A Distributed Markovian Parking Assist System

Mingming Liu, Joe Naoum-Sawaya, Yingqi Gu, Freddy Lecue, and Robert Shorten

***Abstract*— This paper proposes a congestion balancing parking guidance system that suggests to a driver a sequence of streets to follow around the desired destination with the aim to reduce the total distance that is travelled while searching for a free parking spot. The system requires only limited infrastructure information, and neither requires parking spaces to be instrumented, nor vehicles to communicate with each other. Specifically, the system utilizes parking vacancy information on each street. The system also accounts for the added cost of not finding a free space, which is typically expressed as the additional distance that needs to be travelled to find an available parking spot. To avoid local congestion, different drivers respond to different suggestions based on a probability distribution that considers the total distance that needs to be travelled. A mobility simulator is used to model the searching behaviors of vehicles for parking spaces with and without the smart parking algorithm and experimental results are provided using the road network of the city of Dublin, Ireland.**

***Index Terms*— Parking assist system, distributed control, intelligent transportation system.**

I. Introduction

SYSTEMS to assist drivers when looking for a parking space are currently a topic of great interest in a number of academic disciplines [1]. Apart from being of great practical utility, such systems offer great potential in reducing on-street congestion, energy consumption and pollution, in our cities. For instance, [2] indicated in a case study on a small business district in Los Angeles that 730 tons of carbon dioxide where produced and 47,000 gals of gasoline were burned in a year by cars searching for parking. Similarly, another case study by McKinsey [3] reported that the average car owner in Paris for example spends four years of his life searching for parking spaces. Note that in the context of electric vehicles, the cost of searching of parking spaces is exaggerated due to the high marginal cost of wasting battery power. Thus parking guidance systems are becoming an essential part of future sustainable cities.

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At present, a number of different parking guidance systems are available around the world. The most common are information boards displaying the available parking spots at various locations around the city. While the information boards provide valuable guidance to the drivers to avoid areas with potentially limited parking space availability, these systems often lead to localised congestion around areas that have the largest number of available spaces. This is typically due to the fact that all drivers are going to receive identical parking guidance information and it is expected that many drivers choose to go to the areas with a large number of parking spaces which in turn leads to localised congestion of vehicles and an increasing amount of air pollutants in local areas. In contrast to displaying limited information on public boards, advanced systems can provide extensive parking guidance information directly to the drivers either to their mobile devices or to the car. The wealth of information about the parking spaces is provided through the use of an extensive infrastructure that includes sensors that are typically embedded in the streets to monitor the availability of the individual parking spaces. Furthermore, with the deployment of sensors that monitor parking spaces, dynamic pricing of parking spaces has become more widespread in cities as well (e.g. sfpark.org). Such systems thus provide to the drivers the exact location of the currently free parking spaces along with their respective prices.

In this paper, we mainly describe an approach to guide the drivers that are searching for on-street parking spaces. Rather than assuming that individual parking spaces are instrumented, we assume that rough, course gained information, about the availability of spaces in a given area, is available. Specifically, the proposed system mainly requires the availability of information about the probability of finding parking spaces on the streets. Such information is actually readily available can be obtained from the historical data of smart parking meters that are already available in many major cities around the world or it can be evaluated in real time based of flow rate information from loop counters. Thus the proposed system architecture only requires broadcast infrastructure to transmit such probability values, which can easily be enabled through the mobile phones of the drivers or the devices inside the cars. Given such probability values, local in-car computations are then used to suggest to drivers a sequence of the following streets that they should traverse while searching for parking in order to maximize the expected likelihood of finding a parking space. The embodiment of the system described is based on ant colonies optimization which are used to estimate the probabilities of finding a parking space on a particular path.

The remainder of this paper is organized as follows. Related works are provided in Section II. A detailed description of the system model along with the parking search algorithm that is based on an colony optimization are discussed in Section III. The system architecture and implementations based on historical parking data in Dublin city are presented in Section IV. Implementations of the proposed algorithm in the Simulation of Urban MObility (SUMO) packages are discussed in Section V. Finally, a conclusion along with potential future research directions are provided in Section VII.

II. Related Work

Several papers in the literature have discussed parking guidance systems. The commonality among these systems is in providing information to the drivers on the availability of parking places. The focus of such systems can be characterized in two main directions: information collection, and information processing and dissemination.

Information collection is typically based on using the existing infrastructure such as parking meters [4] to predict parking availability. The parking meter data offers rich information that include the street location of the meter where tickets have been bought, the time and date in which tickets have been bought, and the payment amount which indicates the parking duration. From parking meter data, aggregate information on car arrival rates and departure rates and thus expected parking availability can be estimated. While data from parking meters can provide rich insights on parking availability based on existing infrastructure, more accurate information can be obtained by more advanced systems which are often expensive which limits their widespread availability. These systems include in-road sensors or ultrasonic sensors in parking spaces [5]. Such systems offer real-time monitoring and can indicate the exact locations of available parking spaces and can provide very accurate information on car arrival and departure rates and expected parking availability. Crowdsourcing has also been increasingly becoming a common source for parking information [6], [7]. Systems that either rely on user input or smartphone sensors may be used to report parking spots while providing incentives to the contributors of accurate information. The data collection can also be coupled with prediction models to further improve the accuracy of the parking availability forecasts [8].

