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Research Article

The Impact of Bottom-Up Parking Information Provision in a Real-Life Context: The Case of Antwerp

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A number of studies have analyzed the possible impacts of bottom-up parking information or parking reservation systems on parking dynamics in abstract simulation environments. In this paper, we take these efforts one step further by investigating the impacts of these systems in a real-life context: the center of the city of Antwerp, Belgium. In our simulation, we assume that all on-street and off-street parking places are equipped with technology able to transmit their occupancy status to so-called smart cars, which can receive information and reserve a parking place. We employ PARKAGENT, an agent-based simulation model, to simulate the behavior of smart and regular cars. We obtain detailed data on parking demand from FEATHERS, an activity-based transport model. The simulation results show that parking information and reservation hardly impact search time but do reduce walking distance for smart cars, leading to a reduction in total parking time, that is, the sum of search time and walking time. Reductions in search time occur only in zones with high occupancy rates, while a drop in walking distance is especially observed in low occupancy areas. Societal benefits of parking information and reservation are limited, because of the low impact on search time and the possible negative health effects of reduced walking distance.

1. Introduction

Technological advances in the past decade have enabled the development of bottom-up parking information and reservation systems that incorporate both on-street and off-street parking [1]. These systems may have benefits for drivers and the wider society alike, suggesting that it may be warranted for cities to invest in such systems [2]. Drivers might benefit in terms of a reduction in parking search time and walking distance to the destination. The society at large may reap indirect benefits, as a decrease in parking search time may reduce traffic congestion and pollution and may enhance traffic safety and the quality of the urban environment [3]. Possibly, too, an enhanced driver experience may add to the relative attractiveness of urban areas suffering from poor parking conditions, such as historic city centers. Clearly, an improvement in the parking experience for drivers may also lead to rebound effects: it may increase the attractiveness of driving, potentially leading to a modal shift in favor of the car. Furthermore, there may be (indirect) negative health effects, due to shorter walking distances and a shift away from other, more active, transport modes to driving [4, 5].

The complexity of these interrelationships underscores that it is by no means certain that an improvement in the parking experience of drivers will also have societal benefits. But before that question can be answered, it is necessary to identify in more detail whether parking information and reservation systems may indeed enhance drivers' parking experience in terms of reduced search times and walking distances. Recent studies show that the benefits of so-called bottom-up information systems are much smaller than expected and depend strongly on the conditions, notably parking occupancy rates and the combination of parking information with a parking reservation system [6, 7]. These findings relate to simulations carried out in an abstract, strongly simplified, spatial environment. The current paper builds on these papers and analyses the impacts of a bottom-up parking information and reservation system on parking

search time and walking distance in the real-life context of the city of Antwerp.

This paper is organized as follows. Following this introduction, Section 2 provides a brief review of the literature on the impact of information provision on (on-street) parking performance. In Section 3 we provide an extensive description of our methodology, including a description of the employed parking model, the data on parking demand and parking supply, the parking choice heuristics, the parking information and reservation system, and the simulation environment. The results of the simulation runs are presented in Section 4. We end with a conclusion and discussion of the possible policy implications (Section 5).

2. Literature Review

The role of information provision has received substantial interest in parking research. Studies have initially focused on the traditional on-route parking guidance systems [8–10]. The information provided via these parking guidance systems is typically provided in a top-down manner: a central organization, typically a local government, collects information on the parking occupancy rate at various off-street parking facilities and provides it to drivers via dynamic information signs along main routes in a city.

The recent advances in communication technology have enabled a bottom-up approach to the provision of parking information. In this case, information collection and provision are not the responsibility of a centralized organization, but information is gathered and disseminated by local units, such as a car or a parking place sensor. Both a car leaving a parking place and a parking sensor can disseminate information on an available parking place. This information is subsequently disseminated to other local units in the direct surrounding, that is, to cars, which in turn pass on the information. Through this sharing process, each car can ultimately have information on parking availability in a substantial larger area than the area which is in direct view of the car driver. Bottom-up information provision can be used to provide information on off-street and on-street parking availability. An important advantage of bottom-up information provision is that drivers can receive tailored information on parking place availability in the vicinity of their specific destination.

Bottom-up parking information provision can furthermore be combined with a reservation option, whereby drivers can reserve a vacant parking place about which they receive information. Such a system can avoid the problem that multiple cars are heading for the same vacant parking space and can thus further reduce or even eliminate competition over parking spaces among informed drivers. However, reservation systems also have two drawbacks: they require enforcement to avoid car drivers (with or without information) from illegally occupying a reserved parking space; and they imply that a parking place will have to be booked for a time slot that is at least slightly longer than the intended parking duration of a driver, thereby de facto reducing the effective parking capacity [11].

A number of authors have studied the possible benefits of bottom-up information provision, with or without a reservation possibility. While the results of these former type of studies differ [12–15], the most recent studies suggest that the benefits of merely bottom-up information provision are limited. Reduction in search time for drivers with information is paralleled by increases in search time for drivers without information, in most circumstances [6, 16]. These researches serve as a general background for our current study, but more relevant are a number of recent studies that do include a reservation possibility. Some of these later studies have analyzed the impact of parking reservation in off-street parking facilities [17–22], while others have studied reservation of on-street parking places using mathematical and game-theoretical approaches and thus without taken into account the inevitably spatial nature of parking search [23–25]. The latter is highly problematic, because space fundamentally shapes parking search time as was demonstrated by Levy et al. [11].

Four recent studies have employed a spatially explicit simulation model to study the impacts of bottom-up information provision in combination a reservation system, each using a different experimental setup [7, 26–28]. These studies show that the combination of information and reservation may yield benefits in terms of reduced search time but also that the size of the benefits depends heavily on the conditions. The most detailed study along this line was carried out by Tasseron and Martens [7]. They employed an agent-based model to study the impact of a reservation system in a highly stylized grid-style simulation environment. The results of their study show that users of a reservation system benefit in terms of reduced search time and reduced walking distance under virtually all simulated circumstances. However, societal benefits are not as clear-cut. This is so, because the benefits in search time for the users of the system come at a cost to the regular drivers, which see a nearly identical increase in search time. In contrast, users of the reservation system do experience a substantial reduction in walking distance, without affecting other drivers. Tasseron and Martens conclude that the introduction of a reservation system for on-street parking results in a more efficient distribution of available parking spaces among drivers searching for parking.

The aim of the current study is to analyze in detail whether these findings regarding the (limited) benefits of a reservation system also hold in a real-world case. Two circumstances in particular suggest that the results may be more significant in such a case. First, parking demand and supply vary strongly across time and space, which may increase the advantage of a reservation system. Second, the street network in real cities may lead to relatively long search times due to inefficiencies in route choice and search behavior. At the same time, two other circumstances may reduce the benefits of a reservation system: parking pricing and the availability of off-street parking places. As argued extensively by Shoup [29] and empirically supported by Van Ommeren et al. [30], the introduction of parking pricing may lead to a more efficient use of parking space and thus to lower average search times. The availability of off-street parking facilities

may have the same impact, as it reduces demand for on-street parking and drivers selecting off-street parking typically experience little to no search time at all [9]. Given these opposing "forces," the goal of this paper is to estimate the impacts of a parking information and reservation on parking performance in a real-world situation. For this purpose, we analyze a single case study: the inner city of Antwerp, Belgium.

