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The Potential Impact of Vehicle-to-Vehicle Communication on On-Street Parking Under Heterogeneous Conditions

Abstract—The aim of this paper is to study the impacts of bottom-up information provision about on-street parking places on parking dynamics under heterogeneous conditions. Using an agent-based simulation model, performance is compared between a bottom-up vehicle-to-vehicle communication strategy and a strategy that combines parking sensors and vehicle-to-vehicle communication. In the latter approach on-street parking places are all equipped with sensors capable of disseminating their status.

The results show that search time is decreased for informed 'smart' cars, especially under spatially heterogeneous conditions, for the sensor-based strategy. Furthermore, for the case of the sensor-based strategy, the results point out that smart cars outperform regular cars in terms of walking distance under all circumstances. The positive impacts for the vehicle-to-vehicle strategy are limited to walking distance improvements only.

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I. Introduction

Provision of information to drivers in search for parking can reduce cruising for parking and thus reduce air pollution, traffic congestion and other negative externalities related to car traffic [1]–[3]. Hence, cities around the world have installed technologies to provide drivers with information about off-street parking facilities. In contrast, information on the occupancy status of on-street parking places was non-existing until recently. This is however changing rapidly due to a number of start-up companies that have entered the market to provide such information [4]–[6]. By using the widespread penetration of smart phones and in-car navigation devices it is now possible to provide accurate information at the level of individual parking places.

The paper builds on an earlier study in which the impacts of information provision on on-street parking were studied for a highly stylized situation, in terms of driver behavior as well as the spatial setting within which drivers search for parking [7]. The results of this study showed that parking information has only limited benefits, both for the drivers receiving information and for other drivers. Information was mostly beneficial for drivers in terms of walking distance under conditions of very high occupancy rates. Furthermore, the overall result was only improved when sensors were used for continuous transmission of information on a parking place's occupancy status. The question is whether these counter-intuitive results also hold under less stylized conditions. Therefore, in the current paper we analyze the impacts of information provision under more realistic conditions. More specifically, we explore how heterogeneity in terms of driver behavior and in terms of spatial distribution of parking demand and supply influence the effectiveness of information provision on on-street parking places.

The paper is organized as follows. Following this introduction, we describe the way in which car drivers are informed about on-street parking place availability using two distinct communication strategies (Section 2). In Section 3, we describe our agent-based modeling tool called PARKAGENT, as well as the simulation set up. In Section 4, the results of the simulations are presented. This is followed by the conclusions and paths for future research (Section 5).

II. Bottom-Up Information Provision

A. Information and Parking

Information provision regarding live occupancy rates of off-street parking facilities, driver preferences and the role of information in finding these facilities has been studied and modeled (e.g. [8]). In contrast to off-street facilities, research on parking behavior and the role of information on on-street parking using simulation models is studied less [2], [9], [10]. Furthermore, spatially explicit research on the impacts of information and behavior of drivers when searching for on-street parking is scarce [11], [12].

Various technologies allow for provision of information on on-street parking places. One possibility is the use of vehicle-to-vehicle communication using so-called Vehicular Ad-Hoc Networks (VANETs) [13], [14]. VANETs provide a way to share information among the nodes in a network using bottom-up dissemination. Because of their attributes, VANETS are suitable for application in a parking context. The network is formed by mobile agents (in our case, vehicles) that are capable of sending and receiving data via wireless technologies (i.e. dedicated short-range communication, DSRC). All agents in the network equipped with this technology contribute to the network by gathering information and distributing this information to nearby agents. Because of the limited spatial range of this technology, as well as the short-term nature of the information, the networks are referred to as 'ad-hoc'. Another possibility is the use of sensor-based technology. This kind of wireless technology allows for sensing events or changes in the environment. As such it can be used in an urban environment to monitor parking place occupancy by sensing the presence or absence of a vehicle. Additionally, the sensor is capable of sending the gathered information to other nearby sensors and nearby smart cars.

Few studies have explored the benefits of these information technologies for the domain of parking (see [15]–[19] for some first analyses). None of these studies has systematically explored the impact of these technologies on parking dynamics in a explicitly spatial context. The spatial context is especially important in the domain of parking. Only by simulating parking dynamics at the level of individual parking places, the inherent emergent properties of parking dynamics can be fully captured [20]. The sophistication of the software we have used (PARKAGENT) allows for a fundamentally more advanced simulation of the parking process and the impact of information provision. The current paper builds on a previous study in which we started to systematically study the impact of information provision in a homogeneous environment [7]. In that preceding paper, the impacts of a vehicle-to-vehicle strategy (V2V) were compared to a sensor-based strategy (S2V). In the current paper we extend this research strand by incorporating heterogeneity, both in terms of driver behavior as well as in the spatial distribution of demand for parking.

B. Implementation of Communication Protocols

In this subsection, we describe the way information is transmitted between vehicles and parking sensors and vehicles. Important to note is that in the simulations a distinction is made between cars that are able to communicate (V2V) and cars that cannot communicate. Smart cars are able to send and receive messages within a fixed transmission range of 200 meter (which has been shown to be a practically feasible transmission distance, even under non-optimal conditions [21]). Messages are broadcasted by cars and sensors to all entities in the vicinity at a transmission interval of 5 seconds. In the V2V communication strategy, messages are created and disseminated in two situations. First, when a smart car leaves a parking place it will send out a message stating the vacancy of the spot for other drivers. Second, a smart car will disseminate a message when it occupies an empty parking place. All smart cars that are driving around within a 200 meter radius will receive both kinds of messages and subsequently pass them on to other smart cars. The receiving cars are able to subsequently send the messages to other cars within their transmission range. A message can thus traverse the entire network in only a few iterations. It is important to note that vacant parking places at the start of the simulation and departures of cars that are not able to communicate will not lead to the dissemination of a message in case of a V2V communication strategy.