Information processing deals with the fundamental analytics to process the collected parking information and derive insights for a parking guidance system. For instance, an optimization model is proposed in [9] to determine the optimal information to display on parking information boards so as to minimize queue lengths and vehicle travel. Reference [10] proposed a fuzzy logic based approach coupled with integer programming to design a system to accept or reject parking reservation taking into account vehicle arrival rates. Reference [11] showed that the display of real-time parking availability information reduces the search time of vehicles for parking spaces while [12] developed an optimization model to manipulate the parking signals that are sent to the drivers such as parking availability information with the objective of reducing the time and distances involved in finding a parking-place. Furthermore, [13] highlighted the importance of the parking assignment models in spreading the demand for parking among the available parking spaces to avoid queue buildup. Recently, [14] proposed a system for allocating and reserving parking spaces based on factors that include driving distance to the allocated space, walking distance to the desired destination, parking cost, and the expected traffic congestion. Besides parking guidance systems, other models focus on extracting the factors that affect parking choice [15] while problems in road design such as the allocation of parking spaces to lanes and their impact on travel times and traffic flow have also been investigated [16].

In this paper, we focus on designing a parking guidance system for on-street parking. A main characteristic of the proposed system is that rather than reserving a particular spot for a vehicle that is requesting a parking which is challenging in practice due to enforcement and infrastructure investment, the proposed system provides to the drivers the sequence of the streets to follow to maximize the likelihood of finding a parking space. The novelty of the proposed system is in using the ant colonies metaheuristic to estimate the relative probability of finding a parking space if a driver follows a particular street. The model description and the metaheuristic are described in the following section.

III. Model and Algorithm

The general characteristic of a parking guidance system is that it should be capable to guide vehicles that are simultaneously searching for parking spaces while ensuring fairness among them. In the context of this paper, by fairness we mean that the risk of taking a low probability route (where probability refers to the likelihood of finding a parking space) is in some sense equalized between the searching vehicles. The focus of the system that is proposed in this paper is on street-side parking. As opposed to other systems that focus on parking lots (see [14] for a comprehensive survey), reserving street-side parking for a vehicle that did not arrive yet is generally hard to apply in practice mainly due to the significant investment to instrument the streets. In this paper, we focus on the design of an on-street parking guidance system that recommends a sequence of streets to follow to each driver based on a probability distribution that considers the total distance that needs to be travelled before finding a free parking space. This difference is important as it shows that our system does not require strict parking reservation services.

A. Model Description

Our objective is to find an algorithm that recommends to each driver a sequence of streets to follow in order to maximize the probability along the path in which a free parking space can be found.

To develop this algorithm we require, for each street, the probability of a car finding a parking space and the length of each street. Such statistics can be estimated in many ways. For example from knowledge of total number of parking spaces on a particular street and traffic flow information, from instrumented parking spaces, or from networked data from individual vehicles.

We represent the road network model as a directed graph $G(V, E)$ where the edges E represent the road segments and the vertices V represent the intersections. Each edge $i \in E$ is associated with a cost c_i that is proportional to the cost of not finding a parking on the road segment i. In particular, let c_i denote the length of road segment i (since the vehicle has to travel the whole road segment i if a parking spot is not found on i). We assume that each vehicle is equipped with a communication device (e.g., a mobile phone with access to WiFi/LTE networks) which is able to receive a limited amount of information from the infrastructure.

Let $k \in \{1, 2, \ldots\}$ be a discrete point in time in which new information from the infrastructure can be received and let N denote the total number of vehicles. For each segment $i \in E$, let $\mathrm{N}_i(k)$ denote total number of vehicles that are driving on road segment i at time k. In addition, we assume that each vehicle has a probability q of being a vehicle that is searching for a parking space. This probability is assumed to be the same for all the vehicles and can potentially be estimated from historical data. Let $A_i(k)$ be the number of available parking spaces on road segment i at time k, we can then calculate the probability of finding at least one parking space on road segment i, say $p_i(k)$, for a vehicle that is looking for parking on that road segment at time k as follows:

$$p_i(k) = \begin{cases} 0, & \text{if } A_i(k) = 0, \\ 1, & \text{if } A_i(k) > \mathrm{N}_i(k), \\ \tilde{p}_i(k), & \text{if } 0 < A_i(k) \leq \mathrm{N}_i(k) \end{cases} \tag{1}$$

where $\tilde{p}_i(k)$ is defined as

$$\tilde{p}_i(k) = \sum_{m=0}^{A_i(k)-1} \binom{\mathrm{N}_i(k)}{m} q^m (1-q)^{(\mathrm{N}_i(k)-m)}. \tag{2}$$

The proposed guidance system recommends to a vehicle the next street to follow. Thus the street that is recommended next should not only be based on the probability of not finding a parking spot on that street only but should rather consider the fact that the vehicle might need to travel the full street if no parking spot is found. Thus the cost of not finding a parking space on the recommended street should not be too high, i.e. would not require long detours to find a parking space. Thus in the following section, we propose an approach that accounts for the probabilities of finding/not finding a parking spot along with the travel distances.