3. Methodology

Our current study is largely in line with the most recent study of Tasseron and Martens [7], in which they test the impact of parking information provision in combination with a reservation system. Like these authors, we employ the PARKAGENT model to simulate parking search behavior. In order to be able to employ this model for the real-life case of Antwerp, we combine PARKAGENT with an advanced activity-based transport model called FEATHERS [31, 32]. Based on the latter model, we have obtained detailed estimates of parking demand as it changes over time and space, substantially increasing the realism of our simulations. Note that we assume no impact of the parking information system on overall parking demand.

In what follows, we briefly describe the essentials of the PARKAGENT and FEATHERS models. We then briefly present the simulation area and period. We subsequently turn to a description of parking supply, demand, and the parking choice heuristics employed by the agents in our simulations. We then describe the parking information and reservation system used by the smart cars in their search for a parking place. We end with a brief description of the simulation setup and performance indicators.

3.1. PARKAGENT. PARKAGENT is an agent-based model for simulating parking search and choice behavior in a spatially explicit environment [33]. The model generates data on cruising time, cruising distance, walking distance, and spatial distribution of parked cars. The model is built by means of a geosimulation approach [34]. PARKAGENT consists of static objects (such as streets, buildings, parking places) and dynamic objects or agents (i.e., vehicles). Both are represented using a layer of features in a high-resolution geographical information system (GIS).

PARKAGENT enables a highly detailed simulation of the parking choice and search behavior of agents. For this study, two types of agents are distinguished: regular agents (cars) and smart agents (cars). The difference between the two agents is that smart cars are capable of sending information as well as receiving information from parking sensors and other smart cars. As information reduces the inherent uncertainty related to the parking process, this allows the smart agents to make a more informed decision on where to park. The parking choice heuristic will be described in detail in what follows.

A further description of the key features of PARKAGENT can be found in Appendix A in Supplementary Material available online at https://doi.org/10.1155/2017/1812045.

3.2. FEATHERS. The FEATHERS model is an advanced activity-based travel demand model for the Flanders region (Belgium) [31, 32]. In line with the well-known activity-based approach to travel demand modeling, FEATHERS predicts which activities are carried out at what location, at what time, for how long, with whom, and the used transport mode, resulting in a coherent sequence of trips for each simulated individual.

The FEATHERS model uses a synthetic population of agents that represents the actual Flemish population. The synthetic population is based on an extensive Flemish survey (carried out between September 2007 and September 2008) that gathered data on demographic, socioeconomic, household, and travel characteristics. Additionally, different aggregate household and personal data for the Flanders region were used to estimate the characteristics for the entire synthetic population. For each agent/person with its own attributes, the model generates whether a specific activity is pursued or not. If so, the location of the activity, the duration of the activity, and the transport mode are determined based on the characteristics of this individual as well as on the characteristics of the transport network and the spatial environment.

In order to run FEATHERS for the Antwerp study area, several data layers had to be prepared and developed. Where FEATHERS is normally run at the level of transport activity zones, PARKAGENT requires more detail. Therefore, data have been translated from the zonal level to the level of statistical zones. Where the average size of the smallest zone employed in a typical FEATHERS application is 5.7 km^2, the average size of a statistical zone is only 1.3 km^2 (Figure 1). As will be discussed below, parking demand at the level of these statistical zones is translated into parking demand at the level of individual addresses in PARKAGENT.

3.3. Simulation Area and Period. In our analysis, we simulate parking search in the old city center of Antwerp, which encompasses the main pedestrianized shopping area of the city, numerous restaurants, cafes and bars, a number of main tourist attractions, a variety of businesses and services, and residential buildings (Table 1). In total, the area is home to about 8,200 buildings which serve as the destinations of the cars in the PARKAGENT model. The area provides over 9,000 on-street parking places, three free off-street surface lots, and nineteen for-pay parking facilities. We simulate the parking dynamics for 24 hours on a typical Saturday, starting at 03.00 h in the night between Friday and Saturday. We will present data for the "parking rush hours" between 16.00 h and 19.00 h, when visitors to the city are leaving and residents return home. During this period, the availability of on-street parking places is highly unpredictable and bottom-up information and parking reservation services are thus likely to be beneficial for individual drivers as well as society as a whole. The demand for parking is derived from the FEATHERS model, which generates a set of activity schedules for a synthetic population for the entire Flanders region for an entire week. For our study, we only simulate the relevant schedules for the selected area and time period.

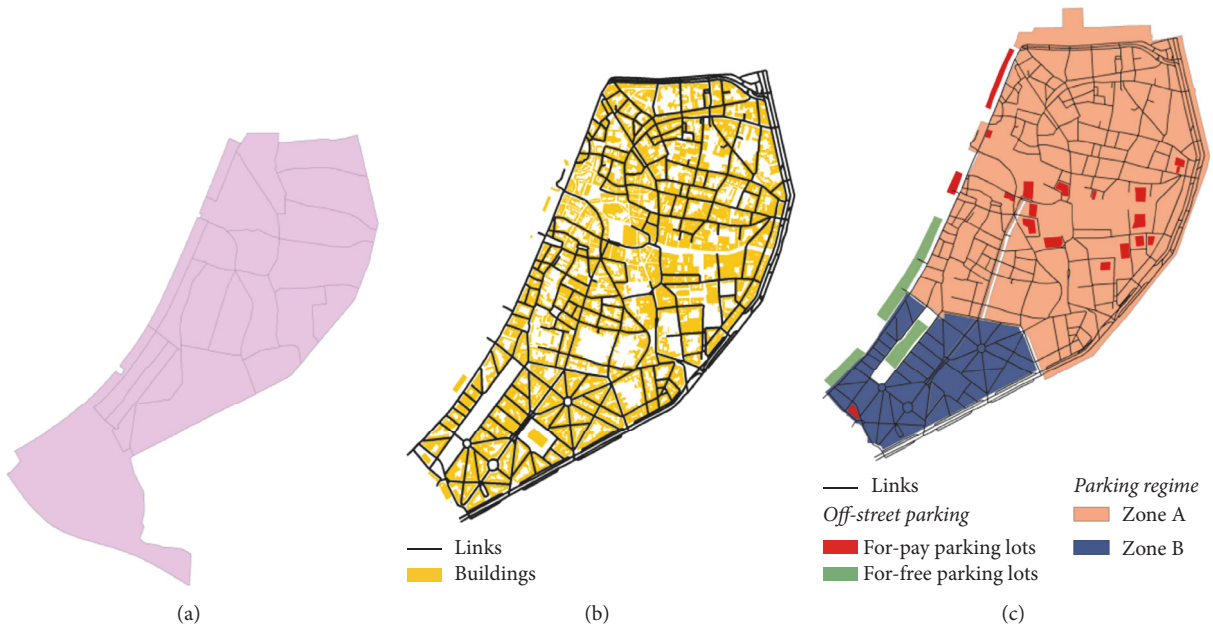

Figure 1: Maps representing (a) the 22 statistical zones used for the Antwerp simulation, (b) the road network and buildings, and (c) parking zones and off-street parking facilities.

Table 1: Characteristics of the study zone.

Type	Number of elements
Buildings	~8200
Residential buildings	~5600
Commercial/public buildings	~2600
Street links	~1100
On-street parking places	~9000
Public off-street facilities	22
Public off-street parking capacity	~9100
Statistical zones	22

3.4. Parking Supply. The parking supply in the study area encompasses on-street and off-street parking places. Based on satellite imagery data, the number and location of on-street parking places were obtained. These parking places fall under one of two street parking regimes. For the pedestrian shopping district and the surrounding area there is a maximum parking limit of 3 hours, indicated by Zone A in Figure 1. The parking costs for this parking zone are € 2.70 per hour. To the south of this zone lies parking Zone B, which has a maximum parking limit of 10 hours and costs € 1.10 per hour. Most residents in the simulated area in Antwerp who own a car have a parking permit for the zone in which they reside, which allows them to park for free for an unlimited time at an on-street parking place.