In the sensor-based communication strategy (S2V), on-street parking places are equipped with sensors that are capable of sensing and communicating the occupation status of the parking place (vacant or not vacant) to nearby vehicles. In the simulations, the sensors will only send out messages on a regular basis when their status is vacant, while only one message is send out if the parking place is occupied . The sensors have the same transmission range as the smart cars in our simulation.

The important difference between both strategies lies in the fact that in the V2V communication strategy the vacancy message is transmitted only once, while in the S2V communication strategy the sensors keeps broadcasting the vacancy at regular intervals. Furthermore, the S2V strategy also guarantees that information is available about vacant parking places at the start of the simulation.

The communication protocol is comparable for both communication strategies. Every message that is transmitted by a vehicle or sensor consists of a number of attributes: (1) the timestamp of the message; (2) the location of the parking place, stored as a coordinate; and (3) the occupancy status of the parking place (vacant or not).

Each smart car that receives a message on an available parking place will process the message. For this purpose, each smart car is equipped with three databases to store messages: a private database, a public database and a database with recently occupied parking places. Each database has a limited capacity and stores only the most relevant messages .

The private database is used for storing information on relevant vacant parking places. The database is only used by cars looking for a parking place. The car selects all incoming messages on vacant parking places according to the distance between the parking place and the final destination of the car. Only the highest scoring messages (according to value V_m) are stored in the private database and ranked according to the relative value of the parking place. The value is based on the distance between the final destination and the parking place and the distance between the current position of the car and the parking place (equation 1).

$$V_m = \frac{d_c}{v_{\mathrm{car}}} + \frac{d_w}{v_{\mathrm{walk}}} \tag{1}$$

Where:
d_c = distance (as the crow flies) between current position and parking place
d_w = distance (as the crow flies) between parking place and final destination
v_{car} = cruising speed of all cars
v_{walk} = walking speed

Each smart car also maintains messages on vacant parking places in a public database for general purpose. This public database holds a limited number of messages which are ranked according to age (time stamp). Similar to the process for the public database, storage of messages on occupied places are ranked by age. When receiving such a message it is not only stored in the database, but the system also deletes entries in the private and public databases with an identical parking place ID but an earlier timestamp.

On a regular interval, all smart cars will broadcast the messages in their public database to cars within the transmission range. Via this method messages on available parking places can traverse the grid in a short time period and thus provide many drivers with information on available parking places. It is important to note that the above described method does not include a reservation system. Thus, it is possible to arrive at a suggested parking place and find it already occupied by another car. Furthermore, note that the private and public databases can overlap, i.e. vehicles may broadcast messages to potential 'competitors' for the same parking place.

The message protocol ensures that the best parking spot that matches the driver's preferences (see next section) is selected as the first choice for the smart car. As soon as a driver receives information about a vacant parking place that suits his or her preferences, it is assumed that the driver will drive to that parking place rather than to the final destination. However, the driver still has the freedom to park at a randomly encountered vacant spot en route or drive on to the suggested parking place. Clearly, the driver will only opt for the former option if the parking place is more attractive than the parking place suggested through the information system. Note that the parking information system does not provide the user with a list of suitable options as is the case in the study by Karaliopoulos et al. [22]. Furthermore, if the car receives a message stating that the parking place it is currently driving to has been taken by another car, the parking place is deleted from the list of available parking places. Subsequently, the updated list is re-ranked and a new parking place is set as the destination for navigation.

A more elaborate description of the process of receiving and disseminating messages in V2V and S2V scenario's can be found in [7].

III. Simulation Description

To study the impacts of bottom-up information provision on parking dynamics under heterogeneity, we use PARKAGENT, an advanced agent-based parking simulation model. An extended description of the PARKAGENT model can be found in Benenson et al. [23]. The speed of vehicles searching for parking is set at 12 km/h [20]. Note that in contrast to earlier simulations with this model, the walking speed has been fixed at 3 km/h. This setting differs slightly from our earlier study [7], which means that results of the current study cannot be compared directly to the previous one.

Using PARKAGENT, we compare the impact of information provision in two different heterogeneous settings: spatially heterogeneous demand and heterogeneity among agent preferences.

A. Spatial Heterogeneity

Spatial heterogeneity refers to the spatial distribution of destinations across the simulation environment. Like in the simulations for a homogenous environment, we have used a Manhattan grid system of streets (see Levy at al. [20]) as the basic spatial structure of the simulation environment. In this environment, a city consists of 11 × 11 city blocks, with 12 destinations and 96 on-street parking places on the inner ring of each city block. Every street segment of a city-block is 100 meter in length and allows for two-way driving. On-street parking places are evenly spaced along all the streets in the network. There are no off-street parking facilities in the simulation area. The current simulation environment differs from [7] in terms of the spatial heterogeneity. Instead of having destinations (buildings) distributed evenly over space, we now simulate the case of concentration of demand for parking in the most central city block. The twelve destinations in this central block have a ten times increased demand in comparison to all other destinations. The study zone of our simulation is defined by the 5 × 5 city block area in the middle of the simulation environment. This zone is defined to filter out border effects, as there is less competition for parking spaces at the outer edges of the environment.

