SUSTAPARK: An Agent-based Model for Simulating Parking Search

Thérèse Steenberghen, Karel Dieussaert, Sven Maerivoet, and Karel Spitaels

Abstract: *SUSTAPARK is an agent-based model (ABM) used to simulate the local parking and traffic situation under different parking-management conditions. In the simulation, each car driver has an activity schedule throughout the day, moving on the network for various purposes toward different locations. The model includes activities and required trips of all the drivers in a city based on travel survey data. Situational characteristics, such as a combination of the driver's behavior, traffic, walking distance to the destination, and the availability of parking places, determine the parking search behavior of agents. Various categories of drivers' parking search behavior reflect the outcome of experiments with observations of drivers under different conditions. The interaction with other cars is modeled as an application of traffic rules. The translation of the physical vehicle movements into a computer program is done by means of traffic cellular automata. We apply the model to the city of Leuven, in Belgium, and calculate various parameters for different scenarios. These parameters include the parking occupancies, the parking search times, the spatial distributions of parking durations, the distances between parking places and destinations, the bottlenecks, and overcapacities of parking. The stability of the model's outcome was assessed by running the same baseline scenario 15 times.*

INTRODUCTION

In many cities, there is rising pressure on public parking spaces, particularly in areas with large amounts of housing constructed before the 1950s when car ownership began to rise sharply. Urban planning practice determines the type of parking places available (on-street parking, parking lots, private parking) and influences other characteristics of the parking spaces as well (price, security, pedestrian system quality). It is important that all these factors should be treated from the viewpoint of what the car driver perceives. Taste heterogeneity is a major factor in this parking type choice, together with the journey purposes (shopping, working, visit) (Axhausen and Polak 1991). An impression of parking availability from the driver's view can defer from reality (Laurier 2005). A whole range of situational factors can influence the driver's parking search behavior, mainly available parking spaces, trip purpose, walking time to destination, parking fee, and comfort. The perception of these factors can change with the elapsed time spent in search of a place. In neighborhoods in the city with safety problems, security also can play an important role in the choice of a parking place (Teknomo and Hokao 1997). We do not understand nearly enough about how individuals respond to parking policy interventions, nor how these responses interact with local circumstances, the availability of alternative transport modes, or alternative destinations (Marsden 2006).

A city influences the local drivers' behavior and perception through the parking policy (Vlaamse Overheid 2008, Litman 2008). Underpricing of on-street parking, for example, can elicit the behavioral reaction of drivers to cruise for on-street parking, which, in turn, can lead to an increase of congestion (Shoup 2006, Anderson and de Palma 2007). Other examples are time restrictions for parking and introducing resident parking cards in the city, to differentiate the parking possibilities for residents and visitors. These general restrictions should be fine-tuned and adapted to the local situation.

Specific individual needs determine the value of an available parking space. That value can change in time as other parking spots become more interesting when search time is increasing. Drivers combine their previous knowledge with an evaluation of observed situational parameters, or they make assumptions based on former experiences. This creates a value for every parking place to a specific driver at a specific time. Some authors model this parking choice using a utility/disutility function (Arentze and Timmermans 2005). Many approaches for modeling parking choice lack in behavioral influence for they assume perfect information knowledge of the system and efficient behavior (Thompson and Richardson 1998).

Agent-based modeling (ABM) is an interesting computational modeling technique for the development of a parking model, because it is a flexible and dynamic way to deal with interactions between car drivers, the city, the traffic, and other road users. Simulated actions and interactions of autonomous individuals, following their own rules and interests, re-create a complex phenomenon and provide information on a higher level. One type of application is oriented toward the modeling of land-use policies and travel behavior choices (Shiftan 2008). Parking models using ABM have the advantage that the drivers' (agents') parking search behavior can interact on a microscale level with the environment (Benenson 1998 and 1999, Benenson et al. 2005 and 2008, Crooks et al. 2008, Martens and Benenson 2008, Torrens and Benenson 2005).

PARKAGENT is an agent-based model for parking in the city, simulating the behavior of each driver in a spatially explicit environment and capturing the complex self-organizing dynamics of a large population of parking agents within a nonhomogeneous (road) space. It is developed as an ArcGIS application and can work with a practically unlimited number of drivers (Benenson et al. 2008). In this model, cars enter the system, drive toward their destination, search for parking, park and stay at the found parking place, and then leave the parking place and the system.

The main objective of SUSTAPARK is to develop a model similar to PARKAGENT, including the local driving and parking behavior. A new module is proposed to simulate the agent characteristics, with trip destinations and motives (activity scheduling), and more elaborate parking search behavior.

The paper is organized as follows. The first section is a description of the general concepts and structure of the model. We then discuss data needs, followed by the outcomes for a case study in the inner city of Leuven, Belgium. The paper ends with conclusions, discussing the potential of tuning agent-based parking models to local circumstances.

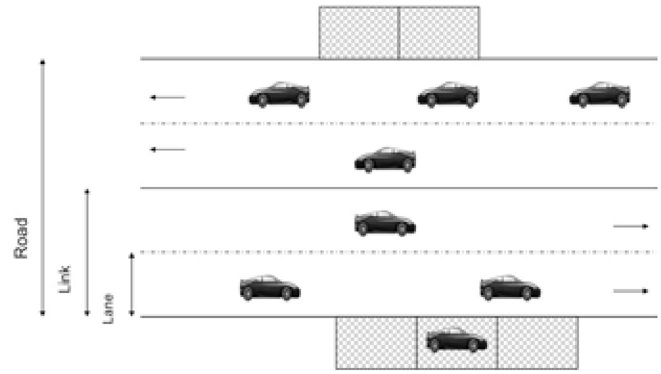

Figure 1. Representation of a road consisting of links and lanes. The crossed zones represent parking places coupled to a position on a lane.

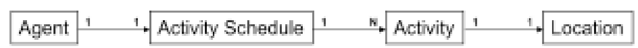

Figure 2. Relationship between agent, activity schedule, activities, and location

THE SUSTAPARK MODEL

SUSTAPARK is a spatiotemporal tool to model parking search behavior. Agents (car drivers) must have the ability to move over a network and park their vehicles to perform their planned activities during a day. The model creates a set of agents representing the total driving population entering and leaving the city throughout a normal working day. Every agent has an activity schedule and a parking search behavior. The activity schedule describes which trip the agent wants to make at a specific point in time. This serves to calculate an initial route (shortest path) from origin to destination, later repeatedly recalculated based on network parameters such as congestion. The parking search behavior determines when an agent starts searching for a parking place and consists of the rules followed when choosing a parking place. This choice depends on local parameters such as available parking places, price, distance, search time, etc.

Multiple agents use the road network and parking places. The traffic simulator models the traffic flows on the road network and the use of parking places.

The programming of SUSTAPARK is object-oriented using Java and was developed on the Eclipse platform.

INPUT

The model requires detailed data, both spatial and nonspatial. The spatial data include roads and parking places (parking lots, private parking, and on-street parking). The nonspatial data include parameters for creating agents, activity schedules, and their parking behavior.

Roads

Features from a GIS layer are imported and translated into a road network with roads, links, lanes (see Figure 1), and intersections based on the attributes of the features: a "from-intersection" identifier, a "to-intersection" identifier, the driving direction (one-way, two-ways, or none), the number of lanes for each driving direction, and the maximum speed. The model translates each road in one link (one way) or two links (two ways) with one or several lanes. Entry/exit gates are intersections where agents enter or leave the network according to their activity schedules.

Parking Places

SUSTAPARK creates three types of parking: parking garages/complexes, private parking, and on-street parking, each of them connected to a lane. The required attributes are: (1) a road identifier, (2) the distance from the start of the road, and (3) the side of the road, to couple each parking place to a position on a lane. Parking garages can hold more cars than on-street parking. They are connected to the lane at their entry or exit points.

