Opportunistically-assisted parking service discovery: now it helps, now it does not

Evangelia Kokolaki, Merkouris Karaliopoulos, Ioannis Stavrakakis

National & Kapodistrian University of Athens
Dept. Informatics & Telecommunications
Ilissia, 157 84, Athens, GREECE

Abstract

In this paper we explore the way the discovery of service can be facilitated or not by utilizing service location information that is opportunistically disseminated primarily by the service consumers themselves. We apply our study to the real-world case of parking service in busy city areas. As the vehicles drive around the area, they opportunistically collect and share with each other information on the location and status of each parking spot they encounter. This opportunistically assisted scenario is compared against one that implements a "blind" non-assisted search and a centralized approach, where the allocation of parking spots is managed by a central server with global knowledge about the parking space availability.

Results obtained for both uniformly distributed travel destinations and a single hotspot destination reveal that the relative performance of the three solutions can vary significantly and not always inline with intuition. Under the hotspot scenario, the opportunistic system is consistently outperformed by the centralized system, which yields the minimum times and distances at the expense of more distant parking spot assignments; whereas, for uniformly distributed destinations, the relative performance of all three schemes changes with the vehicle volume, with the centralized approach gradually becoming the worst solution and the opportunistic one emerging as the best scheme. We discuss how each approach modulates the information dissemination process in space and time and resolves the competition for the parking resources. We also outline models providing analytical insights to the behavior of the centralized approach.

Keywords: vehicular communications, opportunistic dissemination, parking assistance, machine interference problem, vehicular sensor networks

Email addresses: evako@di.uoa.gr (Evangelia Kokolaki), mkaralio@di.uoa.gr (Merkouris Karaliopoulos), ioannis@di.uoa.gr (Ioannis Stavrakakis)

1. Introduction

The efficient use of urban space has always been both a requirement and a challenge in the process of city planning. It calls for several interventions in the way cities are organized, including the efficient management of the car volumes that daily visit the city center and other popular in-city destinations. Part of this task is the effective operation of the sometimes minimal parking space. The reduction of time that vehicles spend searching for parking places does not alleviate only the traffic congestion problems but also the environmental burden.

The real dimensions of the parking place search problem depend on several factors. The existence of popular destinations, personal parking preferences, and the drivers' unwillingness to park but only in close proximity to the destination, aggravate the problem. Academic research but also public and/or private initiatives have made a remarkable effort in the last years to solve the problem through *parking-assistance* systems. Common feature of these systems is the exploitation of wireless communications and information sensing technologies to collect and share *information* about the availability of parking space in the search area. This information is then used to steer the parking choices of drivers with the aim to reduce the effective *competition* over the parking space and make the overall search process efficient.

In this paper, we systematically analyze the capacity of an *opportunistic* system to assist the search for parking space. Vehicles searching themselves for parking space are equipped with sensors, which allow them to sense the location and status of parking spots as they move across the city area. This information is subsequently shared upon encounters with other vehicles, using medium-range radio communication technologies such as 802.11x. We explore the performance dynamics of the opportunistic scheme by comparing it with two other approaches. The first one is a *centralized* system. This time a central server collects both the requests of vehicles for parking space allocation *and* information about the status of individual parking spots. With this information at hand, it assigns parking space to the vehicles, reserves it for them, and directs them thereto. The second one is the current-practice parking search approach, where vehicles wander in the area around their travel destination without any external assistance.

We use both simulations and analysis to systematically compare the three radically different paradigms for collection, sharing, and exploitation of service-related information. Two scenarios drive our discussion. The first one involves vehicles seeking parking space all over the city area (*uniformly distributed destinations*). The second scenario features a single area that acts as an attraction pole for vehicles (*hotspot*). We assess the effectiveness of the parking search process through user-oriented performance metrics, such as the parking search time and route length, and the proximity of the found/assigned parking spot to the user travel destination, but also through system-oriented performance metrics, such as the average utilization of parking spots.

Our results suggest that there is no one-size-fits-all solution; on the contrary, the relative performance of the three schemes varies significantly, and not always intuitively, with the operational conditions. In the hotspot scenario, the centralized system consistently yields the minimum search times and distances. With *global* knowledge of parking space availability throughout the area, it can resolve better the competition amongst the vehicles for the few parking places around the common destinations. If the user is willing to park somehow further than the destination, (s)he can reduce her/his search times significantly. On the contrary, the opportunistic system ends up recycling information that synchronizes the movement patterns of the vehicles and intensifies their competition. Even for moderate number of vehicles, the opportunistic scheme effectively "degenerates" to the non-assisted scheme. When user travel destinations are uniformly distributed, the relative performance of the three schemes changes with the vehicle volume. The initially optimal centralized approach gradually becomes the worst solution since the reservation system ends up wasting part of the parking capacity of the system at high load. The opportunistic scheme ranks top since vehicles exploit the information they collect upon their encounters to make informed searches and reach a vacant parking spot faster. The introduction of dedicated mobile storage nodes that only assist the information diffusion without adding competition for parking space, further benefits the system at small vehicle volumes.

The three parking approaches are described in more detail in Section 2. We define the performance metrics and present the simulation environment used for our evaluations in Section 3. Queuing models for the analytical investigation of the centralized system's performance are introduced in Section 4. We then comparatively evaluate the three approaches, discuss their tradeoffs, and validate our analytical model in Section 5, while Section 6 provides further insights to the sensitivity of the three approaches to different parameters. The possible performance enhancement of the opportunistic scheme when mobile static nodes are introduced is also discussed therein. We outline related research on the subject and position our work against it in Section 7 and conclude the paper in Section 8 with a summary of our results and directions for future work.

2. Approaches to parking space search

We summarize three basic approaches to the parking space search problem. Each one represents a distinct *paradigm* for localizing and occupying vacant parking spots[1]. In the same time, they reflect existing or under development systems; some of them are indicatively presented in Section 7. In all three cases, there is a fixed set of parking spots P, with $|P|$=P, distributed across a city area $\mathcal{A}$, and a finite population of vehicles C, with $|C|$=C moving therein. Vehicles drive towards their travel destinations and enter the parking search process as soon as they approach them, *i.e.*, enter the initial parking search area (Figure 1). The *main differentiation factor* among the three approaches is the way

[1]Note that current navigation systems can locate parking lots, yet they cannot provide information about the availability of parking places therein.

users *(i.e., vehicles) exploit, or do not exploit, information about the availability of parking space within the search area.* Each parking spot is equipped with a sensor providing information about its occupancy status. Vehicles, properly equipped with short-range wireless interfaces and adequate storage and processing capacity, may collect information on the status of each parking spot they encounter. Moreover, they may acquire and store additional global or partial, accurate or imprecise, knowledge about the distribution of the free parking space throughout the area $\mathcal{A}$ via communicating with other vehicles or a central server.

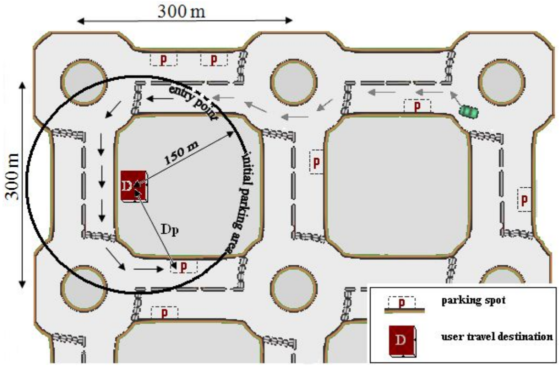


Figure 1: Section of city area $\mathcal{A}$ showing the vehicle's path towards a parking spot close to its travel destination.

2.1. Non-assisted parking search (NAPS)

Usually, the parking space search process begins when the driver anticipates that he has arrived in the proximity of his travel destination (*initial parking search area*). This decision depends on the observed congestion level and the driver's ability to estimate the parking demand in his area of interest. Moreover, he may take into account former experience and knowledge he has acquired about the traffic flow and parking needs in the considered area.

According to the current common search strategy, drivers wander around their travel destination and sequentially check the availability of the parking spots they encounter. Typically, the radius of the search area grows progressively as parking search time increases and indeed, its growth rate depends on the same factors that determine the extend of the initial parking search area. The search process terminates when drivers detect the first vacant parking spot. In other words, it is assumed that no one would ever reject an available parking spot located within the borders of his/her parking search area, under the expectation of a closer-to-destination, yet non-guaranteed, parking option[2].

[2] This is the basic NAPS approach. The interested reader is referred to [1] for comparisons of basic NAPS with scheme variants that maintain memory about the location of parking spots.