The simulated area also features three for-free parking lots, located in the southwest of the area. For these parking lots there is no maximum parking duration. Furthermore, nineteen for-pay parking facilities are located in the area. These parking facilities are owned by different parking operators and the prices vary in a range from €2.00 to € 2.90 per hour.

3.5. Estimating Parking Demand Based on FEATHERS. The demand for parking in the study zone is directly derived from the activity schedules which are generated by the FEATHERS model. The model generates schedules for an entire week. For our purposes, we only use the activity schedules for one particular day (i.e., Saturday) that involve travel by car and have origin and/or destination in the study zone. For this set of activity schedules, the FEATHERS model generates a list of all arrivals and departures for every 5 minute interval. Each entry consists of a unique agent ID, the type of activity, the duration of the activity, and an origin-destination (OD) pair.

The FEATHERS model distinguishes nine types of activities. PARKAGENT can only portray four archetypes of parking agents, that is, resident, worker, guest, or visitor. Therefore, the FEATHERS activities are converted into one of the four basic agent types used in PARKAGENT (Table 2). The OD-pair consists of the origin and destination combination on the level of statistical zones. Agents arriving to or moving within the study area are randomly assigned to one of the actual destinations (addresses) within their destination zone. This assignment is based on the type of land use and capacity of the building, as derived from the GIS layer of the city. Guests and residents are assigned to residential destinations, while visitors and workers are assigned to public and commercial destinations. Agents departing from one of the zones in the study zone area are picked based on their

Table 2: Activity translation table.

FEATHERS activity	PARKAGENT activity
Being at home	Resident
Work	Worker
Bring/get	Visitor
Shopping (daily)	Visitor
Shopping (nondaily)	Visitor
Services	Visitor
Social visits	Guest
Leisure	Visitor
Touring	Visitor
Others	Visitor

unique ID. Besides trips that are planned within the simulated environment, many trips have an origin or destination that lies outside this area. To this end, one unique additional zone is used for agents arriving from, or departing to, the area outside the study zone.

In order to adequately estimate the demand for *public* parking (on-street or off-street), it is important to identify the agents who can make use of a private parking place. In the simulation, we assume that only residents and employees may have a private parking place available. We use the fraction of privately parked vehicles within each statistical zone to define stochastically whether an agent entering the zone will park at a private parking place or at a public parking place. Due to the absence of detailed information on private parking spaces for employees, the fraction of employees that park at a private parking place is estimated for the entire simulation area. This employee fraction is based on a small-scale, unpublished survey that has been carried out by the parking authority of Antwerp. We furthermore assume that guests and visitors always park at a public parking place. The demand for parking thus consists of (1) residents and employees entering the study zone who do not have a private parking place available and (2) all guests and visitors entering the study zone. Only these agents are being simulated and only these agents contribute to the overall results on search time and walking distance.

Obviously, overall parking demand in a specific area is determined not only by cars entering the area, but also by the number of stationary cars (i.e., cars that are parked during the entire simulation period). Furthermore, the balance between parking supply and demand is influenced by the number of cars leaving the study area during the simulation. The number of stationary cars can be derived from the estimate of the initial occupancy rate (Appendix B) minus the cars that either travel within or leave the area during the simulation period. These stationary cars are distributed randomly over the statistical zones and do not receive a FEATHERS ID so that they will not be "activated" during the simulation run. The number of cars leaving the simulation area is derived directly from the trip data provided by the FEATHERS model. The relevant FEATHERS IDs are again randomly distributed over the cars located in each statistical zone. A car will leave its parking place in accordance with the FEATHERS trip data and will be directly removed from the simulation environment (i.e., the actually driving is not simulated).

3.6. Parking Choice Heuristics. The parking choice heuristic that is employed in this paper combines elements of a rational approach and a bounded rationality approach to model choice behavior [35, 36]. The starting point of the parking choice heuristic is the assumption that drivers have information on a set of parking options available to them. This is in line with the traditional rational utility approach to model choice behavior and has also been assumed in similar parking models, such as Sustapark [37] and Pamela [38]. However, in line with the notion of bounded rationality, it is assumed that driver agents neither have full information on all parking options nor necessarily choose the best available option. Rather than using the principle of utility maximization a different decision rule is employed as will be described below. Our approach is largely in line with the choice model proposed by Ottomanelli et al. [36].

The implementation of the approach starts with the creation of the relevant parking choice set. This is done when the agent is initialized. The exact set depends on the type of agent but only includes parking options within the maximum walking distance of 1,000 meter. For resident agents, the relevant set includes only on-street parking in the zone for which they hold a parking permit (see Section 3.4) and free off-street parking, as we assume that resident agents are not willing to pay for parking at all. Guest agents and commuter agents are assumed to have some knowledge of the local parking situation. Therefore, their relevant set includes the on-street parking options, the free off-street parking facilities and two randomly selected for-pay off-street facilities within the maximum walking distance to the destination (one kilometer). Finally, it is assumed that visitor agents are the least knowledgeable of the local parking situation and therefore know about the (price of) on-street parking locations and two random off-street parking facilities (for-free or for-pay) within walking distance. The choice set is different for smart cars, irrespective of the exact driver type (resident, guest, commuter, or visitor). Since smart cars receive information on all parking options through the bottom-up information system, *all* parking options within the maximum walking distance of 1,000 meter are included in their choice set.

Once the parking options are known, the relative utility of each option can be calculated. For every element in the set of parking options the relative utility is calculated based on the price and the distance to the destination, in relation to the activity duration. For each on-street parking option with a distinct parking regime the best parking place (in terms of distance to the destination) is selected and acts as a reference point. This reference point is used to calculate the relative utility of this parking alternative and in case the on-street parking option is selected from the option set, to navigate the car to the right location. For all agent types and all parking options, the distance to the destination is multiplied by two, to account for the fact that agents have to walk this path twice. Additionally, the activity duration is taken into account for cost and distance. The distance is divided by the activity duration in hours to address that agents are willing to

walk further the longer the activity duration, to calculate the distance value ($v(d)$):

$$v(d) = \frac{\text{distance}}{\text{activity duration}}. \quad (1)$$

The cost value ($v(c)$) is multiplied by the activity duration, where parking costs are expressed in terms of a basic cost per unit duration (price per hour). The cost value consequently reflects the overall parking cost:

$$v(c) = \text{parking cost} \cdot \text{activity duration}. \quad (2)$$

Subsequently, the calculated cost and distance values are standardized separately using feature scaling:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}. \quad (3)$$

The cost and distance attribute values are normalized to generate a value per parking option between 0 and 1. This value is used to calculate the probability of selecting a particular parking option according to the following exponential function:

$$p = e^{-\lambda * x}, \quad (4)$$

where p is the probability of the normalized value x (the lambda value for cost is 2, for distance 0.5). Choice probabilities are used instead of raw utility functions so they are easier to compare and are convenient to use for modeling bounded-rational behavior of human agents [34]. The overall probability vector is created with p_i for each available alternative i, given $i = 1$ to $i = j$, where j is the total number of alternatives. By combining the cost vector and the distance vector an overall probability vector is created. For worker agents the relative weight between the cost and distance vector is 1 : 25, while for the other agent types this is 1 : 10. The overall probability vector contains the choice probability of each parking option, totaling to one. To account for bounded rationality in decision behavior of the agents, a similar method as the *random proportional* rule is used [39]. According to this rule, the agents do not automatically choose the alternative with the highest utility. The vector is compared to a random value, r, between 0 and 1, and the chosen parking option will be the first alternative that has a cumulative probability that is greater than r. For example, when the probability vector is [0.7, 0.2, 0.1] for three parking options, the first option is chosen for every value of r that is smaller than 0.7, option two is chosen for a value of r between 0.7 and 0.9, and finally when r is greater than 0.9 option three is chosen.