Agents

A local travel survey (Zwerts et al. 2005) reveals that the following groups tend to follow different activity schedules: students, employees, retired people, unemployed people, people with liberal professions, people working in the household, tourists, and others. The model uses a contingency table to display the number of agents with a particular activity schedule per agent type.

Locations

Origins and destinations of trips are buildings with a certain function (office, residential building) and at least one access point on the road network. The model uses an attraction value of the

Table 1. Table with the coefficients of the MNL model for the parking type choice (Hess and Polak 2004). The "Work" column gives the values of the coefficients if the trip has a "work" purpose; the "Other" column if the trip has some other purpose.

Variable Name	Notation	Coefficient	Work	Other
Access time (min.)	At	1	-0.0513	-0.0283
Search time (min.)	St	β2	-0.0632	-0.0589
Egress time (min.)	Et	β3	-0.0925	-0.0924
Parking fee (/h)	Fee	β4	-1.4104	-0.8267
Ion-street (paid)		Ion-street (paid)	-2.7628	-0.8126
Ioff-street (lot)		Ioff-street (lot)	0.2830	-0.0913
Ioff-street(garage)		Ioff-street (garage)	1.0614	-0.2140

building for a specific motive. For example, the attraction of a school is calculated as its share in the total number of students in the city. Location, access point, and attraction value are stored in a GIS.

Spatiotemporal Activity Schedules

Activity schedules consist of a list of activities with destination in or outside the city, derived from the local travel survey: going home, going to work, educational activities, shopping, business, services, recreation, and tourism. Each road segment has a value as destination derived from the location of shops, hospitals, schools, etc., in the city. This determines the relative attraction of each road segment for each activity. Figure 2 shows the relationships.

To add a time component to every trip, time charts from the same travel survey are used, resulting in spatiotemporal activity schedules (see Figure 3).

Example activity schedule Agent A:
Schedule: Working-Shopping-Home
Activities (hour // destination):
Going to work (8.27 // street X)
Going to the shop (16.33 // street Y)
Returning home (17.48 // outside city)

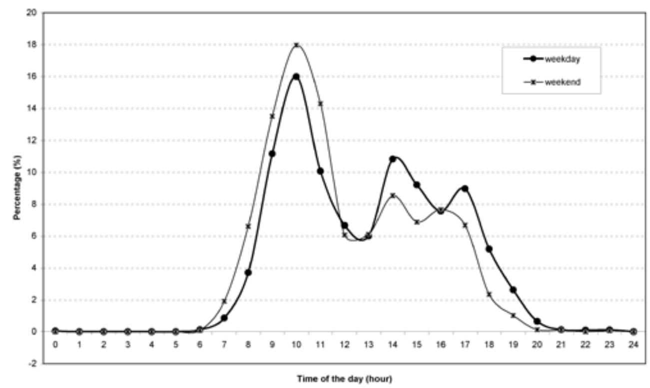

Figure 3. Time chart showing a temporal difference for the trip motive "Shopping"

Parking Strategy

In discrete-choice theory, each possible alternative of the finite choice set is assigned a utility. This utility is a numerical value that represents how much the decision maker values that alternative. The scale of this valuation is of no importance, as long as the same scale is used for all alternatives. After the calculation of the utilities, the person compares these against each other and chooses the one with the highest utility. Comparison of the utilities implies that only differences in utilities matter not the actual values of the utilities.

To calculate the utilities, a function is constructed in terms of the observed properties of the choice set. For example, the price of a trip and the time the trip takes can be two of the properties in deciding which transport mode to use. However, in practice, there always will be unobserved factors and differences in the valuation of certain properties. This means that instead of the deterministic method explained previously, a statistical methodology needs to be used (Train 2003).

For the statistical method, an appropriate error distribution (expressing the unobserved factors and uncertainty) needs to be specified and added to the observed utilities. Based on the assumptions made on the error distribution and the form chosen for it, a number of different statistical models can be derived, allowing a number of different choice behaviors to be simulated. In SUSTAPARK, a logit model is adopted. It is a simplified version of the discrete-choice structure developed by Hess and Polak (2004). The model considers four alternatives: free on-street parking, paid on-street parking, off-street parking in a parking lot, and off-street parking in a parking garage (both underground and aboveground parking structure). Illegal parking is not considered in the current version of the SUSTAPARK model (although the model of Hess and Polak does include it). Table 1 lists the numerical values of the coefficients. Note that the values depend on the trip purpose.

The access time is the expected time to drive to the area around the destination, which is the area where the driver intends to park. Once the driver starts searching for parking, this value will remain constant.

The search time is the time a driver is willing to search for a parking place once he or she has arrived at the parking area. Here it is assumed that the search time only applies to on-street parking places (both free and paid). This means that after a certain time spent searching, all drivers will want to park off-street.

The egress time is the time a driver is willing to walk from the place he or she parked at to his or her actual destination. For the calculation of these times, the assumption is made that the driver has full knowledge of the city, including roads, parking places, and parking garages. As the search of an agent continues, his or her spatial location will change and so will this term.

The parking fee is the amount of money the driver would have to pay for the time he or she spends at the parking place. This can be zero if the parking place is provided free to the driver.

Substantial differences can be seen between the coefficients for the "Work" purpose and for the "Other" purpose. In particular, commuters seem to have a strong dislike of paid on-street parking and seem to prefer garages. Hess and Polak (2004) note that the signs of the dummies for parking lot and parking garage of the "Other" purpose are wrong and should, in fact, be positive.

For the calculation of the expected values, the assumption of full knowledge gives that the (expected) parking fee is the same as the true value. The access, search, and egress times are determined in iterative runs of the model until they converge to stable values. This means that for the search and egress times, the average is taken of all the actual times experienced by the agents in a (small) zone of the city. For the access times, the actual driving time is taken. Note that this represents traffic on a normal day, i.e., without accidents or other disturbances. All these times are given a small random error to represent uncertainty.

After the choice for an appropriate choice model, the main task is to specify and fit an appropriate model for the observed part of the utilities.

It should be stressed that these coefficients come from a study in a British city. The value of time that the coefficients implicitly contain is for this British city and might not be representative of the value of time in Leuven. Research also has shown that the value of time strongly depends on the purpose, which is only taken into account in a limited way. To differentiate among drivers, in parallel with the SUSTAPARK model development, the Centre de Recherche Urbain of the Université Libre de Bruxelles conducted a qualitative research on parking search strategy. It consisted of an experiment with 60 volunteers asked to simulate driving and parking for certain activities in town (shopping in a certain area, delivery at a specific address). A camera in the car filmed the driver and the street during the trip and the search for a parking place. Afterward, the driver answered questions. Data on the trip, traffic, parking availability, and decisions were georeferenced and timed. All these trips support the definition of rules for different search strategies that take economical, cognitive as situational factors into account. Different parking search behaviors were determined, based mainly on how well the driver knew the city (a resident, a frequent visitor, a tourist). Some described individual characteristics (impatience, hesitation) could not be linked to the travel survey data and have not been modeled.

The following choice behavior was implemented in SUSTAPARK. Initially, the following four search strategies are available:

- OnStreet: searching for on-street parking places near the destination, with a mostly random route choice.
- ResidentCard: very similar to OnStreet but represents residents with resident cards, which do not consider the price of a parking place and never switch to another search strategy.
- Private: residents who have their own parking garages and drive to them directly, without searching.
- Complex: drivers who go directly to the parking garages nearest to their destinations that still has free parking places (this operates under the assumption of complete knowledge).

During the parking search, drivers also can switch to two other strategies:

- ComplexOnStreet: originally these drivers followed the OnStreet strategy, but because the choice model indicated to switch to another type of parking, they change toward a Complex strategy (i.e., driving toward a parking garage). While driving toward the parking garage, the driver still checks the streets for free on-street parking places.
- FixedOnStreet: when there is no parking garage with free parking places available within a reasonable distance of the destination, a driver keeps on searching for an on-street parking place, despite having little success with it.