B. Heterogeneous Driver Behavior

Driver heterogeneity can refer to the variation in drivers preferences for their value of time (VOT) [24], search time, walking distance, willingness to pay or on-street or off-street parking. In this paper, it relates only to the agents' willingness to walk to the destination. We have divided the population of agents into three equally sized groups, with respectively a low, average and high willingness to walk. In terms of the model, the former type of drivers only considers parking if the parking place is within 20 meter of the destination. The distance is 120 respectively 220 meter for the other types of drivers. The median value of 120 meter has been proven to be a realistic average for the entire population of drivers [25]. The overall driving and cruising behavior remains the same. Agents enter the simulation environment at a position that is located at 400 meter from their final destination. The shortest route to the destination, according to the Dijkstra algorithm, is chosen and the agent starts to drive towards the destination. To be able to compare the results, all agents observe their environment and assess the local parking situation for a stretch of 180 meter before they start considering to park.

The decision on when and where to park has been changed in our PARKAGENT model in comparison to previous papers. In earlier papers, the maximum allowed distance at which agents were willing to park was only used by the agents if they passed their destination without finding a vacant parking spot and were forced to start cruising for parking. For the current study we also use this maximum preferred distance when selecting a parking space *before* reaching the final destination. That is, drivers will not consider parking until they are within their preferred distance from the destination. Likewise, drivers will not accept parking places suggested by the information system if the place is located further than the preferred distance from the destination. Once the driver passes the destination, we assume that the driver starts circling their destination in search for a parking place. The maximum distance at which agents are willing to park is slowly increasing the longer the driver searches for a parking place. The search heuristic in this stage of the search for parking is thus identical to the search heuristics we have applied in earlier papers.

C. Settings

In line with the previous paper, the simulation runs have been varied in terms of the settings for the initial occupancy rate and the so-called penetration rate. The initial occupancy rate is the percentage of parking places that are occupied at the start of the simulation. The occupancy level remains roughly the same during every simulation, as the number of cars entering the system is equal to the number of cars leaving the simulation environment during the simulation period. By varying the occupancy rate systematically we can assess the influence of the occupancy rate on the impacts of bottom-up information provision on parking under heterogeneous conditions. We only simulate situations with an initial occupancy rate of 90% and above, as under these conditions the time needed to find a vacant parking spot is (rapidly) increasing [20] and bottom-up information provision appears to have an effect on parking performance [7]. The penetration rate defines the ratio of cars that are equipped with communication technology. The penetration rate is varied between zero and one, in equal increments of 20%.

Besides the occupancy level and penetration rate, the turnover level also has an effect on parking dynamics. The turnover level indicates the amount of times a parking place is occupied by a different vehicle in a given time interval [26]. In this study, we did not systematically change turnover during our simulations. Arriving cars will stay parked for the entire duration of the simulation, while the departing vehicles will be selected randomly from the cars parked at the beginning of the simulation. Since our simulation period is short, and a high number of cars is initially parked in the simulation environment, this procedure does not affect the randomness in the departure of cars.

D. Dependent Variables

Four dependent variables are used to measure parking performance: parking distance, search time, parking time and failure to park. Parking distance is defined as the air distance ('as the crow flies') between the final destination and the parking location. The same definition of search time (or cruising time) is used as was coined in our prior paper [7]: search time is the excess time needed to find a parking place in comparison to the most optimal travel time to the most optimal parking place. All drivers that park within that optimal time frame on the optimal parking place or on a parking place en-route to the optimal parking place, are considered to be drivers with zero search time. The third dependent variable, parking time, consists of the time needed to walk to and from the destination and search time (equation 2):

$$\text{Parking time} = 2 \cdot \frac{d_w}{v_{\text{walk}}} + S_t \tag{2}$$

Where:
d_w = air distance between parking place and final destination
v_{walk} = walking speed
S_t = search time

The last dependent variable, parking failure, is defined as the share of cars that fail to park within 10 minutes after entering the simulation. In a real-world setting drivers are more likely to they revert to a (more expensive) off-street parking facility or driver to another (parking) destination if they are searching for a long time. Here, we assume these cars are simply leaving the simulation environment. Note that, like in our previous paper, the maximum search time of ten minutes for drivers that fail to park is included in the calculation of the average search time for the entire agent population.

IV. Results

This section describes the results of the simulation runs that have been carried out to analyze the impacts of bottom-up information provision for parking dynamics under heterogeneous conditions. To analyze parking dynamics systematically, the settings in terms of occupancy rate and penetration rate are varied throughout the different simulation runs. This leads to a large set of results. For some scenarios a clear pattern has emerged irrespective of the exact settings; in other cases parking performance improved under particular conditions, while worsening for other settings. In what follows, we first give a general overview of the results. We then present the most prominent observations for the V2V and S2V communication strategies.

A. Initial Look at the Results

Table 1 provides a broad overview of the results. It provides a summary of the results of the simulation results across the entire range of settings (penetration rate and occupancy rate) for each type of scenario. A positive sign implies impacts of bottom-up information provision across (nearly) the entire range of settings; a double positive sign implies a strong impact. An ambiguous sign (+/−) implies that the impacts of information provision vary across the range of settings.

The overall results show that a V2V communication strategy has a positive impact on walking distance, in particular in case of spatial heterogeneity. In contrast, the pattern for search time is less consistent as smart cars experience reduced search time under some conditions and no or even negative impact in other settings. The same holds true for

Table 1. Results overview for search time (ST) and walking distance (WD) for each scenario and communication strategy.