2.2. *Opportunistically-assisted parking search (OAPS)*

Information about the location and status of parking spots may become available to vehicles with the opportunistically-assisted parking search (OAPS) scheme. With OAPS, vehicles equipped with standard wireless interfaces such as 802.11x in ad hoc mode, share with each other information they acquire in the course of their search [2]. This information can be filtered in time (aging) and space, if timestamps and the geographic addresses (*e.g.*, via GPS) of individual parking spots are stored.

With such information at hand, drivers can make more informed decisions about their search. Rather than wandering randomly in the parking search area, a vehicle can now move towards the parking spot that is stored as the closest vacant one to its destination[3]. If it is actually vacant when it arrives at it, it occupies it. However, if the spot is occupied, it has to repeat the whole search process. In general, if a vehicle encounters a vacant parking spot within its parking search area on its way to the selected 'target' spot, it occupies it and terminates the search.

The opportunistic information dissemination mechanism of OAPS does not enforce global common knowledge about the availability of parking space. As the status of parking spots changes in time, stored data are potentially outdated after some time interval. Therefore, the frequency of information updates is critical for the effective operation of the scheme. The faster information circulates across the wireless networking environment, the more accurate data will be stored in the caches of vehicles. All the same, users should be cautious when they consult their caches. Information should be filtered in order to determine the outdated information (*i.e.*, when the timestamp of a stored record is beyond some threshold value).

On the other hand, depending on the travel destinations of the users, the fast dissemination of information may synchronize the caches and, consequently, the movement patterns of individual vehicles and aggravate the effective competition for given parking spots. As we show in Section 5, how this trade off is resolved for OAPS depends on several factors such as the number of vehicles moving in the area $\mathcal{A}$, their speed, travel preferences (destinations), and the road grid structure.

2.2.1. *Mobile storage node opportunistically-assisted parking search (msnOAPS)*

The inflow of information to each vehicle may increase further through the use of dedicated *Mobile Storage Nodes* (*MSNs*), *e.g.*, city taxicabs. Like normal vehicle nodes, MSNs are equipped with wireless interfaces that allow them to collect parking information and share it with other mobile nodes, *i.e.*, user-vehicles

[3] In the basic OAPS approach, any updates to driver's storage are taken into account only at the moment of decision, once he arrives in the proximity of his destination. [1] studies the main variant of OAPS where the updates generate a continuous message flow to the driver, raising distracting message fusion issues. Many works (*e.g.*, [3]) are devoted to the design of effective safety or infotainment applications.

and MSNs. These nodes act as relays, creating additional contact opportunities between vehicles and, hence, space-time paths for the flow of parking information.

Regarding the storage capability of these nodes, it is assumed that MSNs can handle data about all considered parking places. As the occupancy status of parking places changes with time, the accuracy of their stored information tends to drop. Therefore, the information they disseminate is not always useful.

2.3. Centrally-assisted parking search (CAPS)

With CAPS, the full information processing and decision-making tasks lie with a central processor (server). Vehicles and parking spot sensors are only responsible for transmitting to the server parking requests and spot vacancy information, respectively. The semi real-time two-way communication of the server with the vehicles and the parking spot sensors calls for heavier network infrastructure, both wired and wireless.

When submitting its parking request, each vehicle specifies its destination to the centralized server. In a First-Come-First-Served (FCFS) manner[4] the server queues the requests and satisfies them, reserving for the vehicle that parking spot amongst the vacant ones, which lies closest to its destination. The user is then notified about the reservation, *i.e.*, parking spot he should drive to. Therefore, and contrary to NAPS and OAPS, the vehicle is directed towards a guaranteed vacant parking spot. While waiting for the system assignment, the user keeps on moving towards random directions within the area.

Two more remarks are worth making about the parking search approaches and the way we investigate them in this work. Firstly, the structural difference between distributed and centralized systems also differentiates their installation, operational and maintenance costs. A fixed centralized infrastructure requires not only a large amount of investment upfront but also an elaborated architectural design for maintenance purposes. Furthermore, additional concerns are related to the system scalability with the number of monitored parking places and the burden of potentially re-dimensioning of the sensing web. On the contrary, vehicular networks emerge as a cost-effective networking platform that exploits the powerful, in terms of energy and computational might, vehicular nodes in favor of a wide range of applications. Reference [4] reports installation and operating costs for fixed infrastructure, whereas [2], [4], and [5] highlight the savings of an infrastructure-free system.

Secondly, throughout this study we assume that vehicular nodes are fully cooperative. Partial or no cooperation of vehicles/drivers is a concern for both the CAPS and OAPS approaches. Although the OAPS scheme has inherent

[4]Different scheduling disciplines are generally applicable when processing the parking requests. Herein, we focus on the FCFS policy for exploring the relative performance of the centralized paradigm for sharing and processing information and demonstrating the related tradeoffs.

diversity, selfish and/or malicious behaviors can undermine its performance significantly. Thereby, the detection and penalization of misbehaviors is really challenging. On the other hand, considering that practical implementation of the CAPS approach avail V2I communication infrastructure, supervisory mechanisms can consist a separate level in the overall system architecture. For instance, these mechanisms could vouch for system robustness through either implementing barrier-controlled metered parking spaces or enforcing penalties in a pervasive sensing road platform. In the same notion, the established fixed sensor network need to function not only to monitor the parking space availability but also confirm the parking events (and thus support billing).

3. Performance Evaluation Methodology

3.1. Performance Metrics

1. *Driver-level metrics:* When someone moves towards a specific destination, he aims for the shortest route and minimum travel time (these may not be necessarily compatible objectives). When he needs to park, on top of that, he prefers the nearest to the destination parking place (best parking place). In the ideal case, someone will reach it travelling the shortest possible route from his initial location to that parking place (best way). Therefore, the metrics we consider for comparing the three approaches to parking search are:
   (a) *Parking search time, T_{ps}*: Once the driver enters the initial parking search area (Figure 1), he will start seeking for a parking place. This time is highly dependent on the parking space density in the considered area, traffic congestion level, and competition for parking space around the destination.
   (b) *Parking search route length, R_{ps}*: It refers to the distance a driver travels till he parks his vehicle, measured from the moment he enters the initial parking search area. The parking space density and the demand for parking are the two factors that primarily affect R_{ps} for given city area and vehicle speeds. Besides expressing user satisfaction, R_{ps} and T_{ps} also reflect social objectives in that more travelling results in additional fuel consumption and environmental burden.
   (c) *Destination-parking spot distance, D_p*: It expresses the geographical distance of the two points and, contrary to T_{ps} and R_{ps}, it is exclusively a measure of user satisfaction: the closest the parking spot lies to the destination, the more attractive it is.
2. *System-level metric:* In order to capture the actual exploitation of the road parking capacity, we employ the metric:
   (a) *Availability time, T_a*: It measures the average time each parking spot remains vacant.

3.2. Simulation environment

We have developed a simulation environment in the C programming language that reproduces in adequate detail the three parking search approaches. We briefly summarize it below:

Road grid: The simulator implements a grid of two-lane roads (one lane in each direction) in a city environment; each road traverses the grid from the one side to the other, as shown in Figure 2. Additionally, there are roundabouts in every intersection, connecting up to four converging roads. Parking spots may be located in either lane of the road and are equipped with sensors providing information about their status (vacant vs. occupied).

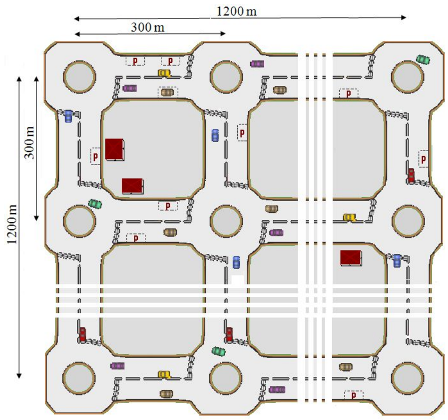


Figure 2: Simulation environment: $1200 \times 1200m^2$ road grid with randomly distributed parking places.

Vehicle movement: Vehicles move within the bounds of this city environment along the horizontal and vertical roads. The vehicle mobility model comes under the broad category of behavioral mobility models. One could identify two levels of behavior: the global, determining how destinations are selected and the way the vehicles chose the route towards them; and the local, determining how the vehicle moves within the roads comprising the route.

At local level, in each simulation time step, the next position of every vehicle depends on its current position and velocity. Every vehicle adapts its speed according to its distance from: a) the front vehicle (they are not allowed to overtake one another); b) the next intersection; and c) the nearest parking spot, assuming that the car decelerates in every parking place it encounters in order to stop in a vacant one. Moreover, they zero their speed when they get stuck in traffic jam, enter a roundabout intersection, and park. Finally, the vehicles start from zero speed and are not allowed to stop or move in the reverse direction of the traffic flow.