The paragraphs below discuss the formulas used in the implementation of the model. As a first step, the exponentiated utilities of all the alternatives need to be calculated. The free on-street alternative is the reference level and therefore has no dummy.

$$U_{\text{on-street (free)}} = \exp(\beta_1 . At + \beta_2 . St + \beta_3 . Et + \beta_4 . Fee)$$
$$U_{\text{on-street (paid)}} = \exp(\beta_1 . At + \beta_2 . St + \beta_3 . Et + \beta_4 . Fee + I_{\text{on-street (paid)}})$$
$$U_{\text{off-street (lot)}} = \exp(\beta_1 . At + \beta_2 . St + \beta_3 . Et + \beta_4 . Fee + I_{\text{off-street (lot)}})$$
$$U_{\text{off-street (garage)}} = \exp(\beta_1 . At + \beta_2 . St + \beta_3 . Et + \beta_4 . Fee + I_{\text{off-street (garage)}})$$

The choice probabilities (to be interpreted as the average chance that a specific alternative is chosen) then are given by

$$P_{\text{on-street (free)}} = U_{\text{on-street (free)}} / (U_{\text{on-street (free)}} + U_{\text{on-street (paid)}} + U_{\text{off-street (lot)}} + U_{\text{off-street (garage)}})$$
$$P_{\text{on-street (paid)}} = U_{\text{on-street (paid)}} / (U_{\text{on-street (free)}} + U_{\text{on-street (paid)}} + U_{\text{off-street (lot)}} + U_{\text{off-street (garage)}})$$
$$P_{\text{off-street (lot)}} = U_{\text{off-street (lot)}} / (U_{\text{on-street (free)}} + U_{\text{on-street (paid)}} + U_{\text{off-street (lot)}} + U_{\text{off-street (garage)}})$$
$$P_{\text{off-street (garage)}} = U_{\text{off-street (garage)}} / (U_{\text{on-street (free)}} + U_{\text{on-street (paid)}} + U_{\text{off-street (lot)}} + U_{\text{off-street (garage)}})$$

By construction, the sum of the probabilities is one. The probabilities form the parameters of a multinomial distribution. Draws from this distribution are made with a random number generator (RNG), ranging from zero to one. The "choice" then is made by comparing the value of the RNG with the range of the intervals

$[0 , P_{\text{on-street (free)}} [$ corresponds to a choice for free on-street parking.
$[P_{\text{on-street (free)}} , P_{\text{on-street (free)}} + P_{\text{on-street (paid)}} [$
corresponds to a choice for paid on-street parking.
$[P_{\text{on-street (free)}} + P_{\text{on-street (paid)}} , P_{\text{on-street (free)}} + P_{\text{on-street (paid)}} + P_{\text{off-street (lot)}}$
$[$ corresponds to a choice for off-street parking in a parking lot.
$[P_{\text{on-street (free)}} + P_{\text{on-street (paid)}} + P_{\text{off-street (lot)}} ,1]$
corresponds to a choice for off-street parking in a parking garage.

Because the driver in the model must make the choice for a parking type repeatedly, the value generated by the RNG is stored so that it can be reused. If not, the choices of the drivers will continuously switch between the possible alternatives, which is not desirable.

A parking spot model is used by the drivers to decide whether they consider specific, empty on-street parking places suitable to park. Because no studies or empirical data were available for this problem, an ad-hoc model was constructed based on assumptions on which variables are relevant. Tests suggest that this model performs as expected.

The variables used (see Table 2) are:

- Exit rate: the number of cars that exit from (on-street) parking places in the street per minute.
- Occupancy: the fraction of the parking places in the street that is occupied.
- Search time: the time the driver already has spent searching.
- Distance: the current distance from the destination (measured along the routes).

Table 2. Table with the coefficients of the parking spot model

Variable name	Notation	Coefficient	Value
Intercept		0	5.88
Exit rate [cars/min.]	Rate	β1	-1.418
Occupancy [fraction]	Occ	β2	8.789
Search time [min.]	St	β3	2.197
Distance [meters]	Dist	β4	-0.05

The coefficients and the parameters are combined in the linear form

$U_{park} = \beta_0 + \beta_1 \,.\, Rate + \beta_2 \,.\, Occ + \beta_3 \,.\, St + \beta_4 \,.\, Dist$

The probability of parking in a given (free) on-street parking spot then is given by

$P_{park} = 1 / (1+ \exp(- U_{park}))$

Every 30 seconds, the discrete choice model reevaluates the current parameter values, and a change in parking strategy can occur. The stored RNG ensures consistency of the driver's behavior.

SIMULATOR

The loop of SUSTAPARK simulates a one-day period (24 hours). The temporal resolution is one second to ensure sufficient detail. The start time is set at 4 A.M., as the moment with the least traffic. The simulation consists of (1) an initialization of both the agent population and the network and (2) a simulation of the activities per agent (AgentSimulator) and of the traffic and parking situation (TrafficSimulator) (see Figure 4).

The initialization phase creates the model input: the road network, parking places in the NetworkCreator, and the activity schedules, home location, and initial parking places close to their homes in the AgentCreator. Residents are present in the city before the time loop starts. Agents from outside the city appear at entry gates of the network when their activity schedule makes them reach the city.

After initialization, the time loop starts. Each time step, the agent simulator updates all agents. Agents remain in the agent simulator even while their activity schedules make them leave the city. Subsequent activities can make them reenter the city. The model time is compared with every activity schedule and the agent's state is set to "Driving" if an activity requires a trip.

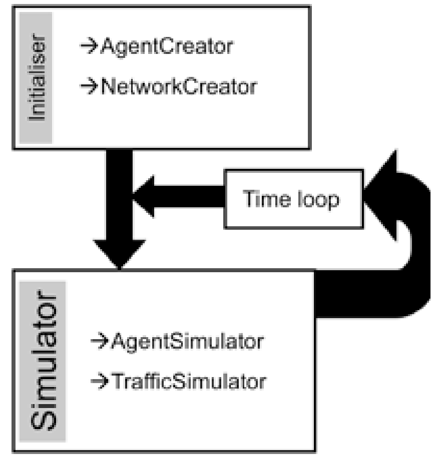

Figure 4. Schematic representation of SUSTAPARK

The traffic simulator updates the road network. Every time step, intersection rules direct traffic at intersections, and roads are updated using a traffic cellular automaton (TCA) (Maerivoet and De Moor 2005). The TCA, used to model the traffic flow, is a discretized representation of a network consisting of several cells. SUSTAPARK is a so-called single-cell model, where each cell can hold only one vehicle at a time, in contrast to the more complex multicell models. As time advances, vehicles can move from one cell to another. The spatial resolution for the TCA is set initially at 7.5 m based on the space between cars. This spatial resolution together with the temporal resolution of one second determines the possible speed rates of the vehicles:

7.5 m/s=27 km/h

Possible speed rates for this resolution are multiples of 27: 0 km/h, 27 km/h, 54 km/h, depending on the amount of cells a vehicle advances in one time step. Several factors limit the actual speed of each vehicle: the maximum speed of the vehicle and of the link where it is located, the parking search behavior (parking speed), and the preceding vehicle:

Actual speed$= f(v_{vehicle}, v_{link}, v_{parkingmode}, v_{traffic})$

The driver's parking search behavior can change the vehicle from "Driving" mode to "Parking Search" mode. From that moment, the network proposes possible empty parking spaces (which the vehicle can reach in one time step) to the driver. The driver decides whether to use a parking place based on the utility of these places. When parking search time is increasing, the utility of the parking places changes. Figure 5 is a schematic representation of the decision strategy.