		Spatial hetero-geneity	Behavioral hetero-geneity	Combined hetero-geneity
V2V				
Improvement for smart cars in comparison to homogeneous scenario	ST	+/−	+/−	+/−
	WD	++	+	++
Performance of smart cars in comparison to regular cars	ST	+/−	+/−	+/−
	WD	+	+	+
Improvement in overall system result	ST	+/−	+/−	+/−
	WD	+	+	+
S2V				
Improvement for smart cars in comparison to homogeneous scenario	ST	++	+	++
	WD	+/−	+/−	+/−
Performance of smart cars in comparison to regular cars	ST	++	+	++
	WD	++	++	++
Improvement in overall system result	ST	+/−	+/−	+/−
	WD	++	++	++

overall search time of smart and regular cars together. The main reason for the limited impact on search time is the fact that the system is dependent on the amount of cars that are able to communicate. First, when a car leaves a parking place, its vacancy is only transmitted to other cars if, and only if, the car is a smart car. Thus, at low penetration rates the chance that a vacancy message is created is rather small. Furthermore, at low penetration rates, the chance that a message dies out before reaching another smart car is another factor influencing the performance negatively.

The S2V strategy has typically stronger benefits for smart cars than the V2V strategy. These impacts are especially clear with regard to walking distance. The fact that the impacts are relatively limited in comparison to the homogenous scenario is related to the relatively large benefits of the S2V strategy even in a homogenous scenario. The positive impact on walking distance remains when looking at the system result. This denotes that smart cars make a more optimal use of the set of available parking places than regular cars. The S2V strategy also leads to an increased reduction in search time for smart cars across (nearly) all settings for occupancy rate and penetration rate. The results are more ambivalent, however, if overall search time for smart and regular cars is considered jointly. In that case, the S2V strategy delivers no or very small benefits, as the reduced search time for smart cars comes at the expense of the search time for regular cars.

B. V2V Strategy in More Detail

1) Comparison With Homogeneous Scenario

The results of the V2V communication strategy show a recurring pattern throughout the three different scenarios. A V2V communication strategy does not improve search time for smart cars in comparison to the base situation for any of the three scenarios on heterogeneity. This matches with the results found in a homogeneous scenario. In contrast, the benefit in walking distance is improved substantially for the spatially heterogeneous scenario in comparison to the homogeneous scenario. For the scenario with behavioral heterogeneity, the performance is similar to that of the homogeneous scenario, except for situations with 100% occupancy rate, in which case V2V communication delivers more benefits under heterogeneous conditions. For the combined heterogeneous scenario the improvement in walking distance is better in comparison to the homogeneous scenario for every setting.

2) Smart Cars versus Regular Cars

The results of the V2V communication strategy show that search time for smart cars is similar to search time of regular cars under almost all conditions. Only for the agent heterogeneity scenario and combined heterogeneity scenario, a 100% occupancy rate and high penetration rates, the smart cars see a benefit in search time in comparison to regular cars. The results with respect to walking distance show a different pattern: regardless of the scenario, smart cars see a small benefit in comparison to regular cars for an occupancy rate of 95%, which grows with each increase in penetration rate. The same holds for 100% occupancy rate, but benefits are even larger in this case. The reduction in walking distance grows from around 5% at penetration rate 0.2, to between 34% and 40% (depending on the scenario) at a penetration rate of 1.0.

3) Overall System Results

If the impacts are considered jointly for smart cars and regular cars, a different picture emerges. An overall search time benefit is not realized at all, regardless of scenario. Benefits do accrue in terms of walking distance for all scenarios, but in each scenario under slightly different conditions.

For the spatially heterogeneous scenario, overall walking distance is slightly improved at an occupancy rate of 95% and penetration rates between 0.6 and 1.0. For an initial occupancy rate of 100%, a substantial improvement is achieved at penetration rates from 0.4 and above. For the scenario with heterogeneous agent behavior a system benefit is only observable at 100% occupancy rate and high penetration rates. For the combined heterogeneity scenario, the joint results of regular cars and smart cars show a slight benefit in overall walking distance for an initial occupancy rate of 95%. A substantial benefit in walking distance is observable for an occupancy rate of 100%, and is even increased with increasing penetration rates. Finally, the number of cars that fail to park is affected negatively using the V2V strategy. For the spatially heterogeneous scenario and occupancy rates of 95% and 100%, smart cars see a similar, or sometimes even higher, chance of failing to park. For the combined heterogeneity scenario the chances of failing to find a parking place are even increasing further. Resulting in almost double the chance of parking failure at pr 1.0 in comparison to base situation at 100% occupancy rate.

C. S2V Strategy in More Detail

1) Comparison with Homogeneous Scenario

The results regarding the S2V communication strategy show that the search time difference for smart cars is changed from a negative effect to a positive effect for some simulation runs at a 90% occupancy rate in comparison to the homogeneous scenario (Fig. 1). For occupancy rates of 95% and 100%, the performance is especially increased for the *spatially* heterogeneous scenario. Results for the *behavioral* heterogeneity scenario are somewhat smaller at occupancy rates of 90% and 95%. For an occupancy rate of 100%, the results show a different picture as results for the *behavioral* heterogeneity scenario outperform that of the three other scenarios. For the combined heterogeneity scenario, the results are better under almost all conditions in comparison to the homogeneous scenario, except for the situation with 100% occupancy rate and penetration rates of 0.4 and above.

Results regarding walking distance show that performance for the different heterogeneity scenarios is not improved much in comparison to the homogeneous scenario. The *spatially* heterogeneous scenario only outperforms the homogeneous scenario at an occupancy rate of 100%. The performance of the *behavioral* heterogeneity scenario is slightly less than that of the homogeneous scenario. The *combined* scenario performance is slightly worse at an occupancy rate of 90% and slightly better at 95% and 100% occupancy rate.