Every time a vehicle frees a parking spot, it chooses a new destination (geographical coordinates within the bounds of the simulation area) and drives towards it. Once it reaches the destination's initial parking search area, the parking search process is initiated. Its initial parking search area is a circular area with the destination at its center and radius equal to half the distance between two adjacent intersections (Figure 2).

Under the NAPS strategy, the vehicle will circulate randomly within its initial parking search area. This random movement has been modelled by the selection of random geographical coordinates that correspond to a point inside the cyclic parking area. On the contrary, with OAPS the vehicles will filter the stored records both temporally (to exclude information that is outdated) and spatially (to consider only information about spots in the current search area).

Out of the remaining records, the user will pick up the one that refers to the nearest-to-his-destination parking spot. If the spatiotemporal filtering step does exclude all the stored data, the user chooses randomly one spot within the parking search area and moves thereto, hoping that it may be vacated in the meanwhile. Finally, under CAPS, the user moves randomly within the parking search area till he is directed by the system to drive to the reserved parking spot. The above procedure defines where the user should drive next. Upon arrival to this location, the user faces two possibilities: a) the location corresponds to a vacant parking spot. The user then occupies it for some time interval that may follow different distributions. When this time interval expires, he vacates the spot and selects another destination; b) the location does not correspond to a parking spot or, if it does, it is occupied - both count as failures. The user then determines whether his parking search area should grow or not. In particular, this decision and more precisely the area's growth rate (exponential or linear), will depend on the number of driver's failures in the current parking search area. The exponential rate signals the persistent search in the proximity of the travel destination, whereas the linear one is synonym of the less conservative search in favor of T_{ps} and against D_p.

3.3. Simulation set-up

For the simulations in this paper we consider a two-lane road grid with dimensions $1200 \times 1200m^2$, as shown in Figure 2. The distance between two adjacent intersections in the grid is 300m and parking places are uniformly distributed alongside road lanes. The numbers of vehicles and parking spots vary to generate different vehicle and parking spot densities. The parking time of all vehicles are i.i.d exponential RVs with means ranging from 300 to 3600s. We assume an exponentially increasing rate for the search area and an increment step fixed to the half of the distance between two adjacent intersections. The duration of simulations is 10^5s, which is enough time to generate a significant number of parking events in all runs. The maximum vehicle speed is set to v_{max}=$50km/h$; note that the actual instantaneous vehicle velocity may range anywhere in $[0, v_{max}]$, as explained in Section 3.2. The vehicle-parking spot sensor communication range is set to 15m, whereas the intra-vehicle communication range is 70m. In all graphs reported in Section 5, we plot the averages of ten simulation runs together with their 95% confidence intervals.

4. Modelling the centralized approach

In this section, we present an analytical model for the centralized approach to the search for parking space (CAPS) and use it to analytically derive its main performance measures. The model is later validated in Section 5.3 against simulation results.

Anytime, the C vehicles may find themselves in one of three *states*: a) travelling towards their destination without yet having issued a parking request to the system; b) driving within the parking search area having issued a parking request and waiting for a parking assignment; and c) parked (or on the way to the parking spot that is reserved for them by the system). The system can be modelled by a finite-source $G/G/r$ queue with r=P servers (parking spots).

$G/G/r$ model input process. A vehicle enters the queueing system when it submits a parking request, *i.e.*, when it crosses the border of the initial parking search area. Under uniform distribution of travel destinations and parking spots in the area $\mathcal{A}$, the time T_t that vehicles spend travelling, from the moment they release a parking spot till the time they issue a new parking request, is a random variable (RV) written as

$$T_t = D_t/v. \tag{1}$$

In (1), v is the vehicle speed and D_t the random variable denoting the line picking distance, whose probability distribution is known for various known geometries such as circular, square, rectangular areas [6]. For example, for square areas of unit side length, $f_{D_t}(x)$ is given by

$$f_{D_t}(x) = \begin{cases} 2x(x^2 - 4x + \pi) & \text{for } \ 0 \leq x \leq 1 \\ 2x[4\sqrt{x^2-1} - (x^2 + 2 - \pi) - 4\tan^{-1}\sqrt{(x^2-1)}] & \text{for } 1 \leq x \leq \sqrt{2} \end{cases}$$

so that the probability distribution function of the travelling time within a square area of side length l can be written

$$f_{T_t}(t) = v \cdot f_{D_t}(vt/l)/l \tag{2}$$

and its expected value and variance are

$$\begin{aligned} \overline{T_t} &= \int_0^{\sqrt{2}l} t f_{T_t}(t)dt \approx 0.52l/v = 1/\lambda \\ \sigma_t^2 &= \int_0^{\sqrt{2}l} (t^2 - \overline{T_t}) f_{T_t}(t)dt \approx 0.06l^2/v^2. \end{aligned} \tag{3}$$

where λ denotes the rate at which each vehicle submits parking requests to the system.

$G/G/r$ model service time. The vehicle (requests) may stay in the queue for variable time T_q, before they are processed, depending on the request backlog and the order in which requests are treated. The service time, T_s, starts when the vehicle is assigned with a parking spot and directed to drive there, and consists of two components: the parking time spent in the reserved parking spot, T_p, plus the travel time, T_f, spent on driving towards the reserved parking spot, starting from its position at the moment the assignment was communicated to it (*final leg travel time*).

Generally, the distribution of T_f depends on the proximity of the assigned parking spot to the vehicle travel destination. Different policies may constrain this distance; for instance, there may be an upper bound on how far from the travel destination a car may park, beyond which vacant parking spots are not considered eligible for a vehicle. The mean and variance of T_s are given by:

$$\mu = \overline{T_p} + \overline{T_f},\ \sigma_s^2 = \sigma_p^2 + \sigma_f^2 - 2\overline{T_p} \cdot \overline{T_f} \tag{4}$$

G/G/r performance measures. In assigning parking spots to vehicles, the server effectively solves an instance of the machine interference problem (MIP), also referred to as the machine repairman problem [7][8], with partially cross-trained repairmen. In our problem, in particular, machines correspond to vehicles and parking spots to cross-trained repairmen, who can serve more than one machine but with variable efficiency, *i.e.*, user satisfaction according to the proximity of the spot to its travel destination. In the general case, the server has to take two decisions: in what order will the requests be processed (*sequencing decision*) and which parking spot should be assigned to which vehicle (*loading decision*).

For the most common scheduling policy, *i.e.*, First-Come-First-Served, the derivation of the main performance measures can draw on the diffusion approximations of Wang and Sivazlian in [9]. The probability distribution function of the number of vehicles, C_{is} that are "in-system", *i.e.*, either parked or travelling towards the reserved parking space or having submitted a parking request to the system, is approximated by:

$$f_{C_{is}}(x) = \begin{cases} K_1 \cdot g_1(x) & \text{for } 0 \le x \le P \\ K_2 \cdot g_2(x) & \text{for } P \le x \le C \end{cases}$$

where $g_1(x)$ and $g_2(x)$ are functions of the means and variances of the variables T_t $(1/\lambda, \sigma_t)$, and T_s (μ, σ_s), respectively, and the ratio $\rho = \lambda \setminus \mu$:

$$\begin{aligned} g_1(x) &= \frac{\left[\frac{(C-x)\rho\lambda^2\sigma_t^2 + x\mu^2\sigma_s^2}{C\rho\lambda^2\sigma_t^2}\right]^{\beta_1}}{(C-x)\rho\lambda^2\sigma_t^2 + x\mu^2\sigma_s^2} e^{-\frac{2(\rho+1)x}{\rho\lambda^2\sigma_t^2 - \mu^2\sigma_s^2}},\ \beta_1 = \frac{2C\rho\left[1 + \frac{(\rho+1)\lambda^2\sigma_t^2}{\mu^2\sigma_s^2 - \rho\lambda^2\sigma_t^2}\right]}{\mu^2\sigma_s^2 - \rho\lambda^2\sigma_t^2} \\ g_2(x) &= \frac{\left[\frac{(C-x)\rho\lambda^2\sigma_t^2 + P\mu^2\sigma_s^2}{(C-P)\rho\lambda^2\sigma_t^2 + P\mu^2\sigma_s^2}\right]^{\beta_2}}{(C-x)\rho\lambda^2\sigma_t^2 + P\mu^2\sigma_s^2} e^{\frac{2(x-P)}{\lambda^2\sigma_t^2}},\ \beta_2 = \frac{2P(1 + \frac{\lambda^2\sigma_t^2}{\mu^2\sigma_s^2})}{\rho\lambda^2\sigma_t^2} \end{aligned} \tag{5}$$