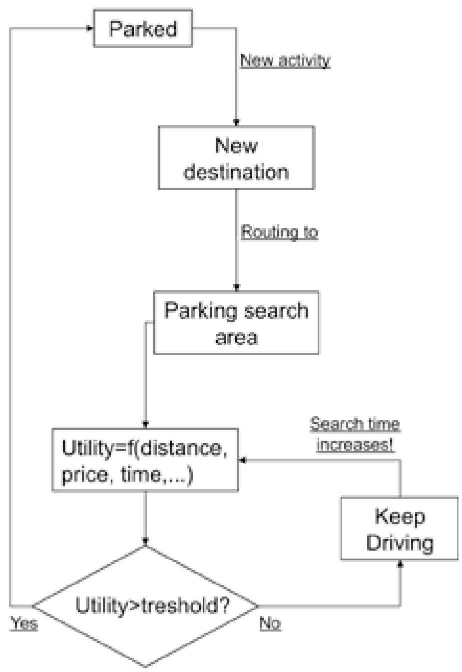

Figure 5. Schematic representation of the parking-decision strategy. The driver parks if the utility of a parking place is greater than a threshold.

Figure 6. Street network of the inner city of Leuven, as implemented in the case study

OUTPUT

The total situation of the network and agents is logged on every time step, resulting in output statistics: time series, parking occupancy per street, parking zone bottlenecks, (average) parking search time per agent. Joining these data to the spatial network provides map visualization.

CASE STUDY FOR LEUVEN, BELGIUM

Leuven is a Belgian city with 97,291 inhabitants (as of January 1,2011), an employment and shopping center, and a large population of students. The study area is the historical inner-city center surrounded by a ring road. This ring road has a diameter of two kilometers with an internal street network of 88 kilometers (see Figure 6). The general parking policy is to keep cars outside the city as much as possible by providing parking lots outside the ring road and stimulating transport by bike and public transport. The mobility plan of the city makes through traffic in the historic center impossible for cars; the center is carfree, connected to the ring road with one-way roads creating loops. Parking places are mainly on-street and in private and public parking garages/complexes. Residents can use on-street parking places without fee or time restriction by using resident parking carda. All others have a maximum of 15 minutes free parking or must pay in the commercial and business areas. In residential streets, parking is free yet limited to two hours maximum.

The GIS service of the city, G@lileo, provided detailed spatial data including the road network, parking complexes, and buildings. On-street parking places were available as the number of parking places per street segment. A local travel survey and local statistics provided data for agents and activity schedules (Zwerts et al. 2005).

SPATIOTEMPORAL PARKING SUPPLY AND DEMAND

Supply of Parking

As input data for on-street parking places and parking garages is available, only residential/private parking places have to be calculated. Car ownership for the total province equals 396 vehicles per 1,000 inhabitants. This may be a small overestimation because car ownership in cities usually is lower than the average for the total province. Given the inhabitants per street, an estimation of the number of vehicles per street is:

$$vehicles_{per\ street} = inhabitants_{per\ street} * 0.396$$

Residents with resident parking cards may park on the street with their resident parking cards. Assuming that all the residents with a car and no resident parking card have access to private parking for their vehicle:

$$private\ parking\ places_{per\ street} = vehicles_{per\ street} - resident\ cards_{per\ street}$$

The municipality seeks to promote parking outside the ring road and to discourage the use of cars in the city. The parking lots outside the ring road are used for different purposes than those in the city: as parking for the railway station, as places where students leave their cars for a week while staying in rooms on campus, as

RoadID	SumOfHOME	SumOfWORK	SumOfSCHOOL
16268	1917	71	0
16274	1167	0	0
16546	2822	166	4484
16570	159	0	0
16582	3595	36	0

Figure 7. Determination of the relative attraction for every trip motive: the buildings with different functions in different colors, and the summary per street and trip motive

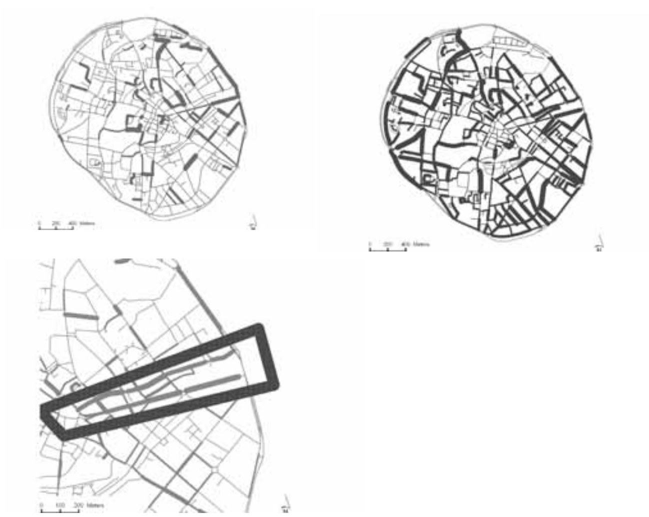

Figure 8. Relative attraction of streets for work (left), going home (middle), and shopping (detail, right)

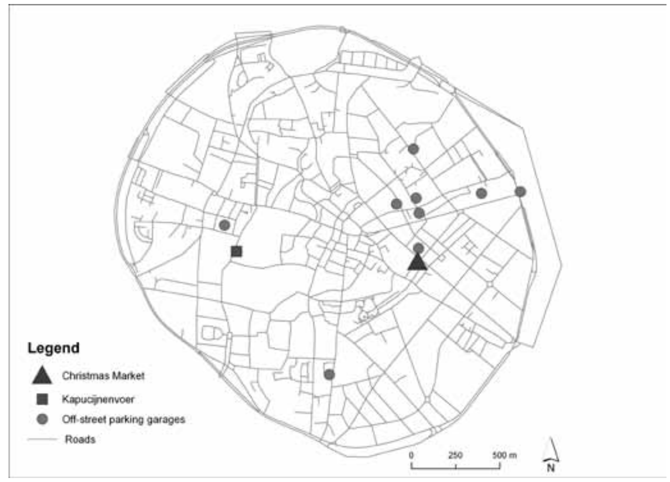

Figure 9. Location of the added parking garage Kapucijnenvoer (square), the Christmas market (triangle), and the other off-street garages (dots)

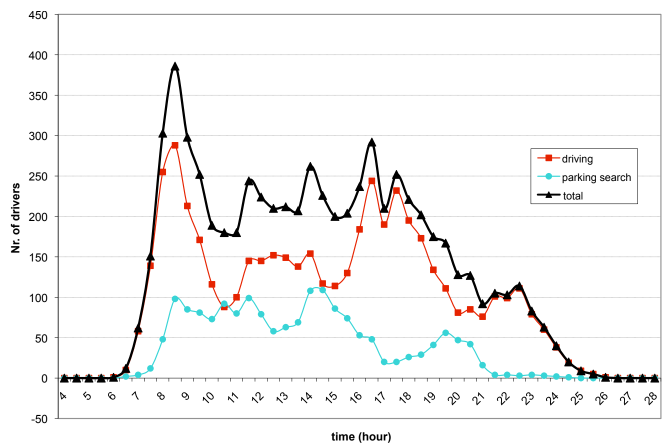

Figure 10. The number of agents simultaneously active (driving and searching) in the model at specific times

park-and-ride for commuters to Brussels, etc. Therefore, these parking lots are not included in the model. Agents not having found a parking place in the city leave the system. In reality, these agents will park in those parking lots outside the ring road.

Demand for Parking

The calculation of the demand for parking in space and time happens in three steps:

- Give all functions of buildings (restaurant, residential, office) an attraction factor per trip motive (recreation, work, shopping).
- Multiply the surface of the building with the attraction factor per trip motive.
- Summarize values per street and trip motive (see Figure 7).

This value is the relative attraction of a street for a particular trip motive and determines the chance a street is chosen as a trip destination (spatial component) when an activity schedule is followed (temporal component) (see Figure 8).

SCENARIOS

Three scenarios were run for this case study to verify the model: (a) a base scenario, (b) the addition of a new parking garage (Kapucijnenvoer), and (c) the special event of the Christmas market (shown in Figure 9).