2) Smart Cars versus Regular Cars

For the spatially heterogeneous scenario, the results of the S2V communication strategy show that search time for smart cars in comparison to regular cars is slightly lower at an initial occupancy rate of 90%. For higher initial occupancy rates (95% and 100%) the benefit is substantial. However, for all initial occupancy rates, the benefits drops as the penetration rate goes up (Fig. 2). This relative decrease in performance for smart cars is the consequence of increasing competition over parking places as the number of cars with communication technology goes up. When all cars are equipped with communication technology (1.0 penetration rate), search time for smart cars is even higher than search time for regular cars in the initial situation with 0.0 penetration rate. Furthermore, at 95% and 100% occupancy rate the regular drivers are penalized for not being able to communicate and face even longer search times than in the initial situation, for every penetration rate between 0.2 and 1.0.

Smart cars do benefit from a reduced walking distance when using an S2V communications strategy in a spatially heterogeneous scenario. While the benefits are minor for an initial occupancy rate of 90%, performance is slightly better at an occupancy rate of 95%, and substantial for a 100% occupancy rate. In the latter case, walking distance for smart cars is about 40% lower than for regular cars (Fig. 3).

Remarkably, performance on average walking distance in meters is not affected by penetration rate. At higher penetration rates the performance benefit for smart cars remains, which indicates that informed cars make a more optimal use of the set of available parking places than regular cars.

The results for walking distance for the behavioral heterogeneity scenario are largely in line with those for the spatially heterogeneous scenario: smart cars outperform regular cars in every situation and also show a similar pattern in comparison to the spatially heterogeneous setting.

For the combined heterogeneity scenario, the S2V strategy shows benefits in terms of search time under all conditions for smart cars in comparison to regular cars. Performance benefit is especially substantial at an initial occupancy rate of 100% (Fig. 4). Results with respect to walking distance show similar results as for the other two scenarios (Fig. 5).

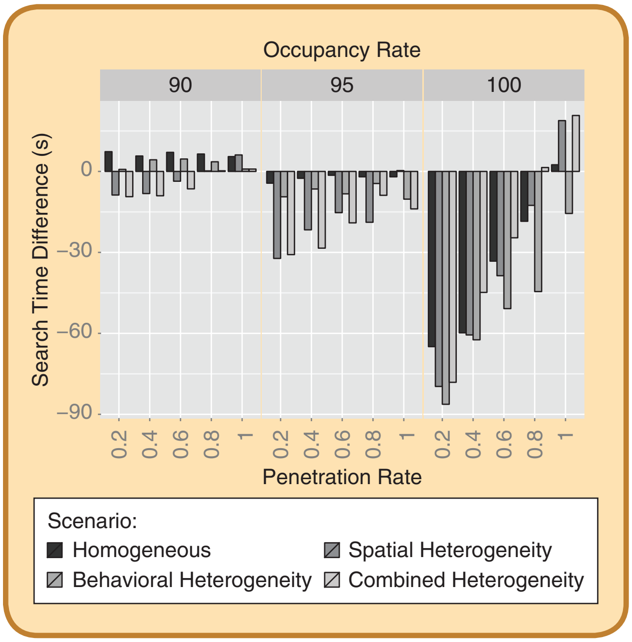

FIG 1 Difference in search time for smart cars in comparison to the base situation for four different scenarios using a S2V strategy.

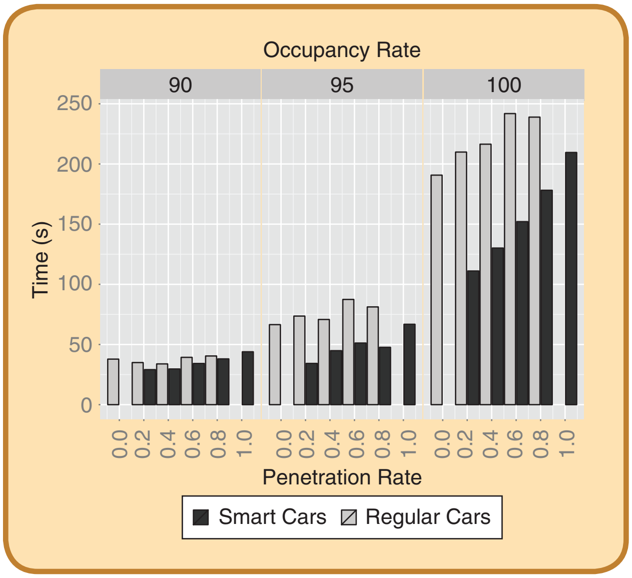

FIG 2 Search time for smart cars and regular cars, for different occupancy rates and penetration rates, using S2V strategy in a spatially heterogeneous scenario.

3) Overall System Results

For the spatially heterogeneous scenario, the results for regular cars and smart cars combined show a less significant picture. Similar to the V2V strategy, the S2V strategy offers no overall benefit in terms of overall search time, as the

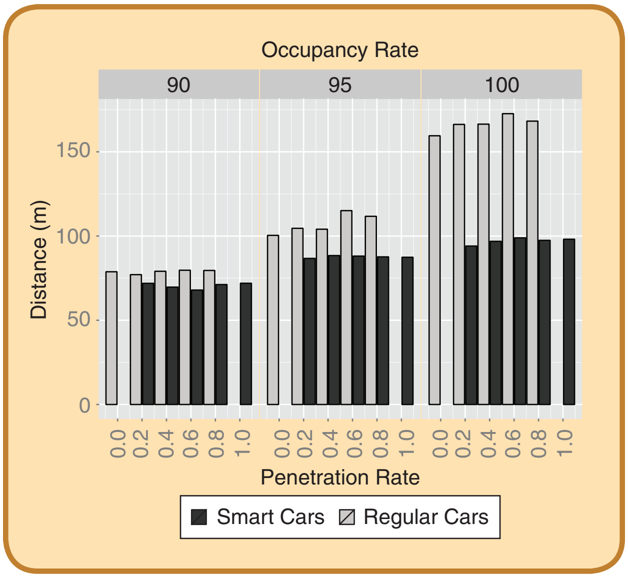

FIG 3 Walking distance for smart cars and regular cars, for different occupancy rates and penetration rates, using S2V strategy in a spatially heterogeneous scenario.