and K_1, K_2, constants given by the solution of the 2×2 system of equations

$$K_1 \cdot g_1(P) - K_2 \cdot g_2(P) = 0$$

$$K_1 \int_0^P g_1(x)dx + K_2 \int_P^C g_2(x)dx = 1 \tag{6}$$

It is then possible to estimate the expected number $\overline{C_{is}}$ of vehicles that are being served or wait for their parking requests to be served, and the expected number $\overline{C_t}$ of travelling vehicles, respectively, as

$$\overline{C_{is}} = \int_0^C x f_{C_{is}}(x)dx,\ \ \overline{C_t} = C - \overline{C_{is}} \tag{7}$$

whereas, the expected number of vehicles already parked or on their final leg to a reserved parking spot, $\overline{C_s}$, is

$$\overline{C_s} = P - \int_0^P (P-x)K_1 g_1(x)dx. \tag{8}$$

The utilization of each parking spot, *i.e.*, the percentage of time it is occupied (or *reserved*) by a vehicle, is

$$\overline{U_s} = \overline{C_s}/P \tag{9}$$

Finally, the mean time vehicles spend on parking search, $\overline{T_{ps}}$, is the sum of the expected time they wait for a parking assignment, $\overline{T_q}$, and the expected final leg travel time, $\overline{T_f}$; or, equivalently, the difference of the mean total time they spend in the system, $\overline{T_{is}}$ minus the mean parking time (Figure 3), the former being given by Little's result [10].

$$\overline{T_{ps}} = \overline{T_q} + \overline{T_f} = \overline{T_{is}} - \overline{T_p} = \overline{C_{is}}/\lambda(C - \overline{C_{is}}) - \overline{T_p}. \tag{10}$$

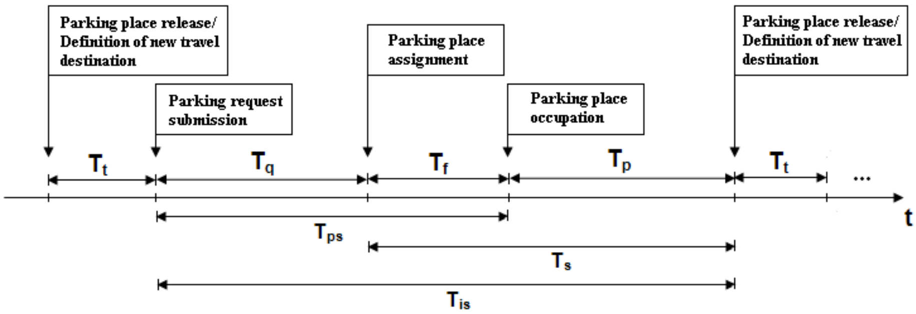


Figure 3: The set of RVs relevant to the parking search process and their time dependence.

G/M/r model approximation. The analysis simplifies considerably when the final leg travel time is negligible compared to the vehicle parking time ($T_f \ll T_p$). In particular, when T_p is exponentially distributed, the main performance measures of the centralized parking space assignment system can be given by the detailed analysis of Sztrik for the $G/M/r$ system, and resemble those of the $M/M/r$ system [11]. The (discrete) probability distribution for the in-system number of vehicles is given by

$$p_n = \begin{cases} \binom{C}{n}\rho^n p_0 & \text{for } 0 \leq n \leq P \\ \binom{C}{n}\frac{n!}{P!P^{n-P}}p_0 & \text{for } P+1 \leq n \leq C \end{cases}$$

with $p_0 = (1 + p_1 + ... + p_C)^{-1}$. The expected number of in-system vehicles and queued parking requests are

$$\overline{C_{is}} = \sum_{i=1}^{C} i \cdot p_i, \; \overline{C_q} = \sum_{i=1}^{C-P} i \cdot p_{i+P} \tag{11}$$

respectively, the time the parking requests are queued is

$$\overline{T_q} = \frac{\overline{C_q}}{\lambda(C - \overline{C_{is}})} \tag{12}$$

and the expected parking search time is still given by Eq. (10).

5. Simulation results and analytical model validation

We show simulation results for all four metrics presented in Section 3.1; we also use them to validate our analytical model. In all cases, the metric values are averaged over all parking events and plotted against the number of vehicles, for fixed number of parking spots.

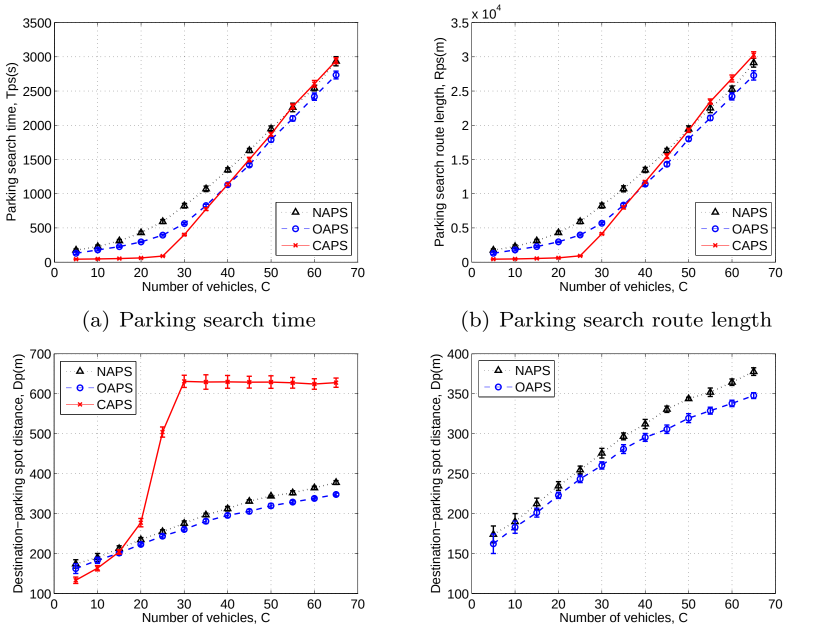
5.1. Uniformly distributed destinations

General trends: Figure 4 compares the three approaches with respect to all three metrics for a fixed number of parking spots, P=25. Intuitively, and for all three approaches, the performance deteriorates with the number of vehicles moving in the city area $\mathcal{A}$. Even when the travel destinations of the vehicles are uniformly spread over this area, their increase results in higher competition for individual parking spots. For NAPS and OAPS, this means that the probability to encounter a vacant spot decreases. Table 1 lists the average number of unsuccessful decisions per vehicle, *i.e.*, how many times on average each vehicle encounters an occupied parking spot while wandering (NAPS) or driving towards a parking spot he became aware of from other vehicles (OAPS). For CAPS, there are no unsuccessful decisions; what increases is the average waiting time for the assignment of a parking spot by the central server. Moreover, the higher competition does not only increase the search/waiting time and the distances that vehicles travel till they eventually park (Figure 4(a) and Figure 4(b)); it also results in the assignment of "worse" parking spots, located further away from the actual user travel destinations.

NAPS *vs.* OAPS: The benefits from information sharing and exploitation become obvious when comparing NAPS with OAPS: the opportunistic system consistently outperforms the non-assisted one for all three metrics, irrespective of the number of vehicles. With NAPS, vehicles spend much of their time wandering "blindly" without even encountering a parking spot, whether vacant or occupied. Whereas with the opportunistic system, the search is more directed and the parking spot encounters more frequent than with NAPS. Increase of the vehicle population leads to: a) higher dissemination rates of information about parking spots amongst the vehicles. The vehicles can therefore make more informed choices as to where they should seek for (vacant) parking spots; b) more competition for the parking spots. Chances are now higher that not only the travel destinations of two or more vehicles are in close proximity but also that vehicles share the *same* information and, depending on their destinations, target the same parking spots. Many of the travels towards these spots prove, in the end, to be useless due to belated arrivals and only add to the total parking search time.

Looking at Figure 4(a) and Table 1, one can see that the tradeoff faster information dissemination versus increased competition is resolved in favor of the opportunistic scheme. With OAPS, the vehicles make much better use of time than with NAPS. Within a given time window, they will discover more parking spots. Some of them will be occupied and on average, as Table 1 suggests, they will end up failing more times than in NAPS. Nevertheless, their persistent directed movement is compensated in that they manage to find vacant parking spots faster than with NAPS.

CAPS: With the centralized approach, two distinct components comprise the overall parking search time: (i) the waiting time, T_q, and (ii) the final leg travel time, T_f (Figure 3). When the vehicles are fewer than or in the order of the parking spots (~ 30), T_f dominates the overall parking search time since



(a) Parking search time
(b) Parking search route length
(c) Destination-parking spot distance
(d) Destination-parking spot distance (zoom-in)

Figure 4: Comparison of the NAPS, OAPS and CAPS approaches: uniformly distributed user destinations, $\overline{T_p}$ = 1800s, P = 25.

there are always one or more vacant spots, where the user can be directed to. As the cars tend to outnumber parking spots, the parking requests in the server's queue start piling up and T_q dominates the overall parking search time (Figure 7).