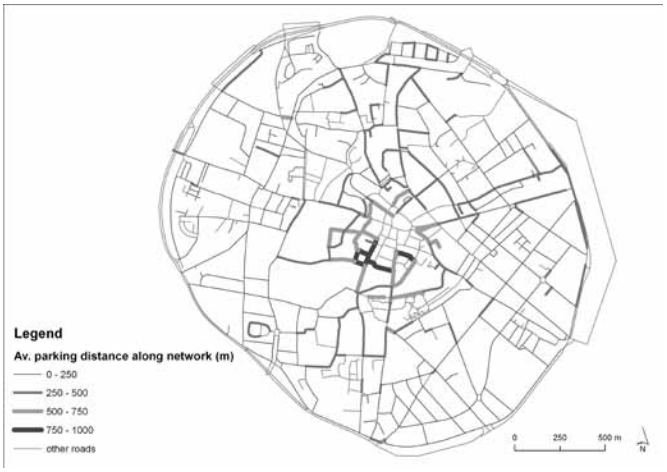

Figure 11. Average distance along the network between the destination (street) and the parking

Figure 12. Average parking search time per street for all agents throughout the day

Base Scenario

This scenario uses the original preprocessed data and rough estimations. The number of agents was estimated as follows: In the regional travel survey calibrated with traffic counts on highways and regional counts, 25,000 car agents make a trip to and from the city of Leuven. This includes major employment centers and university campuses at the periphery of the city. Other indicative numbers were provided by the city: Calculations made for the traffic plan (extrapolations from traffic counts) assume 4,244 cars entering and 7,064 leaving the city during the morning peak. However, these also include employment centers (university hospital and campus, administrative center, bank and insurance quarters) located at the outside of the ring road.

Successive trials of the model starting from 25,000 agents resulted in an unrealistic congestion, because of the limited capacity of the network. By gradually decreasing the number of agents to 14,000 agents, congestion was limited between 7:30 A.M. and 9:30 A.M. and around 5 P.M. This is a realistic situation in the city center. These agents generate a total of 16,186 parking actions. Note that this is a rough estimate.

The parking places include: Nine public parking garages of the city, with just more than 4,000 parking places, 3,000 private, and 6,352 on-street parking places. A calibration consisted of comparing the model results with counts of street and public parking occupancy. Field experts of the city administration assessed the results based on their knowledge of the parking situation on normal weekdays.

New Parking Garage

This scenario simulates the effect of the construction of a large parking garage (2,000 places) at the Kapucijnenvoer. As planned, some of its capacity (500 places) will be rented to residents and the remaining places are for paid off-street parking places, usable by residents and visitors alike. The maximum number of cars having private parking increases from 3,000 to 3,500 compared to the base scenario, while the agent set and network remain the same. The number of public parking places inside a parking garage increases by 1,500.

Christmas Market

In this scenario, the impact of the Christmas market in the city of Leuven is simulated. The number of recreational agents of the base scenario increases by 1,000 to represent the extra attraction of the market. The Christmas market activities start in the evening and continue during the market hours. On the road network, the area around the Christmas market has a higher recreational attraction. The amount of parking places remains unchanged in comparison with the base scenario.

RESULTS

Base Scenario

The total number of agents at any given time in the model (see Figure 10) consists of a fraction of those driving toward their destinations and others looking for parking places. The shape of the curve corresponds with rush hours: a sharp peak in the morning and a broader and lower, albeit broader, peak in the evening. The peak around noon is caused by agents going out or going back home for lunch. During working hours, almost half of the drivers are looking for parking places.

The ring road of Leuven serves as connection structure, both in reality and in the model. Cars only using the ring road in that way, without participating in parking search in the city center, are not included in this graph.

The average parking distance (see Figure 11) measured along the network (average of the whole day and all the cars having this street segment as their destinations) is an indication of the parking pressure. This is the distance between the place where the

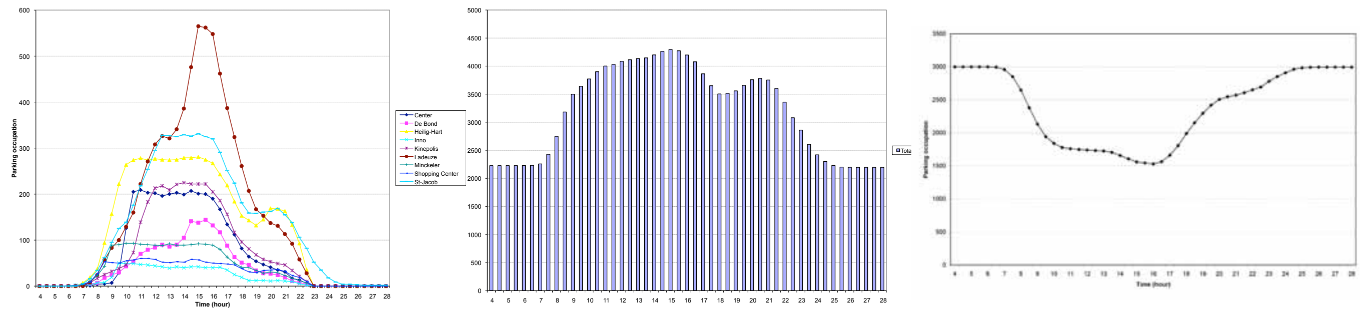

Figure 13. Evolution throughout the day of parking occupation: public (paying) parking garages (top), private off-street parking places (bottom left), and on-street parking (bottom right)

car is parked and the center of the destination road segment. The average length of the road segment in the study area is 82 meters, so the parking distance is on average +/- 41 meters. Around the traffic-free center, which is also the area with the highest overall attraction, the average distance between the parked car and the destination is up to one kilometer. Away from this area, agents usually can park near their destinations. This shows that parking in this city is a local problem.

The average time spent by agents searching for parking places (average of all the driving agents and all times of the day) indicates again the parking pressure around the city center (shown in Figure 12). In the eastern part of the city, the Bondgenotenlaan also stands out. This is a shopping street with no on-street parking places. Drivers, therefore, search for parking places in adjacent streets, resulting in high parking search times and serious pressure on the available parking places.

The nine public parking garages are closed for the night. They fill up during the day, after the morning rush hour. In the model, drivers first saturate the available on-street parking places. These are either free with a two-hour time limit, thus more attractive for agents with activities of less than two hours, or with a charge, but less expensive than the parking garages. The peak use of the public parking garages occurs in the afternoon, mainly because of shoppers (see Figure 13).

The occupation of parking places is the same at the start (4 A.M.) and at the end of the model (4 A.M. the next day), because, it is assumed, every agent starts and ends the activity schedule at home. Public (paying) parking garages and on-street parking places start to fill up as commuters come to the city. The afternoon peak is also the same for both. In the evening, there is another peak as people come to the city for recreational purposes. The private off-street parking occupation follows an opposite curve.

Drivers who go to private parking places or who have resident cards do not change strategies. Table 3 indicates that the large majority of the remaining drivers have initial strategies to look for on-street parking places. For more than 20 percent of their trips, they are unable to find on-street parking places within a reasonable amount of time and switch to strategies aimed at paying parking garages. A few drivers who initially intended to park at parking garages fail to find parking places there and park on-street. In Leuven, driving from one parking garage to another usually requires considerable detours or even returning to the ring road to enter the city from another "gate" or entry point. The agents reflect the driver behavior of searching on-street alternatives in the parking search areas near the destinations. It also is interesting to note that the number of drivers who wind up in parking garages after first looking on-street for parking places is higher than the number of drivers who go directly to parking garages. This is indicative of the reluctance of drivers to go for parking garages if they have on-street alternatives, which is included in the choice model.