Based on the chosen alternative the agent calculates which route to take (see Figure 2). By default the model calculates the route for each agent to its destination, but the end point of the route in case a parking option is selected located some distance away from the destination. If an off-street parking facility is chosen, the route is automatically changed to the location of the off-street parking facility. If the chosen alternative is an on-street parking location, the route is only changed if the on-street parking location is farther than 25 meters away from the destination. Note that the on-street parking location at this moment is the best on-street parking place associated with the chosen parking regime. For regular cars, the decision on which actual on-street parking place to park the car is based on the standard parking choice heuristic included in PARKAGENT. According to this heuristic, a car may move through three stages: estimate on-street parking availability while driving to the destination, search and select an available parking place when approaching the destination, and search for parking after passing the destination. This heuristic assumes that the driver monitors the occupancy level while driving in a street. The driver then uses this information to estimate the number of expected vacant parking places between the driver's current position and the destination. The lower the estimation, the higher the chance the agent will park at the next vacant parking place. When the driver fails to find a parking place before reaching the destination, the driver will pass the destination and make circular movements around the destination looking for an empty spot, while slowly expanding its search radius. The driver will park at the first empty spot which is within the search radius. In case the driver has selected an on-street parking place at a distance from the destination, this parking

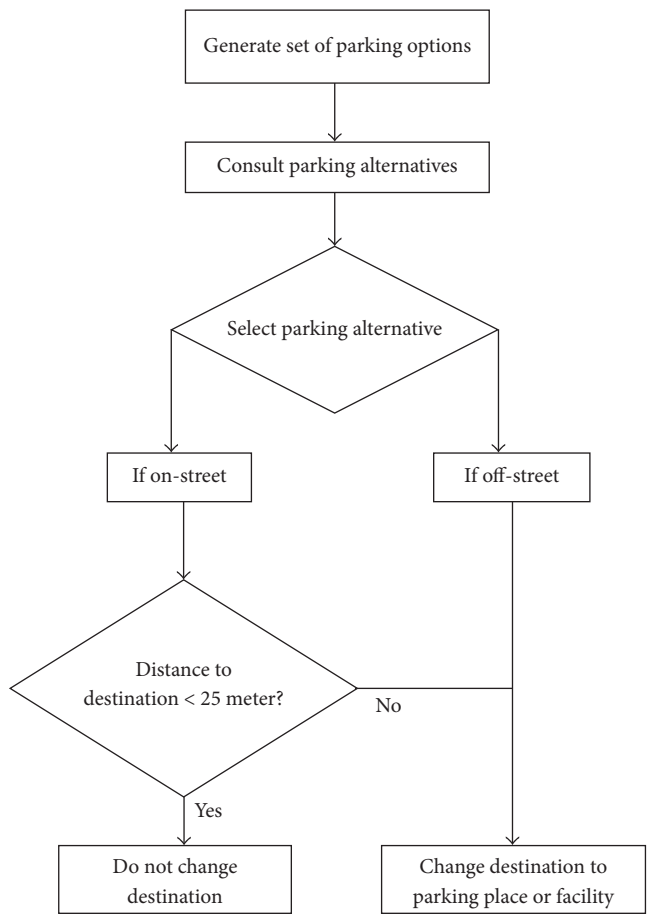

Figure 2: Graphical representation of the parking choice heuristic.

Table 3: Simulation parameters.

Parameter	Value
Number of on-street parking places	9,483
Number of off-street public parking places for free	3,280
Number of paid for off-street public parking places	6,034
Number of departing/arriving vehicles	~17,000
Driving speed while in search	12 km/h
Walking speed	3 km/h
Simulated time	24 hours
Communication range	200 meters
Communication interval	5 seconds
Initial preferred maximum walking distance	120 meters ("as the crow flies")
Maximum tolerable walking distance	1000 meters
Request expiration time[1]	50 seconds
Reservation expiration time[1]	150 seconds

[1]For a definition of these terms, see Appendix B.

place serves as the end point of the route and the same parking heuristic applies. For more detail, see Appendix A.

Since smart cars receive information on the availability of parking places, their parking choice heuristic is somewhat different and will be described in detail below.

3.7. Parking Information Provision and Reservation System. Smart cars have a substantial advantage over regular cars because they can receive information on vacant parking places and can send out requests to reserve an available parking place.

The bottom-up information system is based on both transmitting capabilities of the smart cars and parking sensors. Smart cars are capable of sending messages to other smart cars within a transmission range of 200 meters [40]. Every on-street and off-street parking space are equipped with a sensor, which is capable of sensing the current status of the parking space (vacant or occupied) and is able to communicate (within 200 meters) with smart cars. The transmission interval of messages is set to 5 seconds for both smart cars and sensors. The messages consist of the following attributes: (1) the timestamp at which the parking space became vacant and (2) the location of the parking space, stored as a coordinate.

Upon receiving a message on an available parking space, a smart car will process the message. Messages can be stored in two different databases: a private database and a public database. When looking for a parking space, incoming messages are ranked according to their usefulness and, if useful, stored in the private database. In addition, all incoming message are stored in a public database, which is regularly shared with other smart cars. Both databases have a limited capacity and store the best-scoring messages.

The reservation system is administered in a similarly distributed fashion. Important to note is that the whole process of receiving and sending information, requests, and reservations is executed automatically by the smart car without actual interference needed by the driver. Likewise, each parking space manages the reservation process on its own. Cars can send out at most two pending requests to reserve a parking place. However, at any given time, each car can have at most one reserved parking location. By allowing cars to send out a reservation request even when a successful reservation has been made, it is possible for the car to improve the parking location by making a different reservation. To restrict the number of messages that are sent over the network, cancelation of reserved parking places is not implemented in the model. The earlier reserved parking place is automatically made available for regular cars and smart cars after a fixed amount of time has elapsed (see Table 3).

Upon reception of a confirmation message, a smart car calculates which confirmed parking option is considered the best for the current situation (given the current location of the car, the parking location, and the destination), based on the choice heuristic described in Section 3.6. The car then selects the best ranking parking place.

It is important to note that the reservation system does not always lead to an actual reservation of a parking space. Therefore, it is important to describe the parking process of smart cars in more detail. Like regular cars, smart cars that select on-street parking from the choice set may move through three stages: estimate on-street parking availability while driving to the destination, search and select an available parking place when approaching the destination, and search for parking after passing the destination. In the first stage, smart cars collect data on available parking spaces through bottom-up information provision, as described above. Towards the end of this stage, a smart car may send out reservation requests in case they have received information on the availability of a relevant free parking space. In the second stage, smart cars are willing to park at a vacant spot if it is within their initial preferred walking distance (set at 120 meter) and if the car has not received a confirmation on a reservation request. However, if a smart car has already received a confirmation for a parking space, the car will only park at the encountered parking spot if it is closer to the destination than the reserved parking space. A car enters

the last stage of the parking process, when the destination is passed without finding a parking place. In that case, a car will always park at an empty parking space it encounters along the way, regardless whether it has received a confirmation on a requested parking space or not. The route depends on the situation. If a smart car has successfully reserved a parking space it will keep on driving towards the suggested location. If no reservation has been made, the smart car behaves as a regular car in this stage and will search around the destination with increasingly large circular movements.