The second noteworthy remark about the CAPS approach is the tradeoff between the achieved parking search time (route length) and attractiveness of the assigned parking spots (Figure 4(c)). Leaving aside very small vehicle populations, the centralized system consistently assigns parking spots that lie further away from the actual travel destinations, when compared to NAPS and OAPS. For $C > 35$, all 25 parking spots are constantly reserved. Each vehicle is assigned the first place that becomes vacant, which may be located anywhere within the parking area $\mathcal{A}$. Therefore, the average destination-parking spot distance D_p eventually converges to the expected distance of two randomly selected points within a square area; namely, the expected value of the square line picking problem, which is known to equal $0.52 \times l = 624m$, where l denotes the length of the square sides [6].

CAPS *vs.* OAPS and NAPS: More interesting is the way the performance ranking of the three schemes evolves. As Figure 4(a) and Figure 4(b) suggest, their relative performance with respect to parking search time and route length changes twice. CAPS outperforms the two for $C < 40$, then gets worse than the opportunistic scheme and for even higher number of vehicles $C > 55$ loses to NAPS as well. The reason for this behavior is the combination of the reservation mechanism of CAPS and the more random mobility patterns of the vehicles in

Parking search approach	Scenario	Vehicle number					
		5	15	25	35	45	55
NAPS	Unif.Dis.Dest.	0.27	1.55	4.33	9.19	15.18	21.92
NAPS	Hotspot	1.9	8.38	14.26	21.65	28.03	34.4
OAPS	Unif.Dis.Dest.	0.39	2.39	6.04	15.03	26.85	40.22
OAPS	Hotspot	5.6	18.74	31.71	42.46	51.51	63.4

Table 1: Average unsuccessful parking attempts per vehicle for NAPS and OAPS, $\overline{T_p} = 1800$s, P = 25.

NAPS and OAPS.

More specifically, the better (more intensively) the systems manage to use the availability of parking spots, the better they score with respect to T_{ps} and R_{ps}. For the centralized system, Figure 5 suggests that there is a hard bound as to how efficiently this can be done in the light of the reservation system. As the number of vehicles grows, the parking space availability drops. Eventually, they are being reserved immediately after they are released. However, a reserved spot does not necessarily accommodate a stationary vehicle. The final leg travel time, during which the vehicle drives towards the reserved parking spots, is effectively "wasted" for the system. Even worse, this time grows together with the final leg length which converges to $0.52 \times l$ for $C > 35$, as discussed earlier. On the contrary, both the opportunistic and, for a higher number of vehicles, the NAPS approach manage to benefit from their movement in the area and utilize almost fully the parking space availability. In fact, the comparative performance of the systems in this scenario is an argument in favor of self-organization, and rather cooperative self-organization (OAPS).

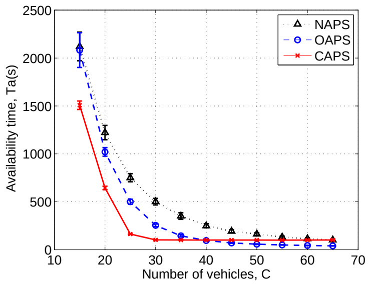
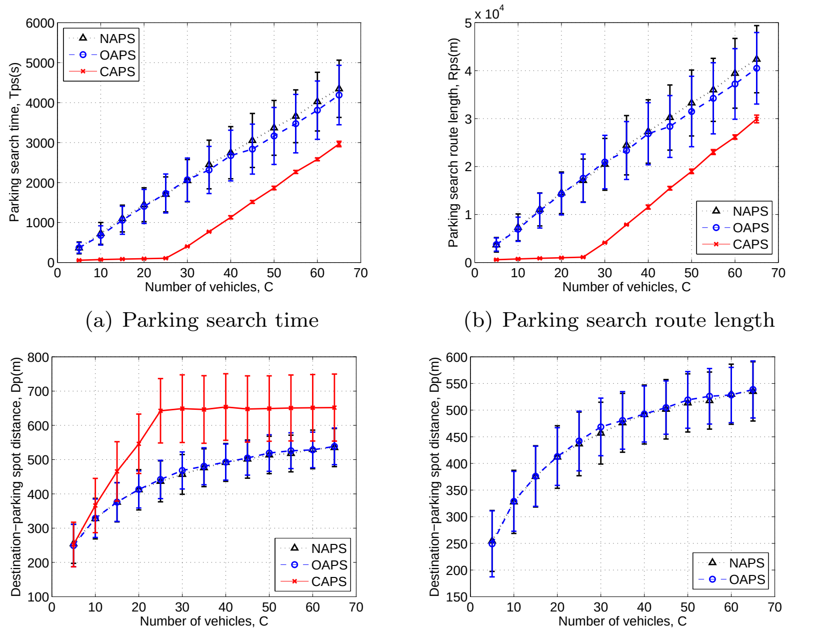


Figure 5: Average time each parking spot remains vacant: uniform distributed travel destinations, $\overline{T_p} = 1800$s, P=25.

5.2. Hotspot scenario

We consider exactly the same setting with Section 5.1, only now the user travel destinations are concentrated within a particular (hotspot) road rather than being distributed uniformly over the area $\mathcal{A}$. In other words, we impose higher correlation in the mobility patterns of individual vehicles and dramatically increase the competition for certain parking spots (those located in the proximity of the hotspot).

General trends: Two are the general remarks that can directly be made when comparing the curves in Figure 6 with those in Figure 4. Firstly, the performance of the non-assisted and opportunistic schemes deteriorates dramatically, whereas the centralized system experiences minimal degradation. Secondly, and closely related to the first remark, the relative ranking of the schemes changes: contrary to what we had when user travel destinations were uniformly distributed, CAPS outperforms NAPS and OAPS throughout the vehicle population range. Moreover, the opportunistic scheme only marginally outperforms the "blind" non-assisted scheme.



(a) Parking search time (b) Parking search route length

(c) Destination-parking spot distance (d) Destination-parking spot distance (zoom-in)

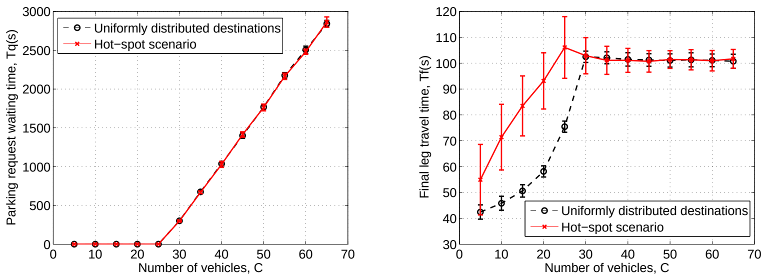
Figure 6: Comparison of the NAPS, OAPS and CAPS approaches: spatially concentrated user destinations (hotspot scenario), $\overline{T_p} = 1800$s, P = 25.

NAPS and OAPS: The correlation in the location of user travel destinations does not affect all parking approaches in the same way. With NAPS, vehicles still wander "blindly", only now this wandering is bounded within a given radius around the popular road. Since the competition for a parking spot is much higher, they encounter more occupied parking spots, as can be seen from the Table 1. Overall, the search time and the route length increase and the vehicles need to compromise with more remote parking spots.

The synchronization artifacts are worse for the opportunistic system. With all vehicles moving in the same area, information about parking spots disseminates even faster and all vehicles end up sharing similar information. And since practically they are all interested in the same set of parking spots, the ranking of parking spots is common for all of them. Therefore, they end up following similar trajectories within the search area and often encounter occupied spots. Even worse, the information they now share is of less "value". Consider one of those vehicles competing for a vacant parking spot in the area around the popular road. The moment it finds one, it occupies it without communicating this to another vehicle. In other words, vehicles share information about *where* relevant parking spots are but less frequently do they become aware of vacant parking spots through information exchanges with other vehicles. Eventually, they may find a parking spot without real help from the system.

The vehicle concentration around the hotspot under NAPS and OAPS also induces congestion. As can be seen in Figure 6(a) and Figure 6(b)[5], when the vehicles grow more, the relationship between the parking search time and route length is no longer linear; vehicles break more often since they encounter more cars ahead of them (ref. Section 3.2). Note that this is different than with uniformly distributed travel destinations, as Figure 4(a) and Figure 4(b) suggest.

