of the simulation

The simulation encompasses the period 17.00–21.00 h, during which visitors leave and residents enter the area. As discussed above, we estimate that 3809 parking places become available for residents in this time interval (including illegal parking places), while 5090 resident drivers enter the area looking for an overnight parking place.

5.2. The basic parameters of the model scenarios

The local scenarios discussed below are based on the estimates of demand and supply as presented above. Furthermore, the following combination of model boundaries, assumptions and estimates is used:

1. The initial number of occupied parking places within the Basel neighborhood at 17:00 h is set at 8707 (80% $\times$ 10,884) and is assumed to be randomly distributed over the area. Of these, 60% are occupied by residents and 20% by daytime visitors. The remaining 2179 (20% $\times$ 10,884) parking places are free.
2. During the period of simulation, an additional 1632 (2179 $\times$ 3/4) parking places are freed by daytime visitors. The cars leaving the area are selected randomly from the group of daytime visitors. The distribution of the egress time is uniform for the time interval 17:00–21:00 h.
3. During the period of simulation, 5090 residents enter the area. The distribution of the arrival time is uniform for the time interval 17:00–21:00 h. We assume that all residents return to the neighborhood during this time interval and occupy both legal and illegal parking places. In reality, most illegal parking places are only taken after parking enforcement efforts end (at 21.30 h).
4. The destinations for the arriving resident cars are randomly assigned on the basis of the layer of buildings and their capacity. The destination set is instantaneously reduced with each resident car's arrival.

5. Each car enters the system at an aerial distance of about 250 m from the destination.
6. The cars that search for parking do not enter road segments that cross the Basel neighborhood border, and thus cannot leave the neighborhood.
7. The maximum search time for each driver is 10 min. If the driver fails to find a parking place within this time period, she parks at the closest paid parking lot within the Basel neighborhood.
8. We consider two performance indicators: (1) the distribution of search time; and (2) the distribution of distance to destination. Both are calculated for the drivers whose destinations are in each of two rings (NBH1 and NBH2) separately.

We run the model for a number of scenarios, differing in terms of the size *N* of the additional off-street parking facility. We assume that the additional facility is exclusively used by the drivers whose destination is within NBH1, and randomly exclude *N* drivers with destinations within NBH1 from the on-street parking search. In the base scenario, no additional parking places are provided ($N = 0$). We compare this base case with four scenarios, with values of $N = 50$, 100, 150, and 200. Furthermore, we compare two scenarios in which 1000 parking places are added to the Basel neighborhood.

6. Results of the model study

6.1. Changes in average values of the performance indicators

It is intuitively evident that even the maximal possible capacity of the new parking lot – 200 places – cannot have a large effect on the average parking situation in an area where parking supply is about 11,621 − 10,340 = 1281 places below demand. The model investigation confirms this: even for 200 new off-street parking places and for drivers whose destination is within NBH1, the decrease in average search time and walking distance for on-street parkers is low. Figs. 7 and 8 present the results averaged over five repeated runs for each set of parameters for the last hour of the investigated period (20:00–21:00 h). The decrease in mean search time is about 7% (18 of 245 s), and in distance 12% (20 of 165 m). Obviously, the effects are even smaller in case less additional capacity is provided. The variation between the results of the model runs with the same parameters is very low, with the coefficient of variation CV ≈ 1–1.5%.

The reason for the limited impact of the additional parking supply on the average search time and the distance to destination is evident: with the increase in supply within NBH1, drivers with

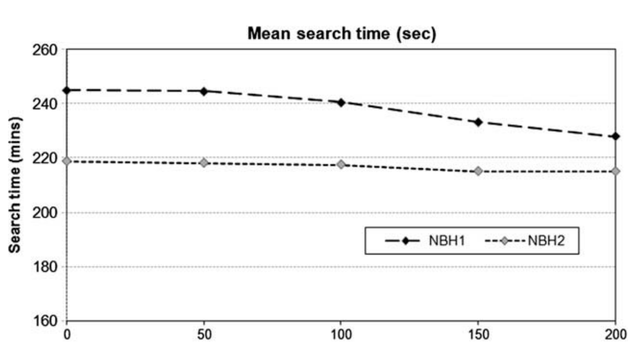

Fig. 7. The average search time for an on-street parking place (in s) for the drivers whose destinations are within the NBH1 and NBH2 areas, as dependent on the capacity of the additional parking facility.

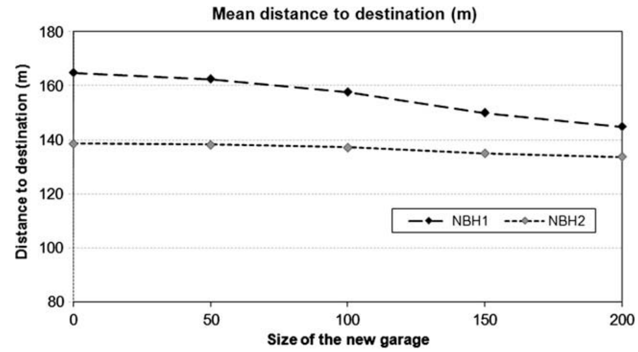

Fig. 8. The average distance between the on-street parking place and the final destination (in m) for the drivers whose destinations are within the NBH1 and NBH2 areas, in terms of the capacity of the new parking facility.

destinations within NBH2 will park more often within NBH1, effectively changing the demand/supply ratio in NBH1.