Note finally that we assume perfect enforcement of the parking reservation system, implying that no (regular or smart) car will park on a parking place if it is reserved by another car.

3.8. Simulation Setup and Performance Indicators. For reasons of feasibility, our simulation of the center of Antwerp is limited to a limited time period on a typical Saturday. In what follows, we will present results of the impacts of bottom-up information provision and parking reservation for the period between 16.00 h and 19.00 h. These are the Saturday evening peak hours, with the highest number of arrivals (and departures). For technical reasons, the simulation runs for 24 hours (03.00 h–03.00 h), while information gathering and disseminating are enabled one hour before the actual monitoring of parking dynamics is started (so at 15.00 h).

In line with other studies, we are interested in the impact of bottom-up information provision and parking reservation under different levels of technology uptake or "technology penetration levels." In our simulation, we have analyzed the base situation in which no information provision and no reservation system are available and scenarios with a varying penetration rate, increasing from 0.2 to 1.0, with increments of 0.2. This means that 20% to 100% of the vehicles in the simulation are so-called smart cars, that is, being able to send and receive messages on parking place vacancies and able to make reservations. In all scenarios except the base case we assume that all on-street and off-street parking places are equipped with a smart parking sensor.

We have carried out two simulation runs for every simulation setting. This low amount of runs is the result of the extensive simulation time required for each run (on average ~5 hours), which is strongly related to the high number of vehicles included in the simulation (~17,000 cars) and the rapid increase in computing time as the penetration rate, and thus the number of messages goes up. The results presented in what follows always relate to the average for two runs of the same simulation settings.

Parking performance is assessed at the individual level and at the system level. Both are based on three indicators: search time, walking distance, and total parking time. In line with Tasseron et al. [16], search time is defined as the excess time needed to find a parking space from the moment the car enters the simulation environment (i.e., at a distance of 400 meters from the destination), in comparison to the optimal travel time to the most optimal parking location with respect to the destination. All drivers that park within that optimal time frame on the optimal parking space or on a parking space en route to the optimal parking space are considered to be drivers with zero search time. While this way of estimating search time has some problems for off-street parking, it does enable a comparison between regular and smart cars, which is the focus of our analysis. Walking distance is defined as the air distance between the destination and the selected parking space. Total parking time, in turn, is the summation of search time and the time necessary to walk to the destination and back at a speed of 3 km/h.

At the individual level, search time walking distance and total parking time are averages across the two types of agents (i.e., regular and smart cars) in order to assess the benefits of an information and reservation system for smart agents. At the system level, the values are calculated for all cars together.

3.9. Model Calibration and Validation. We have calibrated the parking choice heuristic of regular drivers based on a comparison between the observed parking occupancy rate at night in the simulation area and the occupancy rate as generated by our simulations. We have obtained the observed overnight occupancy rate per statistical zone from the Municipality of Antwerp. The occupancy rate as generated by our model depends on three key factors: parking supply, parking demand, and the parking choice heuristic. Each of these has been described in detail above. The estimate of parking supply is considered to be very reliable, as it is based on data from the Municipality of Antwerp (for off-street parking facilities) and from analysis of satellite imagery data (for on-street parking). The estimate of parking demand is derived from FEATHERS, which has been validated in a separate publication [32]. In our trial runs, parking supply and parking demand have thus been considered fixed, while we have adjusted the relative weights of parking costs and walking distance in the parking choice heuristic to generate parking occupancy rates at 03.00 h in the night. We have adjusted these relative weights and the values of λ for cost and distance, until the generated occupancy rate for the 22 statistical zones was largely in line with the observed occupancy rate. Furthermore, the occupancy rates for each statistical zone at the start of the simulation (3:00) should be similar to the occupancy rates at the end of the simulation run (24 hours later), assuming that people have returned to their homes and workers and visitors left after finishing their activity. These settings have subsequently been used in all simulation runs presented below.

4. Results

In this section the results from the simulation runs are presented, first at the individual level (Section 4.1), then for the overall system (Section 4.2), and finally for a selected area in the city center of Antwerp (Section 4.3).

4.1. Results for Smart Cars and Regular Cars. Against expectations, the simulation runs show that bottom-up information provision to smart cars does not lead to a reduction in search time for smart cars for on-street parking (n = 6,132, totaled for all six penetration rates) (Figure 3). This is in contrast with the results from earlier papers [6, 16]. The main reason for the difference is the average on-street occupancy rate.

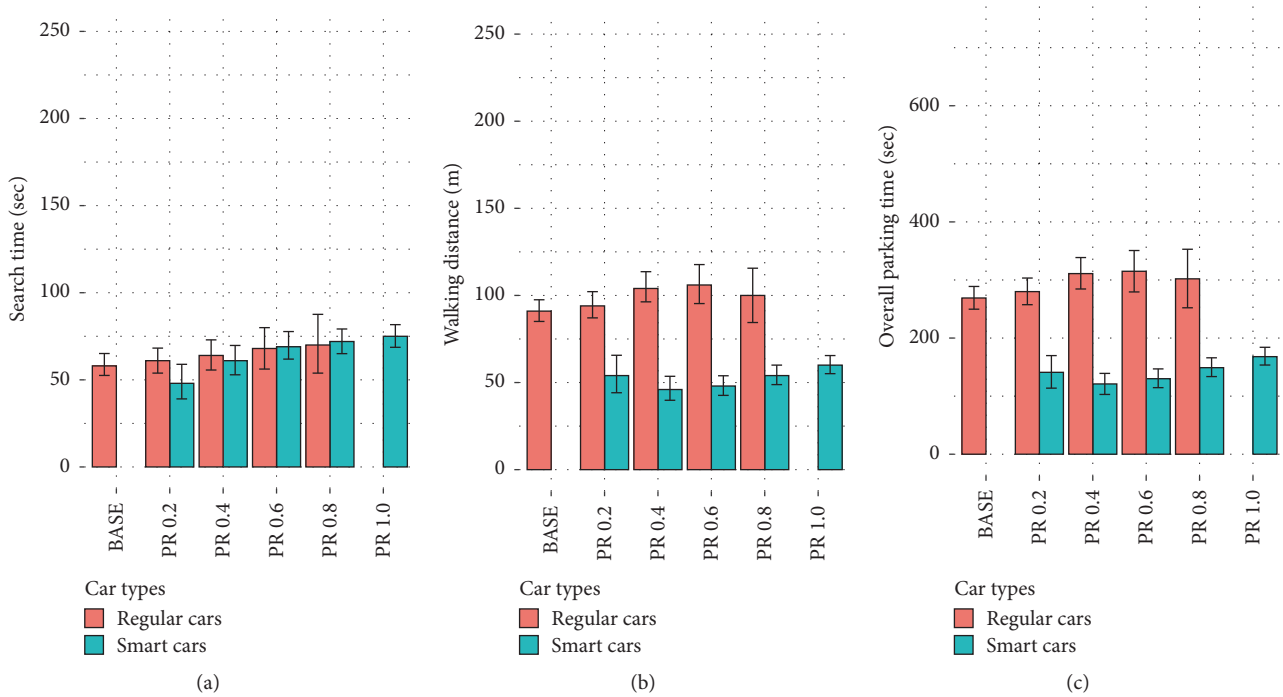

Figure 3: Results for individual drivers for on-street parking: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

The average occupancy rate of the entire simulation area is around 65%, which is well below the "threshold values" of 85% or 90%, above which cruising is likely to occur [3, 41]. Furthermore, due to the low occupancy rate regular cars have a higher chance of parking their car before reaching the destination (which implies zero search time) in comparison to smart cars (who may be able to reserve a parking place close to but also after the destination, which implies a search time according to our definition of search time).