CAPS: The centralized approach emerges as the winning approach in the hotspot scenario. The existence of popular destinations has a different impact on the two components of the overall parking search time (see discussion in Section 5.1). The waiting time in the system queue T_q for the parking spot assignment remains practically the same. The central server sees a similar load of parking requests, irrespective of their destinations. Contrary to the other two approaches, having global view over the status of parking spots over the whole area $\mathcal{A}$, it can better resolve competition amongst vehicles and make faster parking space assignments to them. Only this comes at a penalty: the assigned parking spots lie further away from the popular road. This is why the final leg travel time, T_f, significantly exceeds its counterpart under uniformly distributed travel destinations (Figure 7). Even if for high vehicle numbers, the destination-parking spot distance converges to the same value, *i.e.*, the expected value of the square line picking problem. Higher destination-parking spot distances emerge also for NAPS and OAPS, but the penalty is higher for the CAPS system.



(a) Parking request waiting time (b) Final leg travel time

Figure 7: Components of the overall parking search time under CAPS: $\overline{T_p} = 1800$s, P=25.

5.3. *Validation of the analytical model for the CAPS scheme*

In this section, we compare the simulation results with the predictions of the analytical model for the performance of the CAPS approach, as derived in Section 4. We do this for various numbers of vehicles and different values of

[5]These findings for T_{ps} and R_{ps} are confirmed by the measurement of the average vehicle velocity under both the first ($\overline{v}$=10m/s) and the second scenario ($\overline{v}$=9.5m/s).

the expected parking time $\overline{T_p}$, for both parking space distribution scenarios-uniformly distributed and hotspot. Figures 8(a)-8(d) plot the results for $\overline{C_t}$, $\overline{C_q}$, $\overline{C_s}$, *i.e.*, the expected numbers of vehicles travelling towards their destination, waiting for a parking assignment and parked or about-to-park (on their way to occupy a reserved parking spot), respectively; whereas, Figures 8(e)-8(f) depict the expected parking search $\overline{T_{ps}}$. Lines correspond to the model predictions in equations (3)-(4) and (10)-(12), and "x" marks stand for the simulation results. Confidence intervals are also plotted, but in most cases they are too tight to be visible in the plots.

In all cases, the simulation results are in excellent agreement with the model predictions suggesting that the model can give a much faster yet accurate estimation of the centralized system performance. Since the existence of a popular road does not practically affect these performance measures for $C > P$ (ref. Section 5.2), the model can also predict the performance of CAPS for a broad range of parameters in the hotspot scenario.

6. Sensitivity analysis

The additional simulation runs in this section let us study the impact of two parameters upon the performance of the parking search approaches, the mean parking time, and number of parking spots. Moreover, for the OAPS scheme only, we assess the possible performance benefits due to the introduction of additional mobile storage nodes that further leverage the information exchange among vehicles.

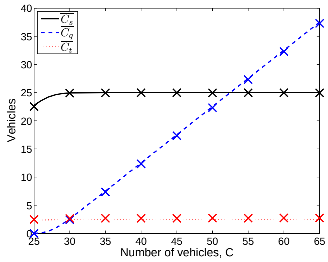
6.1. The impact of the average parking time on NAPS, OAPS and CAPS

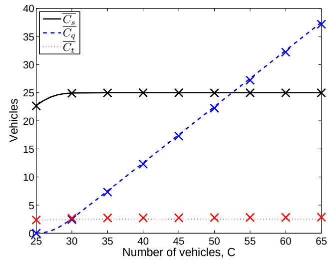
As Figures 9(a), 9(c) and 9(e) suggest, the higher the average parking time interval is, the more vehicles are found parked at each time instance. Vehicles spend more time in search of a parking spot, since they encounter occupied parking spots within their parking area of interest, more frequently.

In particular, the increase rate of the parking search time depends on the redundancy of the available parking choices. For $C < 25$, there is always at least one vacant parking spot so that the increase of the average parking time affects only the location of the respective best parking spot (ref. Section 3.1), for given destination coordinates. On the contrary, when vehicles outnumber

Parking search approach	Average parking time	Vehicle number					
		5	15	25	35	45	55
NAPS	300	0.16	0.63	1.22	1.95	2.81	3.73
OAPS	300	0.21	0.84	1.78	3.10	4.73	6.71
NAPS	600	0.19	0.94	2.04	3.58	5.35	7.42
OAPS	600	0.28	1.30	2.89	5.67	9.32	13.53
NAPS	3600	0.30	1.96	6.77	16.85	29.79	43.76
OAPS	3600	0.40	3.68	9.55	28.37	52.76	78.21

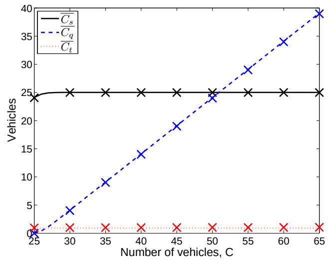
Table 2: Average unsuccessful parking attempts per vehicle for NAPS and OAPS: uniformly distributed travel destinations, P = 25.

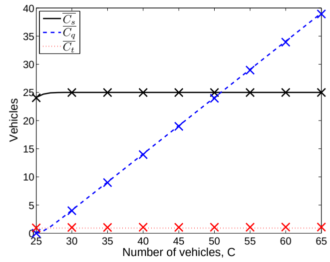




(a) Expected vs. average number of vehicles in different states, $\overline{T_p}$=600s

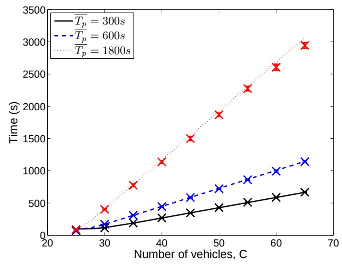
(b) Expected vs. average number of vehicles in different states, $\overline{T_p}$=600s

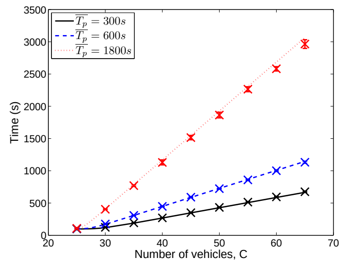




(c) Expected vs. average number of vehicles in different states, $\overline{T_p}$=1800s

(d) Expected vs. average number of vehicles in different states, $\overline{T_p}$=1800s





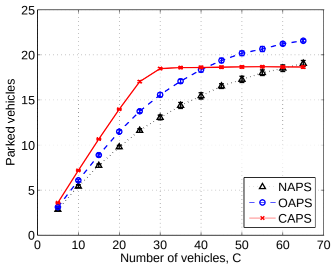
(e) Parking search time, T_{ps}

(f) Parking search time, T_{ps}

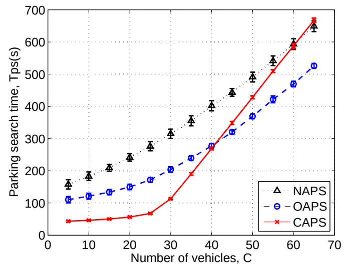
Figure 8: Comparison of the model predictions with the simulation results for CAPS: uniformly distributed user destinations (left) and hotspot scenario (right), P = 25.

parking spots, any additional increase in the average parking time decreases the parking capacity levels at any time instance; and for high parking time values, the first encounter of an empty parking place will delay significantly. Table 2 bears out the aforementioned assertion as it reveals the analogical relation between average parking time and average unsuccessful attempts until parking.

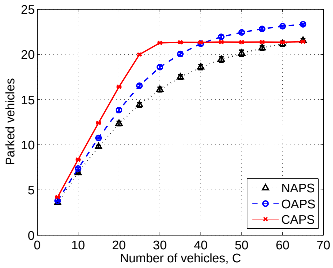
Another noteworthy remark is the invariability of the performance ranking of all three approaches (Figures 9(b), 9(d) and 9(f)). In particular, OAPS outperforms NAPS irrespective of $\overline{T_p}$. Indeed, the improvement factor gradually grows as the $\overline{T_p}$ decreases. However, the intersection point of the three corresponding curves shifts to the left, since the centralized system deteriorates faster with the parking time. Specifically, the increased parking time results in further increase of the first component of the overall parking search time in CAPS, *i.e.*, the waiting time, T_q which presides over CAPS's dramatic parking



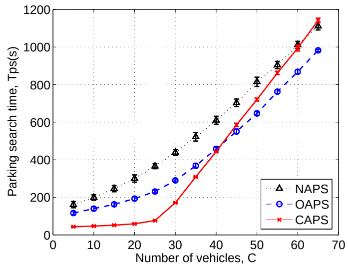
(a) $\overline{T_p}$=300s: Average number of parked vehicles



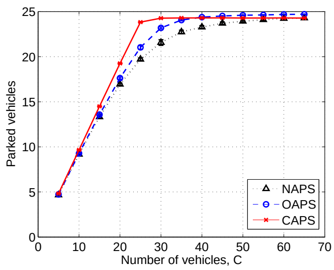
(b) $\overline{T_p}$=300s: Parking search time



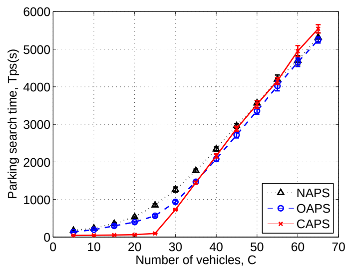
(c) $\overline{T_p}$=600s: Average number of parked vehicles



(d) $\overline{T_p}$=600s: Parking search time



(e) $\overline{T_p}$=3600s: Average number of parked vehicles



(f) $\overline{T_p}$=3600s: Parking search time

Figure 9: Comparison of the NAPS, OAPS and CAPS approaches on different average parking time values: uniformly distributed user destinations, P = 25.

search time deterioration. Specifically, any increase in the average parking time, further delays the vacancy of the occupied parking spots and consequently the serving of the parking requests in the server's queue.