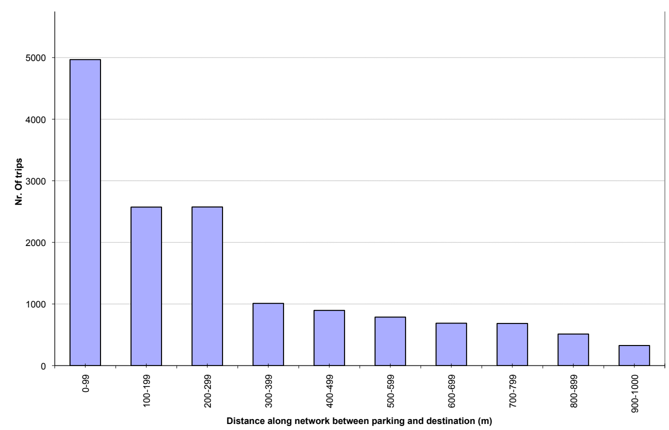

Figure 14. Number of trips compared with the distance between destination and parking

When the distance between the eventual parking place and the destination are studied (shown in Figure 14), it is clear that

		Initial parking strategy				
Final parking strategy		Parking garage	On street	Private parking	Resident card	Grand Total
	First on street, then garage		2270			2270
	Parking garage	1904				1904
	On street when garage is full	141	179			320
	On street		7270			7270
	Private parking			2740		2740
	Resident card				1682	1682
	Grand Total	2045	9719	2740	1682	16186

Table 3. Comparison between the initial and the final parking strategy for all trips

two-thirds of the drivers find parking places within reasonable distances of their destinations (less than 300 meters). In fact, one-third of the drivers manage to park within 100 meters of their destinations. In contrast, the fraction of drivers who park at a much farther distance than 300 meters is very large. This indicates that after searching for a while near their destinations, drivers decide to go for another alternative where they know they can park, instead of continuing the search nearby their destinations.

A graph of the average search times for a parking place, stratified by distance between the eventual parking place and the destination, Figure 15 shows that the drivers who park close to their destinations spend substantially less time searching for parking places than drivers who find parking places further away. The agents who manage to park within short distances include a large share of drivers who park in private parking garages or have residence permits. Drivers who park further away are frequently drivers who first searched for on-street parking places and then switched to parking garages, which are on average further away from their destinations.

To validate the results from the model, parking counts were conducted on 44 roads, during four days (June 24, 2008, to June 27, 2008), between 7 A.M. and 9 P.M. The results are summarized in Table 4.

Table 4. Comparison between the counted and the modeled parked cars

Hours	Number of Parked Cars: Counted	Number of Parked Cars: Model	%
7–8	1,820	2,606	70
8–9	2,601	3,284	79
9–10	2,069	3,467	60
10–11	2,842	3,595	79
11–12	2,359	3,640	65
12–13	3,402	3,679	92
13-14	3051	3735	82
14-15	2469	3745	66
15-16	1944	3648	53
16-17	2276	3362	68
17-18	1902	3161	60
18-19	2145	3324	65
19-20	1820	3494	52

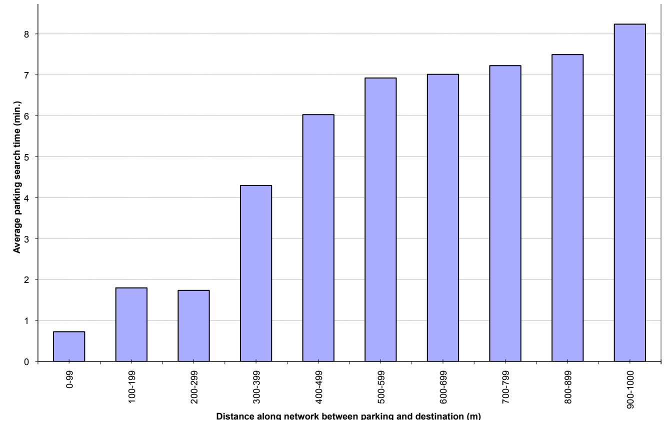

Figure 15. Average search time for a parking place compared with the distance between destination and parking

The number of cars parked on the street generally is overestimated in the model (68 percent). This is, at least in part, because the real capacity of on-street parking spaces for cars always was lower in reality than the theory: construction work on houses, illegal parking of trailers using several parking spots, moving vans, motorbikes, etc. Also, the space was far from optimally used by the parked cars. Other reasons could be that the choice model needs further refinement.

Christmas Market

The Christmas market leads to a large additional evening demand in the relatively small area where it is organized. This results in an increased parking garage occupation (see Figure 16). The nearest garage is right under the Christmas market (parking Ladeuze). The pressure on the parking places in this area generates longer parking search times (shown in Figure 17). There is only a small increase of the distance between parking and destination, explained by the reluctance of visitors to exceed a maximum walking distance to the destination. When search time increases, choosing for an off-street parking garage is also an option for visitors who did not originally have that intention. The location of parking Ladeuze explains the lack of increase in parking distance. This result is a direct consequence of the search behavior implemented in the model. In December of 2012, the Christmas market generated daily gridlocks, because the parking Ladeuze was full and the exit was blocked by queuing cars. In this case, perfect driving behavior assumed in the model did not correspond with the obstruction of intersections and parking exits in reality.

NEW PARKING GARAGE

As is inherent in creating 500 extra “private” places in the model of the city, a shift occurs in resident parking (as trip motive equals “going home”) from on-street parking toward private parking. The new parking garage also provides 1,500 extra places for paid off-street parking. From the comparison between Figures 13 and 18, it is clear that although the new parking garage Kapucijnenvoer

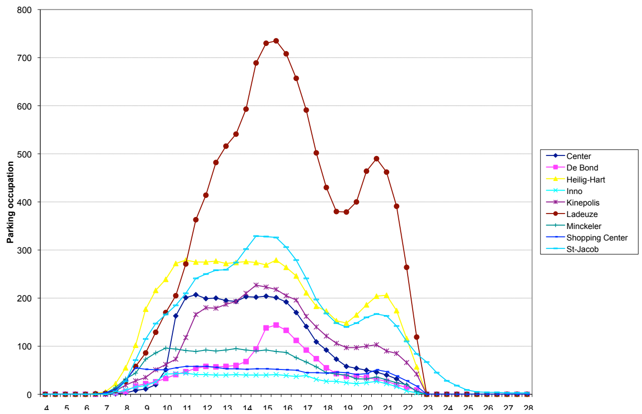

Figure 16. Evolution throughout the day of the total occupation of the parking garages in the Christmas market scenario

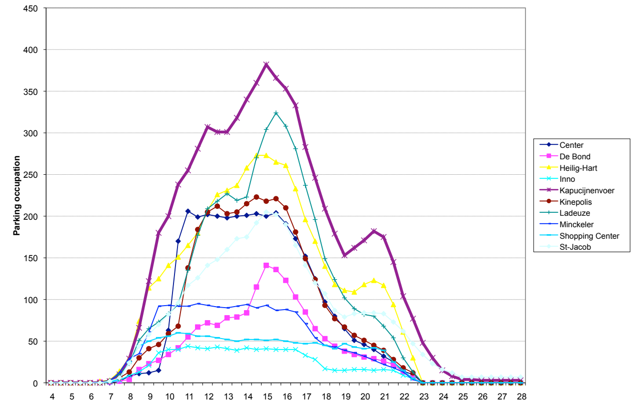

Figure 18. Evolution throughout the day of the total occupation of the parking garages for the Kapucijnenvoer scenario

Figure 17. Average parking search time per street for the Christmas market scenario

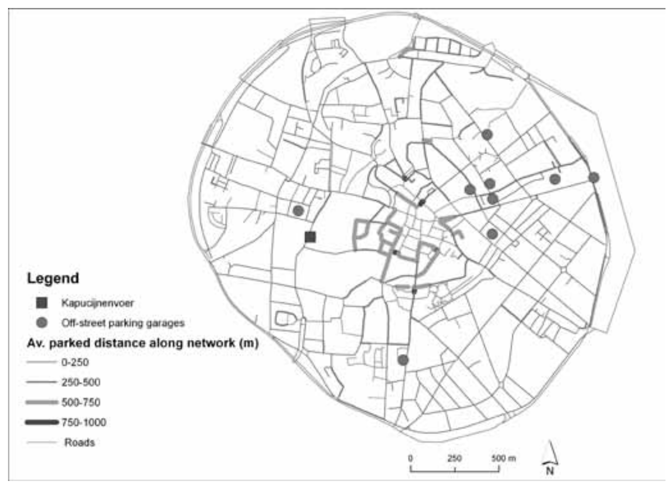

Figure 19. Average distance along the network between the destination (street) and the parking for the Kapucijnenvoer scenario

is used by many drivers, the overall amount of off-street parking changes little. What does happen is a large shift toward the new parking garage from the other parking garages. This shift causes a substantial reduction in the average distance drivers park from their destinations (in Figure 19) but not in the search times. This means that the main effect of the new parking garage is that some parkers can park closer to their destinations if they decide to park off-street. However, this is only a substitution and does not attract drivers (or only very little) who currently park on-street.