In contrast to search time, performance in terms of walking distance does improve for smart cars, for all penetration rates. The walking distance is reduced by about 50%, irrespective of the penetration rate. Walking distance for regular cars is not significantly affected by the introduction of smart cars, again irrespective of the penetration rate.

When search time and walking distance are combined in the total parking time, results are fully in line with expectations: smart cars outperform the regular cars under all circumstances (Figure 3). Regular cars show a large variation in total parking time and are confronted with a slight negative effect on performance. The performance of smart cars shows much less variation, irrespective of penetration rate, underscoring that the reservation system improves not only total parking time, but also reliability of parking time. The latter, in turn, also may also imply a decrease in the uncertainty and anxiety that may go hand in hand with parking search. These possible "psychological" benefits for smart cars, however, go hand in hand with a decrease in reliability and thus an increase in "parking stress" for regular cars.

Results regarding search time and walking distance for off-street parking facilities show a clear benefit for smart cars (Figure 4). Recall that regular cars only have knowledge about two to five off-street parking facilities (depending on the agent type) that are within walking distance of their destination, while smart cars (regardless of agent type) have knowledge about all parking facilities. Thus, the smart car is able to choose the best parking location in relation to its driving route, the location of parking facilities, and the location of the destination, which enables the smart car to select an option that limits both travel time and walking distance. The results indeed show that smart cars are confronted with lower search times than regular cars. However, due to the low number of observations (cars that park at the off-street facilities in the studied time slot) the difference is not significant ($n = 286$, totaled for all six penetration rates).

The results furthermore show that smart cars parking at an off-street parking facility do benefit in terms of a reduced walking distance to the destination. The variation in results is high, as indicated by the error bars. This is due to the low number of agents that park in a parking lot during the afternoon peak hours. The walking distance to the destination is on average higher than the walking distance to the destination when parking on-street. Again, due to the high variation it is not possible to draw conclusions on the development of walking distance over the various penetration rates.

4.2. Overall System Results. The impact of parking information on the overall system is obtained by combining the

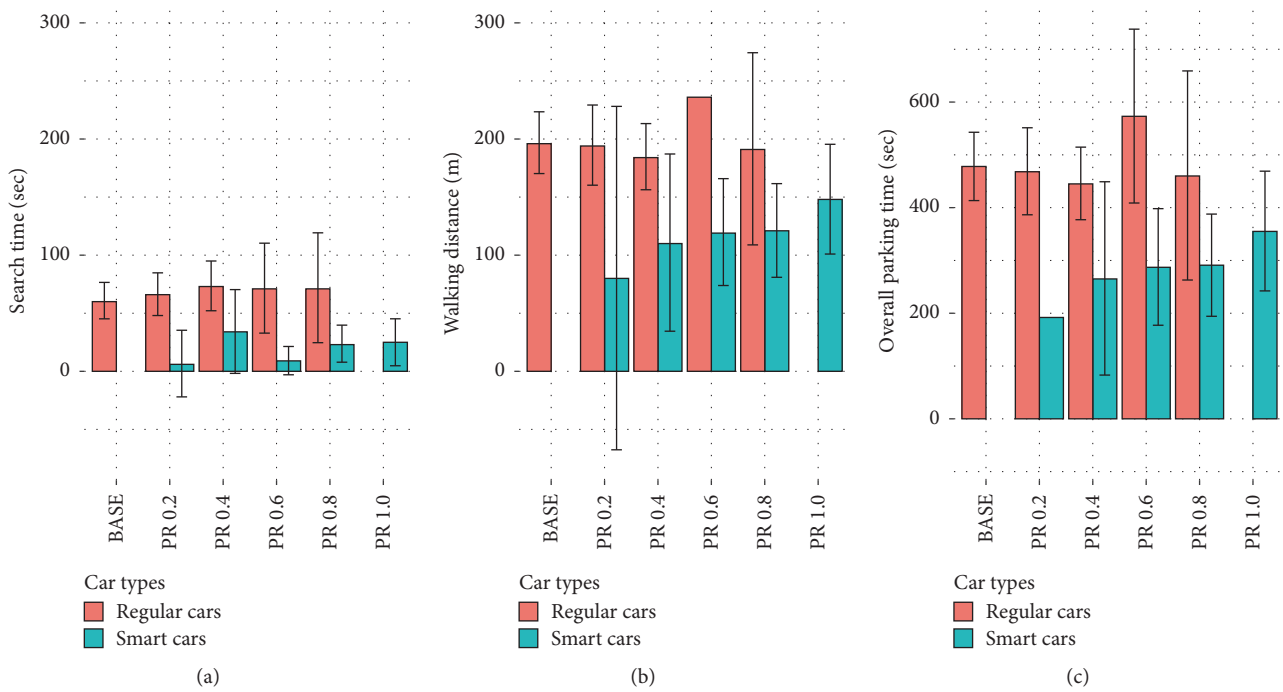

Figure 4: Results for individual drivers for off-street parking: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

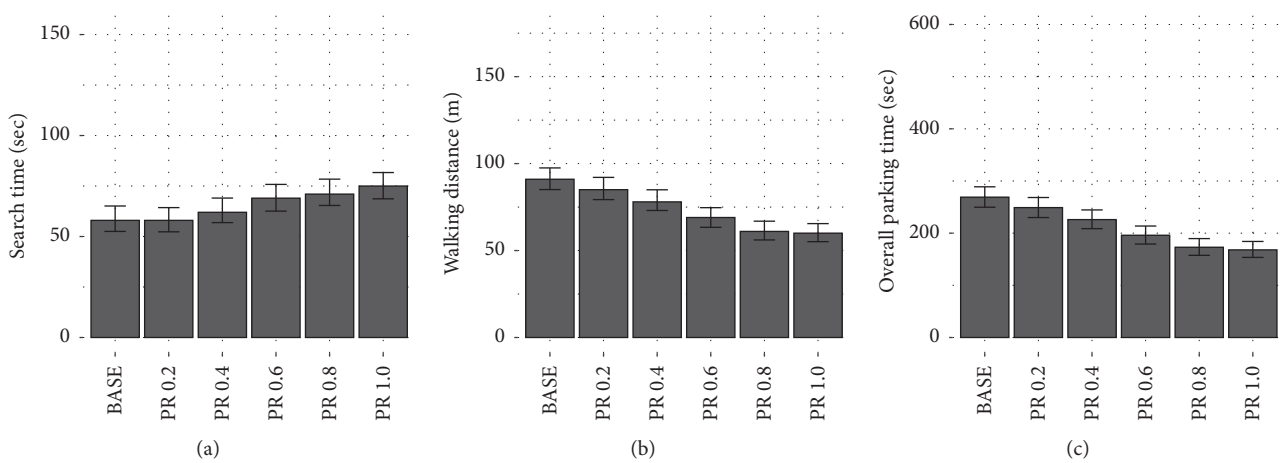

Figure 5: Results at the system level for on-street parking: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

results for regular cars and smart cars. The results show that, for every increment in penetration rate, overall search time increases, overall walking distance decreases, and total parking time (search time combined with the time needed to walk to and from the destination) decreases (Figure 5). These results can be explained by the combined effect of three key factors: first, by the parking choice heuristic of smart cars: given the relative weights of search time and walking distance, smart cars typically prefer parking close to the destination over a reduction in search time; second, by the low average occupancy rate; third, by the way in which parking search time is defined (see Section 3.8). In combination, these factors are likely to lead to an increase in search time for smart cars vis-à-vis regular cars, as regular cars are very likely to find a parking place before reaching the destination under conditions of a low occupancy rate (resulting in zero search time), while smart cars are willing to accept some search time to obtain a shorter walking distance.