Finally, it is worth stressing that these results assume exhaustive parking search attempts, *i.e.*, attempts that are only terminated upon the detection of an empty parking spot. Nevertheless, there is some evidence that the duration of the parking search process is upper bounded by some time limit T_{up}. For example, ref. [12] reports a T_{up} value equal to 15 minutes; otherwise, the drivers resign from their effort to park, *e.g.*, they might stop looking for a (cheaper or free-of-cost) public parking spot and decide to visit a much more expensive private parking lot. This would practically correspond to a "parking failure event". In our case, as Figure 9 suggests, the T_{up}-min threshold would introduce several parking search failure events while reducing the search delays for those users that are successfully “served”. More generally, T_{up} introduces a tradeoff between number of parking search failures and average search delays of successful parking searches.

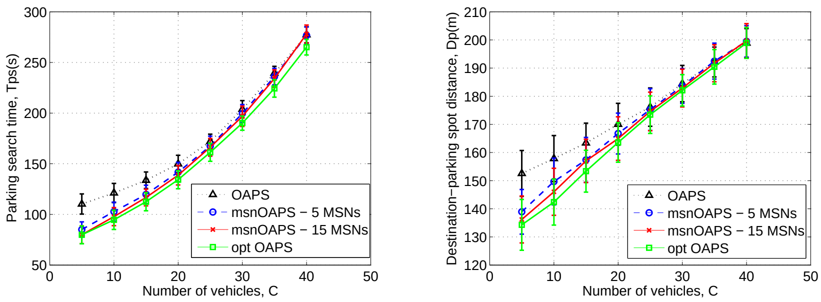
6.2. The impact of mobile storage nodes

6.2.1. Uniformly distributed destinations

The introduction of MSNs increases the contact opportunities between vehicles and thus the speed of information spread. These nodes act as vehicles that travel constantly within the area $\mathcal{A}$ and are not interested in parking. Consequently, the MSNs foster the information diffusion process without introducing additional competition burden.

According to the plots in Figures 10(a)-10(b), even 5 MSNs improve the overall performance, as long as there is some flexibility in the parking assignment process (*e.g.*, low competition). In particular, for $C < 25$, the MSNs indicate potentially unknown to the users alternative parking choices or update the already stored parking information. Indeed, Figure 10(b) suggests that the exploitation of the data collected and transferred by MSNs directs users to more attractive parking spots.

The growth of the MSNs’ population results in further increase of the frequency of the user memory updates. However, the gain obtained from the increased MSN number proves to be important only when the contact / communication probability between vehicles is low. In particular, starting from an improvement rate in the order of 20%, the parking search time improvement is gradually minimized. Furthermore, the Figure 10 includes, additionally, a plot regarding an ideal real time information scheme (plot opt OAPS) that maximizes the speed of information spread and thus the memory update frequency. It emerges that even a few service cars result in time and distance gain comparable to that achieved in the optimal approach.

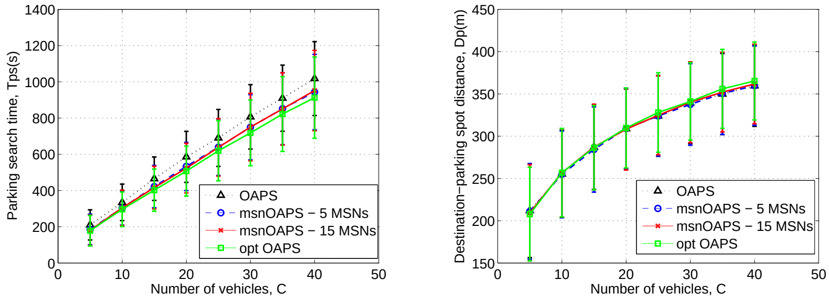


(a) Parking search time (b) Destination-parking spot distance

Figure 10: Study of the impact of the implementation of MSNs on the efficiency of OAPS: uniformly distributed user destinations, $\overline{T_p}$ = 300s, P = 25.

6.2.2. Hotspot scenario

As MSNs circulate constantly, monitoring all parking places within the area considered, they feed users new information that they usually ignore due to



(a) Parking search time (b) Destination-parking spot distance

Figure 11: Study of the impact of the implementation of MSNs on the efficiency of OAPS: spatially concentrated user destinations (hotspot scenario), $\overline{T_p} = 300$s, P = 25.

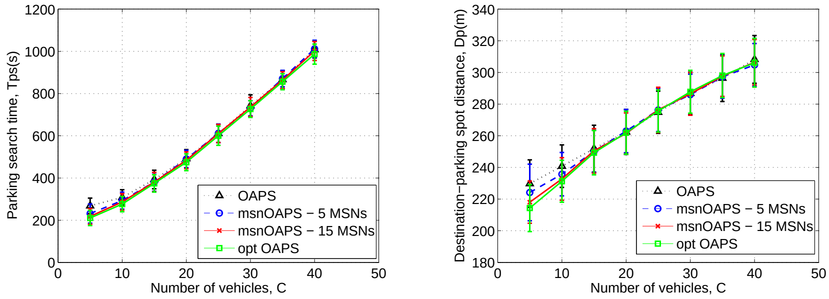
their persistent movement along specific roads. Unlike the uniformly distributed destination case, the improvement factor of the MSN activity over the parking search time varies around a particular ratio ($\sim 8\%$) irrespective of the vehicle volume (Figure 11(a)). For $C < P$, the intensive competition among users for a particular set of parking spots as well as the different movement patterns of vehicles and MSNs diminishe the value of the enhanced information diffusion, against the previous scenario. However, for $C > P$, the need for information is higher now, since vehicles recycle information about only a limited subset of the parking spots, upon their encounters with each other. Finally, as Figure 11(b) suggests, any further increase in the update frequency of drivers' memory does not change the place they park.

6.2.3. Mobile storage nodes and number of parking places

In general, the higher the parking density is, the more alternatives exist for parking space assignment. Since users can occupy an empty parking spot they encounter on their way, the increment in parking places increases the encounter possibility of an empty one, and thus decreases the search time needed (Figures 10(a), 12(a) and 13(a)). Moreover, since parking places and user destinations follow the same uniform spatial distribution, it stands to reason that the increase in the number of the alternative parking choices results in decrease of the average destination-parking spot distance D_p (Figures 10(b), 12(b) and 13(b)). Finally, concerning the msnOAPS approach, the implementation of MSNs nodes is justified when many parking places are offered and the induced competition is less (due to either lower number of parking demanders or less overlapping preferences of parking space).