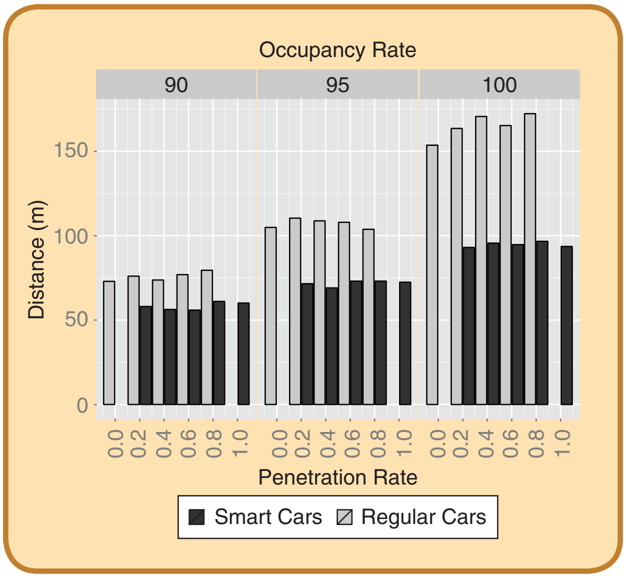

FIG 5 Walking distance for smart cars and regular cars, for different occupancy rates and penetration rates, using S2V strategy in a scenario with heterogeneous driver behavior and heterogeneous demand.

performance increase for smart cars leads to a decrease in the performance for regular cars. In contrast, overall performance regarding walking distance does improve. This is due to the fact that the increase of performance for smart cars only has a slight negative effect on the walking distance for regular cars. Thus, even at high penetration rates, the overall system benefits in terms of a smaller average walking distance to the final destination. Finally, the number of cars that fail to park increases with every increment in penetration rate. For instance, for an occupancy rate of 100%, the number of cars that fail to find a parking place increases from 12.5% in the base situation to 20% for 1.0 penetration rate. This is the result of the spatial concentration of parking demand and the fact that multiple smart cars may therefore be heading for the same suggested parking place.

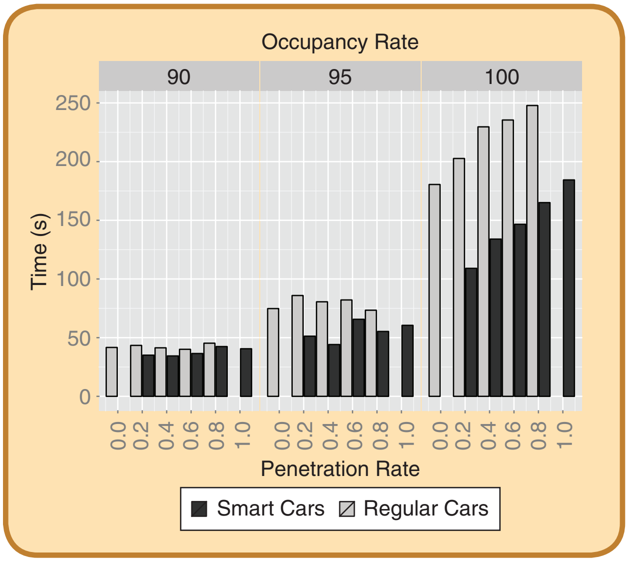

FIG 4 Search time for smart cars and regular cars, for different occupancy rates and penetration rates, using S2V strategy in a scenario with heterogeneous driver behavior and heterogeneous demand.

For the behavioral heterogeneity scenario, the S2V strategy results in slightly decreased overall search times for initial occupancy rates of 95% and 100%. Regarding overall walking distance, the results are similar to the spatially heterogeneous scenario. However, results with regard to the share of cars that fail to park within 10 minutes differs from the spatially heterogeneous scenario. For the base situation without information provision, 7% of the cars fail to find a parking place within ten minutes for an occupancy rate of 100%. For smart cars this share is typically below 5%, except for a penetration of 1.0 when it increases to 6%. The difference with the spatially heterogeneous scenario is due to the fact that competition for parking places is less severe in a environment with uniformly distributed demand.

For the combined heterogeneity scenario, the overall result for the S2V strategy shows that performance is not improved with respect to search time. In contrast, overall performance regarding walking distance is improved considerably (Fig. 6). However, the share of cars that fail to find a parking place increases considerably (Fig. 7) at higher penetration rates (for an occupancy rate of 100%), which is again a consequence of the spatial concentration of demand for parking.

V. Conclusions

In this paper the effect of bottom-up information provision on urban parking dynamics under heterogeneous conditions was studied using agent-based computer simulations.