These observations are underscored by an analysis of the differences in search time across the entire study area. For this purpose, search time for regular and smart cars has been calculated at the level of a single on-street parking place. This value is determined by averaging the search time for each type of car for all parking places within a radius of 100

Figure 6: Spatial variation in search time for on-street parking: difference in seconds between regular cars and smart cars, at afternoon peak hours and for a penetration rate of 0.2.

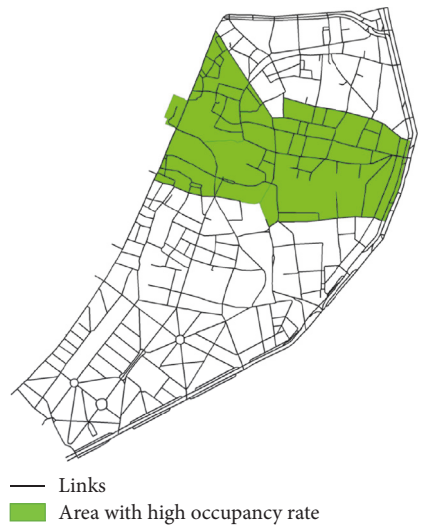

Figure 7: Part of the simulation area with a high occupancy rate throughout the simulation period.

meters. For each parking place, this results in one search time value for regular and smart cars. By comparing the value between both, it is possible to create a "heatmap," which indicates the size of the difference in search time between regular and smart cars. Figure 6 shows the results. A positive difference means that smart cars have, on average, a shorter search time than regular cars, while they have a negative difference points at the opposite. Zone A, where parking is restricted to a maximum of 3 hours, has a relatively high parking turnover and a relatively high occupancy rate (see Figure 7). Under these conditions, a parking information and reservation system provides a considerable advantage, as a random search for on-street parking is relatively inefficient [see [6, 7]]. The same conditions apply in a small part of Zone B. This area is relatively close to a high demand area in Zone A but offers a more attractive parking regime that Zone A, in terms of both lower time restrictions and lower prices. As a result, the area highlighted in Figure 6 is a hotspot for cars that do not want, or are not eligible, to park in Zone A, in particular visitors to the city. Because of the high demand for parking in this area, smart cars benefit from the available information and the possibility of reserving a parking place. In contrast, the remaining part of Zone B shows a benefit in search time for regular cars. This is the result of the lower occupancy rates, which allow regular cars to exchange the certainty for a parking place on the way to the destination against a relatively long walking distance: they tend to park at a parking place before reaching their destination resulting in zero search time in the model.

These findings are in line with earlier studies, which have shown that the crucial impact of the occupancy rate on parking search time and on the relative benefits of a parking information and reservation service on search time at the system level [7, 11, 42]. For this reason, we now analyze the impact of parking information and reservation in more detail for an area within the city center of Antwerp with particularly high occupancy rates.

4.3. Results for Areas with High Occupancy Rates. Earlier studies have shown that smart cars generally only benefit in terms of search time if the parking occupancy rate is above 90% [6, 7]. In our case, these occupancy rates occur mostly in the central area of the study zone, which contains the main, pedestrianized, shopping streets of Antwerp (see Figure 7) and is characterized by a very high occupancy rate (average of 98.6%) during the simulation period (16.00–19.00 h).

The results for this area show that the smart cars indeed benefit in this situation from being better informed than regular cars (n = 1,087, totaled for all six penetration rates) (Figure 8): the former experience lower search times and shorter walking distances than the latter. Both smart and regular cars are faced with a substantially higher search time in this particular area in comparison to the entire study zone, but the difference is much higher for regular than for smart cars (~130% versus ~95% higher). However, when the penetration rate of the technology increases, the search time benefit for smart cars drops, due to the increased competition between smart cars. Furthermore, the reduction in walking distance for smart cars is less pronounced as compared to the results for the entire city center. This shows that, in case the number of vacant parking places is limited, also smart cars have trouble finding a parking place close to their destination within a reasonable amount of time.

The benefits at the system level for the specified area are limited but nonnegligible (Figure 9). While search time is hardly influenced in comparison to the base situation, overall walking distance does show some decrease specially for higher penetration rates (≥0.6), even though the decrease

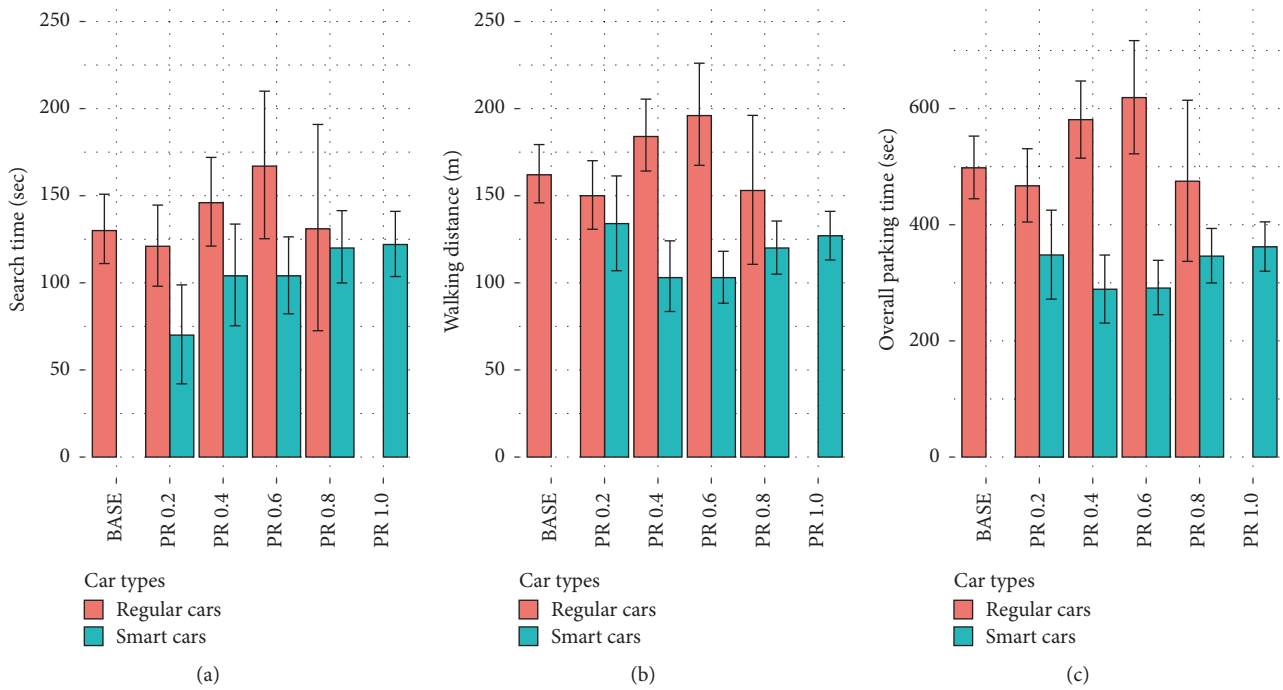

Figure 8: Results for individual drivers for on-street parking in high occupancy area only: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