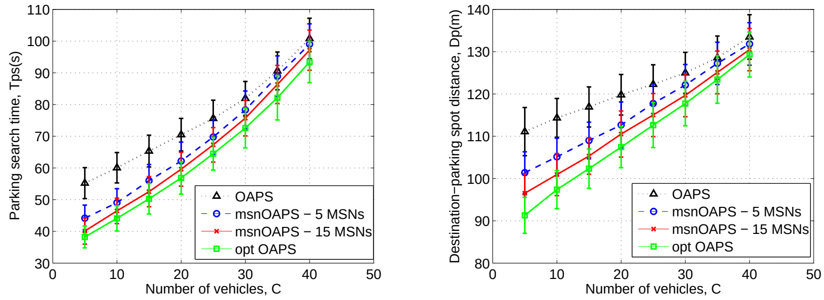
7. Related work

Various aspects of the broader parking space search problem have been addressed in the literature. A multimode system for parking information dissemination, including real-time dissemination through the radio, and non-real-time through newspaper advertisements and leaflets, is considered in [13]. The authors find that it influences considerably travelers' decisions during parking



(a) Parking search time (b) Destination-parking spot distance

Figure 12: Adding mobile static nodes to the OAPS scheme: uniformly distributed user des



(a) Parking search time (b) Destination-parking spot distance

Figure 13: Adding mobile static nodes to the OAPS scheme: uniformly distributed user destinations, $\overline{T_p} = 300$s, P = 50.

search. The user behavior while searching for parking space is also studied in [14], the focus being this time on its impact on traffic flows in urban environments. Closer to our work, a more sophisticated variant of our CAPS approach is introduced in [15]. The scheme monitors and reserves parking places within a city and is shown to better distribute the car traffic volume. Likewise, the authors in [4] present, design, implement, and evaluate a system that generates a real-time map of parking space availability. The map is constructed at a central server out of aggregate data about parking space occupancy, collected by vehicles circulating in the considered area. In a study with broader scope [16], Lu *et al.* propose SPARK for reducing the parking search delay. SPARK consists of three distinct services, *i.e.*, real-time parking navigation, intelligent antitheft protection and friendly parking information dissemination, all making use of a roadside infrastructure. A bandwidth efficient protocol for disseminating parking information has been proposed in [5]. This protocol uses a topology-independent scalable information dissemination algorithm for discovering vacant parking spots and thus it could be paralleled with our OAPS approach. Finally, in [17], a mathematical model for parking lot occupancy prediction, based on disseminated parking data, proves to make considerably accurate a priori estimates on the status of parking spots.

Regarding real-world developed systems, the simplest and most common instances of parking space management are the counters placed at the entry and exit points of parking garages, which keep account of the remaining spare parking space [18]. This information is often displayed on electronic signs-boards located near parking facilities or adjacent highways. Moreover, light parking management systems have already been applied in airports and rail stations in order to ease passengers' parking [18][19].

Our study departs from earlier work in literature in two directions. Firstly, we are interested in the fundamental properties and performance dynamics of the three generic strategies for parking space search. We use both simulation and analysis to compare them and gain additional insights to their advantages and limitations. Secondly, we view them as three distinct paradigms of information management and focus on the way they resolve the tradeoff between information dissemination and competition. Note that this tradeoff is of wider interest in a variety of opportunistic networking settings, where nodes making up the information dissemination layer are also information consumers and compete with each other.

8. Conclusions

We have looked closely into the capacity of vehicular sensor networks to assist the provision of a real-world parking service discovery in city areas. We have compared such an opportunistic system against a centralized scheme, where the sole responsibility for collecting information on parking space availability and deciding on its allocation to vehicles lies with a central server. The two schemes, together with the current-practice unassisted scheme, represent distinct, sometimes even extreme, paradigms as to how spatially distributed and dynamically changing information can be exploited to assist the parking search task.

Our results suggest that no parking search solution can always serve optimally the users' parking expectations. On the contrary, the particular driver preferences, *e.g.*, the distribution of travel destinations, and the density of traffic may dramatically modulate the relative performance of the centralized and opportunistic approaches and give rise to tradeoffs that only the user can resolve.

Specifically, when users (vehicles) tend to travel towards destinations randomly spread in space, the cooperative opportunistic scheme leverages the vehicle mobility and, for moderate-to-high traffic density, can collect and disseminate fast information with broad spatial scope. The benefits from the information diffusion across the vehicles outweigh the increased competition due to overlapping interests in parking spots. On the contrary, the performance of the centralized scheme deteriorates more quickly with the traffic intensity and its reservation system appears to cancel the flexibility of more self-organizing schemes to make use of the spatially distributed parking space resource. This relative performance of the three parking strategies seems to be independent of the average parking time. On the contrary, when traffic concentrates in a smaller section of the area (*e.g.*, a road), the user is faced with a harder tradeoff: either he goes for shorter parking search times and routes and parks his vehicle further away from his travel destination (centralized system); or he prefers to spend much more time and fuel in favor of a parking spot closer to his travel destination (opportunistic scheme). Notably, what he gets in the second case is marginally better than he would achieve by randomly wandering around the area of interest since the information circulated by the opportunistic scheme has highly local scope and ends up leveraging the competition amongst the vehicles. One way to strengthen the dissemination performance of the system without further aggravating competition, is through the introduction of mobile storage nodes. At low competition burden, these dedicated nodes further strengthen the information dissemination overlay and result in more favorable parking space assignments.

We have also introduced an analytical model, drawing on the machine interference problem, for the performance of the centralized parking assistance system. The model yields excellent agreement with simulation results under a wide range of operational scenarios. We are currently expanding this model to scenarios catering for non-cooperative behaviors. Our intention is to repeat the comparison of the two parking search approaches under a richer mix of user behaviors, catering for various expressions of selfishness.

9. Acknowledgements

This work has been supported in part by the European Commission IST-FET project RECOGNITION (FP7-IST-257756) and the Marie Curie grant RETUNE (FP7-PEOPLE-2009-IEF-255409).

References

[1] E. Kokolaki, On different approaches to the parking space search process, Master's thesis, Department of Informatics and Telecommunications, University of Athens, Greece (2010).

[2] I. Carreras, I. Chlamtac, H. Woesner, H. Zhang, Nomadic sensor networks, in: Proc. 2nd European Workshop on Wireless Sensor Networks (EWSN), Istanbul, Turkey, 2005.

[3] A. Wagh, X. Li, J. Wan, C. Qiao, C. Wu, Human Centric Data Fusion in Vehicular Cyber-Physical Systems, in: Proc. IEEE INFOCOM CPNS Workshop, Shanghai, China, 2011.

[4] S. Mathur, T. Jin, N. Kasturirangan, J. Chandrasekaran, W. Xue, M. Gruteser, W. Trappe, Parknet: Drive-by sensing of road-side parking statistics, in: Proc. 8th ACM MobiSys, San Francisco, CA, USA, 2010.

[5] M. Caliskan, D. Graupner, M. Mauve, Decentralized discovery of free parking places, in: Proc. 3rd international workshop on Vehicular ad hoc networks, VANET '06, Los Angeles, CA, USA, 2006, pp. 30–39.

[6] A. Mathai, An introduction to geometrical probability: distributional aspects with applications, Gordon & Breach, Science Pub., The Netherlands, 1999.

[7] L. Haque, M. J. Armstrong, A survey of the machine interference problem, European Journal of Operational Research 179 (2) (2007) 469 – 482.

[8] S. Iravani, V. Krishnamurthy, Workforce agility in repair and maintenance environments, Manufacturing and Service Operations Management 9 (2) (2007) 168–184.

[9] K.-H. Wang, B. Sivazlian, Comparative analysis for the G/G/r machine repair problem, Computers Industrial Engineering 18 (4) (1990) 511–520.

[10] S. Agnihothri, Interrelationships between performance measures for the machine-repairman problem, Naval Research Logistics 36 (1989) 265 – 271.

[11] J. Sztrik, On the finite-source G/M/r queue, European Journal of Operational Research 20 (2) (1985) 261–268.

[12] A. le Fauconnier, E. Gantelet, The time looking for a parking space: strategies, associated nuisances and stakes of parking management in France, in: Proc. European Transport Conference, Strasbourg, France, 2006.

[13] A. Khattak, J. Polak, Effect of parking information on travelers' knowledge and behavior, Transportation 20 (1993) 373–393.

[14] K. Dieussaert, K. Aerts, T. Steenberghen, S. Maerivoet, K. Spitaels, Sustapark: An agent-based model for simulating parking search, in: Proceedings of the 12th AGILE International Conference on Geographic Information Science, Hannover, Germany, 2009.

[15] J. Boehlé, L. Rothkrantz, M. van Wezel, CBPRS: A city based parking and routing system, Tech. Rep. ERS-2008-029-LIS, Erasmus Research Institute of Management (ERIM), University Rotterdam. (2008).

[16] R. Lu, X. Lin, H. Zhu, X. Shen, SPARK: A new VANET-based smart parking scheme for large parking lots, in: Proc. IEEE INFOCOM 2009, Rio de Janeiro, Brazil, 2009, pp. 1413–1421.

[17] M. Caliskan, A. Barthels, B. Scheuermann, M. Mauve, Predicting parking lot occupancy in vehicular ad hoc networks, in: Proc. 65th IEEE Vehicular Technology Conference, Dublin, Ireland, 2007, pp. 277–281.

[18] S. Shaheen, C. Rodier, A. Eaken, Smart parking management pilot project: A bay area rapid transit (bart) district parking demonstration, Tech. rep., Institute of Transportation Studies, UC Davis (2005).

[19] R. N. Charette, Smart parking systems make it easier to find a parking space, IEEE Spectrum Magazine.