At the same time, and as can be expected, the overall number of drivers who failed to find a free parking place decreases proportionally to the size of the new garage. For the scenario in which no additional parking places are provided ($N = 0$) the number of the drivers who did not find a parking place during 10 min of search varies between 1300 and 1310, that is, slightly above the parking shortage of 1281 places. A garage of size *N* decreases this number by just about *N* cars, and the maximal possible garage will result in 1040–1050 long searchers.

To conclude, a new parking lot will hardly change the average residents' perception of the parking situation in the area. Still, about 20% of the arriving residents will not find an on-street parking place, while those who do find an on-street parking place will hardly feel the small average improvements in search time of distance to destination. The only residents experiencing and perceiving a real improvement in their parking situation are the ones who purchase or rent a parking place in the new garage.

6.2. A second experiment

The situation changes if space is taken into account more explicitly. Let us consider the Basel neighborhood as a whole and analyze the impact of adding 1000 freely available parking places. This number may be expected to essentially improve the parking situation in the area, given the existing parking shortage of about 1281 places. The question is how the new capacity should be distributed over the area in order to obtain maximal effect.

In order to answer this question, we compared two scenarios: one in which all 1000 parking places are provided at the location of the planned garage, and one in which four parking lots are established, each with a capacity of 250 places, and located close to the corners of NBH1 (Fig. 6). The latter partition accounts for the resident's tendency to search consistently for parking places not farther than 300–350 m from their destination. We also assumed that the driver continues searching for on-street parking until the distance to the destination exceeds 350 m and the new parking lot is closer to the driver's destination than his/her current position. As above, the maximal time for the parking search is 10 min.

As we saw above, the average search time and walking distance hardly react to changes in parking supply as long as the demand/supply ratio is around or above one (Shoup, 2006). We therefore compare the two scenarios in terms of the number of "long-searchers", i.e. the number of drivers who search for parking for more than 10 min. In the case presented above, the number of long-searchers dropped by nearly the same amount as the number of additional parking places provided. That was because the parking places were available to specific local residents only. In case all residents can choose between on-street and free off-street parking, the situation is different. In that case, space comes into play. That is, if the driver knows that the off-street parking places are located too far away from the desired destination, she continues her search for on-street parking.

The results show that, in the case of four parking lots, the number of "long-searchers" – who do not find a parking place within 10 min – varies between 280 and 320, slightly higher than the overall lack of parking places, but substantially lower than in the case when one large parking lot is added. In the latter case, the number of long-searchers varies between 400 and 450.

In line with common-sense expectations, the PARKAGENT model thus enables us to quantify the impact of different spatial scenarios. As the example suggests, the model could be used to compare various distributions of off-street parking facilities over the city under various conditions and for various user groups, and generate an optimal solution.

It may be assumed that a reduction in search time is not only positive for local residents, but also for the city as a whole, as it reduces air pollution and traffic congestion caused by cars cruising for parking (see e.g. Carrese et al., 2004). While the model itself cannot quantify these results directly, it could estimate the reduction in *total* search time as input for air pollution estimates. Note that this is an estimate of the *minimum* reduction in air pollution; additional effects will be achieved following the reduction in congestion, which is not included in the current version of the model.

6.3. Reflection on results

The results presented above suggest that adding small parking lots in the dense areas of central Tel Aviv could lead to small improvements in the parking situation for the average car-owning resident. This finding should of course be treated with care. As in the case of road capacity, more supply may generate more demand for parking. Thus, the improvements in search time and walking distance may be short-term effects. If more residents will purchase cars *because* of the improved parking situation, the long-term effect of additional capacity is actually likely to be negative. Given the high parking pressure and the still relatively low level of motorization in central Tel Aviv, it is not unlikely that the small improvement in the parking situation may be enough for the *marginal* resident to purchase a car, or for car-owning rather than carless households to move in.

7. Conclusions and discussion

In this paper, we have presented the PARKAGENT model – a spatially explicit, agent-based, model for parking in the city. The small case-study discussed in the paper provides a window to its possible applications.

Unlike traditional models, PARKAGENT simulates the behavior of each driver in a spatially explicit environment. Because of this, the model is able to capture the complex dynamics that can occur between large sets of agents, as well as the impacts of non-homogeneous (road) space. As stressed by Arnott (2006), current models are able neither to capture this heterogeneity, nor to estimate its possible impacts. The PARKAGENT does this in full – its application to the Basel neighborhood in Tel Aviv is based on high-resolution GIS and accounts for numerous one-way streets and turn restriction in the area. We have not compared the Basel results to those for less complicated situations; however, it can be demonstrated that these local irregularities essentially influence the distribution of search time and distance to destination (Benenson & Martens, 2008). In addition, the agent-based PARKAGENT model is capable of capturing the effects of heterogeneity of the population of drivers, and we aim at studying these effects in the future.

PARKAGENT's ability to simulate the complex dynamics of the parking system in detail *and* generate data about the system performance for different groups of drivers is especially important in saturated parking situations. In such situations, with an instantaneous demand/supply ratio essentially varying around one or even substantially exceeding one, mere averages are unlikely to capture the essential performance of the parking system due to the inherently uncertain nature of the car parking system (Thompson & Richardson, 1998). Since parking management is especially called for in saturated situations, traditional approaches to parking modeling thus fail to deliver relevant outputs when these are needed most. Under these exact circumstances, when an in-depth exploration of the possible effects of policy interventions is most needed, high-resolution, spatially explicit, models may be able to capture the complex dynamics of the parking system and generate data on key parameters deemed relevant by policy makers. This paper is only the first step in this direction, and further explorations with the PARKAGENT model are needed to determine whether the model will indeed be able to deliver on this potential.

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