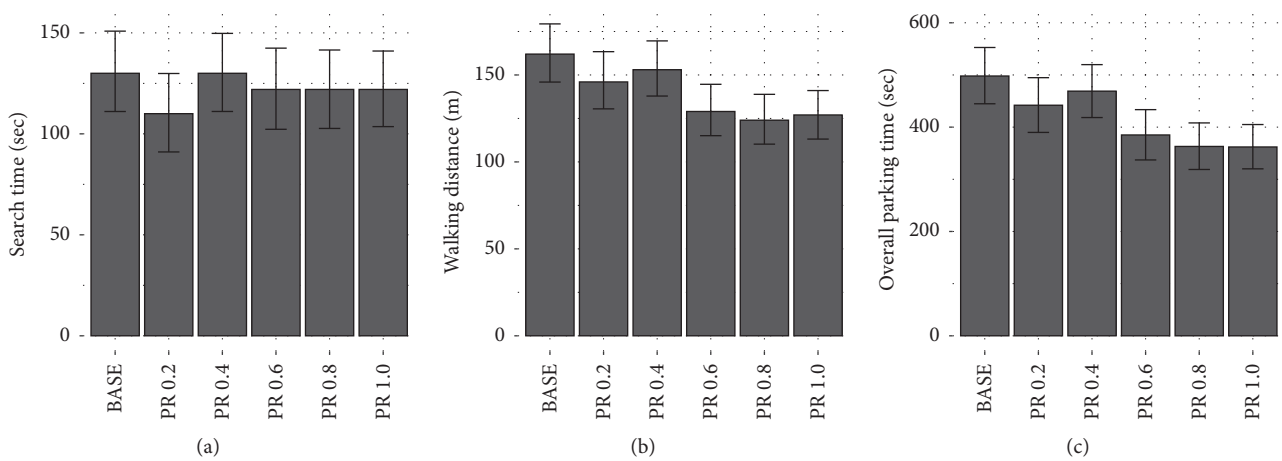

Figure 9: Results for at the system level for on-street parking in high occupancy area only: (a) search time, (b) walking distance, and (c) total parking time, for regular cars and smart cars, for a 95% confidence interval at afternoon peak hours.

is less pronounced than for the entire simulation area. Total parking time shows a small but significant reduction at the system level.

5. Conclusions and Discussion

In this paper the impact of information provision and reservation in a realistic, real-world simulation environment was studied. While our analysis only relates to a specific period and area (i.e., a Saturday afternoon in historic city center), the findings do provide a first assessment of the potential benefits of a bottom-up parking information system in a real-life setting.

The results are perhaps against expectations. Smart cars did not experience a significantly lower average search time than regular cars, while at the system level the introduction of smart cars even lead to an increase in overall search time. In contrast, walking distance did improve significantly for smart cars. When all cars are equipped with communication technology the average walking distance decreases by more than 30%. Combining search time and walking distance leads to a reduction in total parking time under all penetration

rates. If all cars are equipped with information technology, total parking time is even reduced by about 35%.

The benefits are different in the central part of our study zone, which is characterized by very high parking occupancy levels during the period of simulation. For this specific area, smart cars gain in terms of *both* search time and walking distance. However, the search time gains for smart cars come at the expense of regular cars. This negative externality hardly occurs for walking distance, with the result that total parking time still shows a substantial reduction with every increase in the share of smart cars. When all cars are able to receive information and reserve a parking place, average walking distance decreases by ~22% and total parking time by ~27% in contrast to the base situation with zero smart cars.

The counterintuitive results in terms of search time are the result of two interacting factors: the particular parking conditions in the simulated area and the employed parking heuristics. First, and as shown in previous research, parking information is especially effective in case of high competition over parking places. This condition only occurs in part of our simulation environment. Substantial parts of the inner city of Antwerp show relatively low occupancy rates, implying that also regular cars will be able to find a parking place without much search time. This condition of low occupancy level interacts with the way in which smart cars select a parking place. In our heuristics, smart cars aim to minimize total parking time, which leads to a preference for nearby parking places in order to reduce walking distance. This preference often implies that smart cars do not park *before* reaching the destination but rather continue driving to select a more nearby parking place after passing the destination, resulting in slightly longer drive and park times for smart cars. Since we have defined search time as the difference between the minimal time to drive to and park as close as possible to the destination on the one hand and the actual drive and park time on the other, this parking heuristic is likely to result in relatively long search times vis-à-vis regular cars that select a parking place *before* reaching the destination.

The overall benefits in terms of total parking time are impressive, certainly in contrast to the minimal benefits in terms of search time, but it should be taken into account that they accrue to the population of drivers only. Society would primarily benefit from a bottom-up information and reservation system if such a system would lead to a reduction in *overall search time*, as search time is related to multiple externalities (congestion, traffic (un)safety, air and noise pollution). The increasing literature on transport and health even suggests that a decrease in walking distance may well have societal costs, as "active travel" (i.e., walking in this case) is strongly correlated with positive health outcomes. Thus, the societal case for a bottom-up parking information and reservation system is weak at best.

Clearly, our findings should be interpreted with care, for at least four reasons. First, the smart cars are optimized to select the parking place that requires the driver the lowest possible time to reach the destination, taking into account driving and walking distance. As a consequence, smart cars are more likely to benefit in terms of walking distance than in terms of the time they need to search for a parking place. If the decision mechanism is changed to stronger value search time than walking distance, the results will change more in favor of a shorter search time (and longer walking distance). It is expected, however, that it would not fundamentally change the total sum of benefits of a bottom-up information and reservation system.

A second remark concerns the PARKAGENT simulation model. This model makes no explicit distinction between drivers that are making a regular shopping trip and drivers on a nonregular shopping trip. Van der Waerden [38] shows that there is a significant difference between these two groups: nonregular visitors tend to park for a longer period of time, are willing to accept a longer walking distance, and have a lower aversion to pay for parking. This could potentially result in different outcomes for these two different agent groups. On the other hand, due to the stochastic choice behavior and considering the fact that the agents in our model take into account the activity duration when choosing a parking location, the parking choices of our agents may well reflect the differences observed between these the two groups of agents.

Third, our results only relate to the "objective" benefits of a parking information and reservation system, in terms of search and walking time. Such systems may well have additional psychological benefits, as they may reduce car drivers anxiety about finding an available parking place, thus generating substantial additional benefits for users of the system (and possibly also for other users of the street space through improved behavior of drivers searching for parking).

Finally, we have only analyzed the added value of a bottom-up information provision for a limited time period, in part due to software restrictions. It may well be that the information system delivers more benefits during other time periods, for instance, on Sunday's when parking is for free in some parts of the inner city, or in evening hours when residents returning home may have difficulty finding a free on-street parking place. Clearly, more research is needed to gain a more complete understanding of the potential benefits of a bottom-up parking information system for individual drivers and the wider society. However, our findings do show that benefits in terms of search time may only be expected under conditions of high occupancy rates.

Disclosure

This paper is based on a chapter of the Ph.D. thesis of one of the authors [43].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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