Theoretically, provision of information to drivers about available on-street parking places could decrease the need to cruise for parking. In line with our previous studies [7], this theoretical conjecture does not hold for most simulation runs using the V2V communication strategy. However, for the S2V strategy, the theoretical expectation is confirmed. For all three heterogeneous scenarios, using a S2V communication strategy leads to a decrease in search time in comparison to a homogeneous environment with homogeneous agents, for almost all simulation settings. Furthermore, the average search time for smart cars is decreased in comparison to regular cars, in particular for the spatially heterogeneous scenario. The positive impacts for especially this scenario is the result of the increased competition between drivers over parking places, which gives informed drivers an advantage over regular drivers.

These improvements in results in comparison to our earlier study, using a homogeneous environment and homogeneous agent behavior, show that heterogeneity plays an important role in information provision in the field of parking. Interestingly, improvements in results regarding walking distance are less pronounced than search time results in comparison to homogeneous simulation settings. This is most likely due to the fact that walking distance is already improved considerably during the simulation runs with homogeneous settings, which does not leave much room for further improvement. Information indeed seems to enable drivers to identify and occupy a parking place closer to their destination.

The results of this study should, of course, be placed in context. They concern a rather straightforward situation, in which the street network resembles a Manhattan grid. Considering the positive effect of spatial heterogeneity on results, the use of bottom-up parking information could even have bigger impacts, in terms of walking distance and search time, in the case of a more complex road network, similar to the ones that can be found in most historic cities.

It should also be noted that we have assumed that informed drivers cannot reserve the on-street parking place of their choice. This implies that a parking place may already be occupied by another car when a driver arrives at the designated location. In future research we want to address this issue by either implementing a reservation strategy or by providing drivers with aggregate information on available parking places, for instance on a city block or a street segment. By aggregating information on occupancy on a higher level than a single on-street parking place, it may be possible to provide a more accurate estimation of parking availability upon arrival. Furthermore, this principle would allow for a reduction in costs when applying a sensor strategy, as not all parking places need to have a sensor in order to determine the occupancy rate at an aggregate level.

In spite of these remarks, this research shows that the benefits of bottom-up information provision may well be substantially smaller than may be expected on theoretical grounds. Indeed, the societal benefits of providing information to drivers on parking availability do not necessarily offset the costs for implementing a sensor system in a large area. Of course the benefits of such a system are dependent on the specific circumstances. As mentioned before, a more realistic environment might lead to a greater reduction in search time. Besides the impacts on walking distance and search time, drivers could also ascribe substantial (monetary) value to a reduction in the inherent uncertainty of finding an on-street parking place.

All considered, bottom-up information provision may deliver positive societal benefits, especially in situations with heterogeneous demand. However, the extent to which information provision contributes to a reduction in air pollution

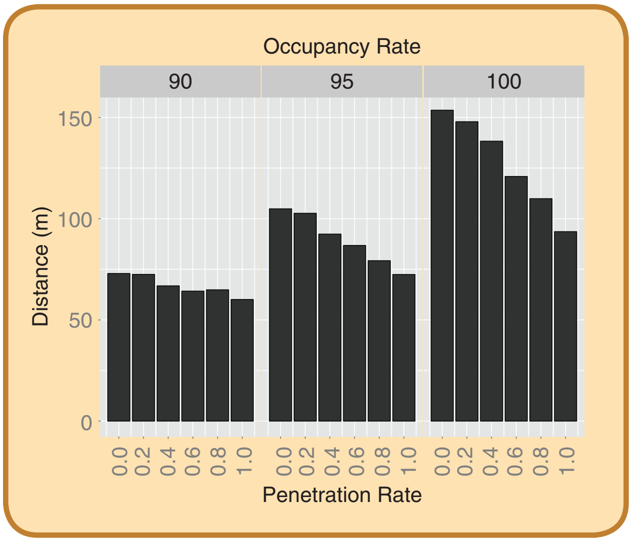

FIG 6 Walking distance for overall system, for different occupancy rates and penetration rates, using S2V strategy in a scenario with heterogeneous driver behavior and heterogeneous demand.

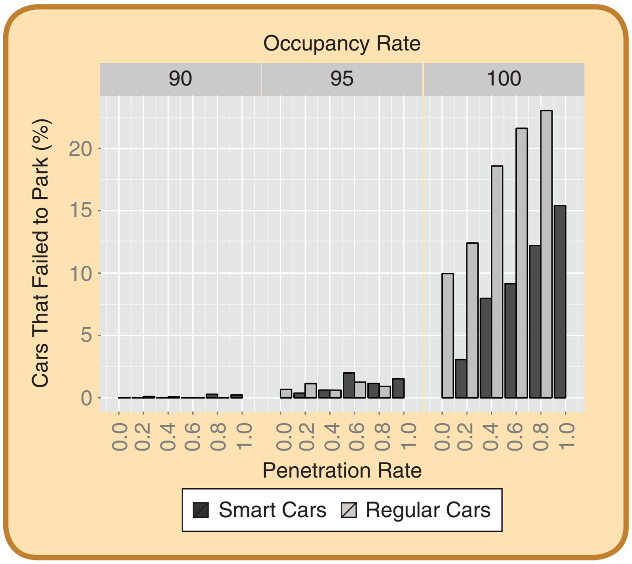

FIG 7 Parking failures for overall system, for different occupancy rates and penetration rates, using S2V strategy in a scenario with heterogeneous driver behavior and heterogeneous demand.

and traffic congestion requires additional analyses. These analyses should include experiments with a more complex street network and realistic distribution of parking demand over space and time, as well as experiments that include information provision at a higher level of aggregation or a reservation system. Such studies could provide additional insight into the benefits of bottom-up information technologies and especially into the dynamics that arise when implementing parking sensor technology in real-world situations. The latter may, in turn, provide valuable input to decision-making about whether or not to invest in a sensor-based system.