This effect is partly because of the way the model works. However, the result does make sense. Without measures to change the current balance between on-street and off-street parking, it does not seem useful to add a large additional capacity for off-street parking places. Merely adding additional off-street parking places (under the assumption of equal demand for parking places and the same price structure as other garages) is not likely to increase the demand for off-street parking places. Where the new parking is more conveniently located for some people, it may attract some more drivers who currently park on-street. However, the distance to the center is likely to motivate drivers to look for on-street alternatives closer to their trip destinations.

One other—currently not modeled—effect might be of importance: Adding such a large amount of parking places may encourage car use in the inner city, through a modal shift from other transport modes or through additional trip generation.

COMPARISON

Figure 20 shows the comparison of the three scenarios for the number of searching agents during the day. Around 8 P.M., a big difference can be seen for the Christmas market scenario. The number of agents searching for parking places peeks. The reason for this is the increase of the agents that all move to the same area around the same time. This increase already starts from around 2 P.M. because the motive of the agents already is adapted from that moment.

Comparing the total parking occupation for the three scenarios (shown in Figure 21) reveals interesting effects. For the public parking garages, the effect of the Christmas market is relatively high. From 2 P.M., the total occupation is higher than in the other scenarios, with a peek around 8 A.M. The new Kapucijnenvoer parking does not increase the total public parking garage occupation. On average, a fixed number of agents used parking garages for both scenarios, only a shift between the parking garages happened to the closest parking garage, resulting in smaller distances between their parking places and the trip destinations for the area around the new parking garage.

The comparison for on-street and private parking places is quite similar: an increase of the on-street parking places for the Christmas market scenario from 2 P.M.

For the Kapucijnenvoer scenario, the 500 extra private parking places available for the inhabitants result in more available on-street parking places. However, the difference is not 500 during the whole day. When pressure on the parking places increases around 12 P.M., these 500 “extra” on-street places are used more.

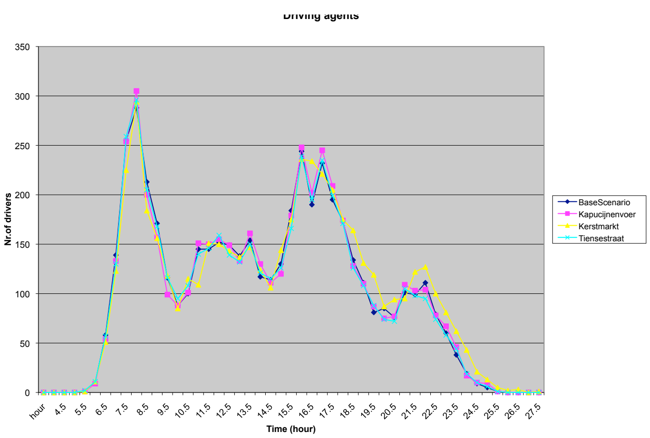

Figure 20. Searching agents throughout the day for the three scenarios

STOCHASTIC FLUCTUATION

Because SUSTAPARK is a model based on stochastic draws with a random number generator, we expect fluctuations in the results. How severe are these fluctuations? For example, how large is the difference between consecutive runs of the model and how comparable are the results for the same scenarios? To try to answer this question, we ran SUSTAPARK 15 times on the same baseline scenario. During each run, we collected all the vehicles’ search times on all the roads for each block of five minutes during the day. In total, this gave some 16,000 data points for each run, with a grand total of some 80,000 data points for the entire exercise.

Consider the results of one run, we can estimate the percentiles from the distribution of the vehicles’ search times (the 50 percentile corresponds to the median). With each new model run, we combine its results with those of the previous set of runs. This systematically increases the population size, giving a better estimation of the true distribution of vehicles’ search times. The results when calculating the percentiles after each set of runs indicate that it seemingly does not matter how many runs of SUSTAPARK are executed. Each time, the percentiles lie closely to each other (see Figure 22).

Only for the very high percentiles (i.e., 99 and above) is there is some variation in the results. This means that for the extreme values of the search times (i.e., exceptions such as small streets where only one car is searching for a long time), increasing the number of model runs may stabilize the result. All in all, the previously sketched experiment seems to indicate that each run of SUSTAPARK is quite stable in itself, implying that no averaging of consecutive runs is necessary.

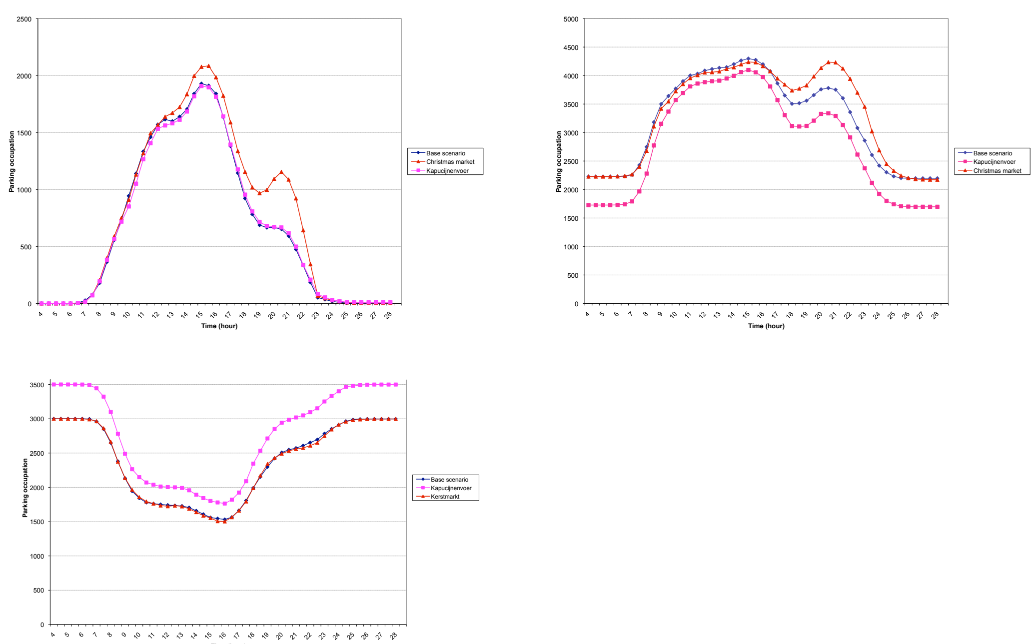

Figure 21. The evolution of the total occupation of parking places throughout the day for the three scenarios: parking garages (left), on-street (right,) and private parking places (bottom)

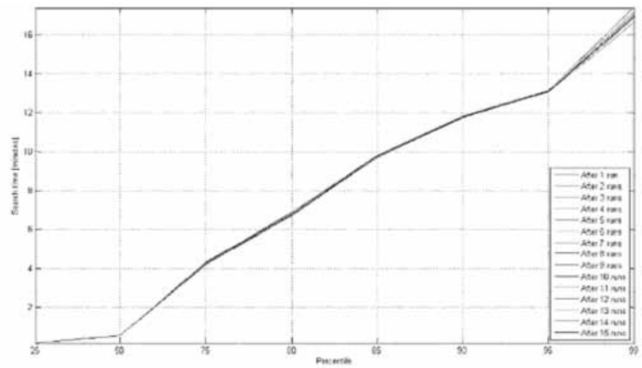

Figure 22. Stochastic fluctuation of 15 model runs

DISCUSSION AND CONCLUSIONS

This paper describes the general concepts used in the development of the SUSTAPARK model to simulate on a high-detail level the parking situation in an urban environment. The application of the model for the case study of Leuven demonstrates that an agent-based approach can be used to simulate 24-hour traffic and parking in an entire city. In fact, the complexity of modeling parking in a city decreases by dividing the problem into its basic components, resulting in simple rules that agents have to follow.