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References

[1] J. N. Van Ommeren, D. Wentink, and P. Rietveld, "Empirical evidence on cruising for parking," *Transp. Res. A, Policy Pract.*, vol. 46, no. 1, pp. 123–130, Jan. 2012.

[2] R. Arnott and E. Inci, "An integrated model of downtown parking and traffic congestion," *J. Urban Econ.*, vol. 60, no. 3, pp. 418–442, Nov. 2006.

[3] F. Caicedo, "Real-time parking information management to reduce search time, vehicle displacement and emissions," *Transp. Res. D, Transp. Environ.*, vol. 15, no. 4, pp. 228–234, June 2010.

[4] Streetline: Parker Mobile. [Online]. Available: http://www.streetline.com/find-parking/parker-mobile/

[5] LA Express Park. [Online]. Available: http://www.laexpresspark.org/

[6] SFpark. [Online]. Available: http://sfpark.org/

[7] G. Tasseron, K. Martens, and R. van der Heijden, "The potential impact of vehicle-to-vehicle and sensor-to-vehicle communication in urban parking," *IEEE Intell. Transp. Syst. Mag.*, vol. 7, no. 2, pp. 22–33, 2015.

[8] P. Van der Waerden, H. Timmermans, and A. Borgers, "PAMELA: Parking analysis model for predicting effects in local areas," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1781, pp. 10–18, 2002.

[9] L. D'Acierno, M. Gallo, and B. Montella, "Optimisation models for the urban parking pricing problem," *Transp. Policy*, vol. 13, no. 1, pp. 34–48, Jan. 2006.

[10] Z.-C. Li, H.-J. Huang, and W. H. K. Lam, "Modelling heterogeneous drivers' responses to route guidance and parking information systems in stochastic and time-dependent networks," *Transportmetrica*, vol. 8, no. 2, pp. 105–129, 2012.

[11] E. Kokolaki, M. Karaliopoulos, and I. Stavrakakis, "Parking assisting applications: Effectiveness and side-issues in managing public goods," in *2013 IEEE 7th Int. Conf. Self-Adaptation and Self-Organizing Systems Workshops*, 2013, pp. 77–82.

[12] J. L. Boehlé, L. Rothkrantz, and M. van Wezel, "CBPRS: A city based parking and routing system," Rotterdam, Report, 2008.

[13] I. Leontiadis and C. Mascolo, "Opportunistic spatio-temporal dissemination system for vehicular networks," in Proc. 1st international MobiSys workshop on Mobile opportunistic networking, 2007, pp. 39–46.

[14] V. Prinz, R. Eigner, and W. Woerndl, "Cars communicating over publish/subscribe in a peer-to-peer vehicular network," in Proc. 2009 Int. Conf. Wireless Communications and Mobile Computing: Connecting the World Wirelessly, 2009, pp. 431–436.

[15] M. Caliskan, D. Graupner, and M. Mauve, "Decentralized discovery of free parking places," in *Proc. 3rd Int. Workshop on Vehicular Ad Hoc Networks - VANET '06*, 2006, p. 30.

[16] T. Delot, N. Cenerario, S. Ilarri, and S. Lecomte, "A cooperative reservation protocol for parking spaces in vehicular ad hoc networks," in *Proc. 6th Int. Conf. Mobile Technology, Application & Systems - Mobility '09*, 2009, pp. 1–8.

[17] P. Szczurek, B. Xu, O. Wolfson, J. Lin, and N. Rishe, "Learning the relevance of parking information in VANETs," in *Proc. Seventh ACM Int. Workshop on Vehicular Internetworking - VANET '10*, 2010, p. 81.

[18] P. Szczurek, B. Xu, J. Lin, and O. Wolfson, "Spatio-temporal information ranking in vanet applications," *Int. J. Next-Gen. Comput.*, vol. 1, no. 1, 2010.

[19] V. B. Vaghela and D. J. Shah, "Vehicular parking space discovery with agent approach," in *Proc. Int. Conf. Workshop on Emerging Trends in Technology*, 2011, pp. 613–617.

[20] N. Levy, K. Martens, and I. Benenson, "Exploring cruising using agent-based and analytical models of parking," *Transportmetrica*, vol. 9, no. 9, pp. 773–797, 2013.

[21] S. Demmel, A. Lambert, D. Gruyer, A. Rakotonirainy, and E. Monacelli, "Empirical IEEE 802.11 p performance evaluation on test tracks," in *IEEE Intelligent Vehicles Symp. (IV), 2012*, 2012, pp. 837–842.

[22] M. Karaliopoulos, K. Katsikopoulos, and L. Lambrinos, "Bounded rationality can increase parking search efficiency," in Proc. 15th ACM Int. Symp. Mobile Ad Hoc Networking & Computing, 2014.

[23] I. Benenson, K. Martens, and S. Birfir, "PARKAGENT: An agent-based model of parking in the city," *Comput. Environ. Urban Syst.*, vol. 32, no. 6, pp. 431–439, Nov. 2008.

[24] D. C. Shoup, "Parking on a smart campus," *Calif. Policy Options*, 2005.

[25] I. Benenson and K. Martens, "From modeling parking search to establishing urban parking policy," *Zeitschrift Künstliche Intelligenz*, vol. 3, no. 08, pp. 8–13, 2008.

[26] D. C. Shoup, "The trouble with minimum parking requirements," *Transp. Res. A, Policy Pract.*, vol. 33, no. 7, pp. 549–574, 1999.

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