By using an agent-based approach, the situation of every individual is simulated during the execution of the model resulting in several parking situation indicators: maximum and average parking occupation, walking distances, congestion zones, etc. Different scenarios can be run by adapting the number of agents, their behavior, the traffic, or the infrastructure of the city.

In the case of Leuven, the base scenario shows that there is an overcapacity of parking places, but that there are local problems around the traffic-free center. Also, many cars are parked in the streets while there still is unused capacity in the public parking garages. The city used these figures to further restrict on-street parking. Another finding is that the city distributes 1,682 resident cards, using 26 percent of the on-street parking places, while the parking garages are empty at night and not full during the day, except for the parking near the station and the parking Ladeuze when there is an event such as the Christmas market at that location. The model results thus indicate that more cars could be taken off the streets by offering opportunities for residents in the parking garages, instead of giving them facilities to use the streets as private parking places.

The model has a very high level of detail and enables the modeling of interactions at a very small scale. The model structure allows for further extension and improvements with additional features. The keys to ensure realistic output are a good understanding of the parking behavior and a representative agent population with activity schedules that approximate real life (at the moment we work with a rough estimate of the parking demand). This is obtained from travel surveys and local GIS data on urban land use. The increasing availability of both is reflected in, i.e., the indicators and the number of cities in the European Urban Audit database (EC 2011). Another aspect is to understand the local driving and parking behavior. In Flanders, Belgium, drivers can experience parking as a problem from the moment they have to search for suitable places (Zwerts and Nuyts 2005). In SUSTAPARK, these driver characteristics are included in the agent simulator.

The current model and the methodology adopted do have limitations at this point. The estimation of the total demand for parking in the test case is a very rough approach. This could be improved for cities having traffic counts. Another shortcoming is that driving and parking are modeled as being perfect. This is not the case in reality. The parking counts in the base scenario showed a suboptimal use of on-street parking space, and the Christmas market generated gridlocks because of the obstruction of intersections and parking, not included in the model.

While the adopted agent methodology enables a high level of detail in the model, it comes with a price of considerable data requirements. A significant amount of time was needed to process the data and prepare them for the model input. Furthermore, the model also has city-specific parameters and requires fine-tuning to local circumstances before use in another urban context.

A further extension could include a mode choice model to embed the effects of price and availability of parking in an overall urban mobility system. It is clear that much more research is needed in the field of parking behavior. We hope the SUSTAPARK project will contribute to the scientific body of knowledge on parking. The tool can be used to simulate effects of planned parking measures in a city.

Acknowledgments

This project is funded by the Federal Science Policy in the Science for a Sustainable Development Programme. The authors would like to thank the city of Leuven for the provided data.

About the Authors

Thérèse Steenberghen
SADL, K.U.Leuven
Celestijnenlaan 200E
BE3001 Heverlee
Belgium
therese.steenberghen@sadl.kuleuven.be
http://www.sadl.kuleuven.be

Karel Dieussaert
Geosolutions
Veldkant 33B
BE2550 Kontich

Belgium
karel.dieussaert@geosolutions.be
http://www.geosolutions.be

Sven Maerivoet
Transport & Mobility Leuven
Diestsesteenweg 57
BE3010 Kessel-Lo
Belgium
sven@tmleuven.be
http://www.tmleuven.be

Karel Spitaels
Transport & Mobility Leuven
Diestsesteenweg 57
BE3010 Kessel-Lo
Belgium
karel@tmleuven.be
http://www.tmleuven.be

References

Anderson, S., and A. de Palma. 2007. Parking in the city. Papers in Regional Science 86(4): 621-32.

Arentze, T., and H. Timmermans. 2005. Information gain, novelty seeking and travel: A model of dynamic activity-travel behavior under conditions of uncertainty. Transportation Research Part A 39: 125-45.

Axhausen, K. W., and J. W. Polak. 1991. Choice op parking—stated preference approach. Transportation 18(1): 59-81.

Benenson, I. 1998. Multi-agent simulations of residential dynamics in the city. Computers, Environment and Urban Systems 22(1): 25-42.

Benenson, I. 1999. Modeling population dynamics in the city: From a regional to a multi-agent approach. Discrete Dynamics in Nature and Society 3(2-3): 149-70.

Benenson, I., S. Aronovich, and S. Noam. 2005. Let's talk objects: Generic methodology for urban high-resolution simulation. Computers, Environment and Urban Systems 29(4): 425-53.

Benenson, I., K. Martens, and S. Birfir. 2008. PARKAGENT: An agent-based model of parking in the city. Computers, Environments and Urban Systems 32: 431-39.

Crooks, A., C. Castle, and M. Batty. 2008. Key challenges in agent-based modeling for geo-spatial simulation. Computers, Environments and Urban Systems 32(6): 417-30.

European Commission. Directorate-General regional policy. The urban audit. Http://www.urbanaudit.org, accessed October 30, 2011.

Hess, S., and J. Polak. 2004. Mixed logit estimation of parking type choice. Presented at the 83rd Annual Meeting of the Transportation Research Board, Washington, DC.

Hess, S., and J. Polak. 2005. Mixed logit estimation of parking type choice. Imperial College. London, working paper.

Laurier, E. 2005. Searching for a parking space. Intellectica 2-3(41-42): 101-16.

Litman, T. 2008. Parking management: Strategies, evaluation and planning. Victoria Transport Policy Institute.

Maerivoet, S., and B. De Moor. 2005. Cellular automata models of road traffic. Physics Reports 419(1): 1-64.

Marsden, G. 2006. The evidence base for parking policies—a review. Transport Policy: Special Issue on Parking 13(6): 447-57.

Martens, K., and I. Benenson. 2008. Evaluating urban parking policies with agent-based model of driver parking behavior. Transportation Research Record 2046: 37-44.

Shiftan, Y. 2008. The use of activity-based modeling to analyze the effect of land-use policies on travel behavior. Annals of Regional Science 42(1): 79-97.

Shoup, D. 2006. Cruising for parking. Transport Policy 13: 479-86.

Teknomo, K., and K. Hokao. 1997. Parking behavior in central business district—a case study of Surabaya, Indonesia, Eastern Asia. Society for Transportation Studies Journal 2(2): 551-70.

Thompson, R., and A. Richardson. 1998. A parking search model. Transportation Research A 32(3): 159-70.

Torrens, P. M., and I. Benenson. 2005. Geographic automata systems. International Journal of Geographical Information Science 19(4): 385-412.

Train, K. E. 2003. Discrete choice methods with simulation. Cambridge University Press. Available online at http://elsa.berkeley.edu/books/choice2.html.

Vlaamse Overheid. 2008. Vademecum duurzaam parkeerbeleid, Departement Mobiliteit en Openbare Werken Afdeling Beleid Mobiliteit en Verkeersveiligheid.

Zwerts, E., and E. Nuyts. 2005. Ministerie van de Vlaamse Gemeenschap. Onderzoek verplaatsingsgedrag Vlaanderen; Rapport OVG stadsgewesten, Vlaams-Brabant (2000-2001).