B. Ant Colony Optimization

Ideally, all the different paths can be enumerated and the probability of finding a parking space and the corresponding cost are calculated, however this is computationally intractable. Searching for a parking space can be characterized similarly to other activities occurring in nature such as ants searching for a path between their colony and a source of food. Particularly, ant colony optimization is a well known probabilistic swarm intelligence optimization technique that has been successful in dealing with the problems of finding good paths through graphs [17], [18]. The basic idea is that ants wander until they find a source of food and then return home while laying down pheromone. Other ants are likely to follow the pheromone trail and reinforce the pheromone concentration while returning home after finding a food source. Since pheromone evaporates, then the pheromone density is higher the shorter the path is from the food source. For the parking space search, a food source represents an available parking space and the ant home location is the current location of the vehicle. The attractiveness of a car to follow a particular path is then proportional to the amount of pheromone on that path. Thus an ant colonies search approach can be constructed by simulating a large number of ants that start from the home location and travel on the road networks graph $G(V, E)$ until they find a parking spot. The amount of pheromone that is deposited by each ant on the traveled path is proportional to the travel distance of the ant from the home location. Particularly, the pheromone level f_i at edge i is updated as follows

$$f_i(k+1) = \rho f_i(k) + \lambda \frac{1}{\text{path length}} \tag{3}$$

where ρ is a decay factor parameter and λ is a pheromone strength parameter. Both parameters can be adjusted empirically to potentially improve the performance of the ant colony optimization. The path length is the total distance that is travelled by an ant from the source location until an available parking the spot is found, i.e. the sum of the distances of all the edges that are traversed by the ant. As detailed in Section III-A, the length of each edge i that is travelled by the ant is c_i and the probability of finding at least one parking spot on edge i is $p_i(k)$. A sketch of the ant colonies search algorithm is as follows

For Algorithm 1 to be executed, we assume that the parameters $N_i(k)$, q, $A_i(k)$ are available at every intersection of the road network and thus before Algorithm 1 is executed. While, we assume that q is constant and is estimated from past data, the number of vehicles $N_i(k)$ that are on a road segment i along with the available parking spots $A_i(k)$ need to be updated in real-time, i.e. at every time period k.

By running Algorithm 1, the resulting pheromone levels at each of the links indicate the attractiveness of this link for

Algorithm 1 Ant Colony Optimisation (ACO) Algorithm

Initialisation:
Set the time limit T;
Initialise the pheromone level $f_i = 1, \forall i \in E$;
Generate Q number of ants and set the current position of each ant to the home location;
At each node $j \in V$, let $\underline{\mathrm{M}}_j$ be the set of edges that are connected to node j;
Let a_{ij} denote the probability of moving an ant at node j through edge i and set $q_{ij} = \frac{f_i}{\sum_{k \in N(j)} f_k}$ $\forall i \in E,\ \forall j \in V$;
while total time is less than T **do**
  for every ant in Q **do**
    Select an edge i from $\underline{\mathrm{M}}_j$ based on q_{ij};
    Absorb the ant on edge i with a probability $p_i(k)$;
    if the ant is absorbed **then**
      Update f_i for all edges traversed by the ant;
    end if
  end for
end while

finding a parking space. The following section proposes a fair signaling for vehicle guidance based on pheromone levels.

C. Fairness Through Signaling

As discussed earlier, a main advantage of parking guidance systems is to alleviate the congestion that is due to vehicles searching for parking in the same areas which results from the drivers receiving the same signal either by visually observing the streets or based on drivers' perception of the availability of parking spots. To alleviate the congestion, different signals may need to be sent to different drivers although they are searching for a parking spot at the same time and place.

The differentiating signaling is inherent to the guidance system that is proposed in this paper and directly results from the application of Algorithm 1. Particularly, given a vehicle currently at node j, the potential streets that can be travelled next by the vehicle are $\underline{\mathrm{M}}_j$ with each street $i \in \underline{\mathrm{M}}_j$ associated with an attractiveness level f_i as determined by Algorithm 1. Therefore, a signal advising the driver to take street $i \in \underline{\mathrm{M}}_j$ is generated with a probability $q_{ij} = \frac{f_i}{\sum_{h \in \underline{\mathrm{M}}_j} f_h}$ which balances the flow of vehicles to the different streets according to the attractiveness of each street. We note that the proposed signaling strategy is essentially a Markovian signaling strategy. It assumes that drivers honestly respond to recommendations.

The proposed system as described requires considerable information; for example, the number of available parking spaces on each street, the number of drivers searching for parking spaces, and the probability that individual will park at a space he/she detects it. We make these assumptions to develop our model and setup our simulations. Knowing that the availability of such information might not be feasible in practice, Section VI presents results on coarse-grained information that is actually available from the infrastructure, particularly from the smart parking meters that in the City of Dublin.

IV. System Implementation

In this section we discuss the system implementation and the experimental testing. We use the road network from Dublin, Ireland that is obtained from OpenStreetMaps [19] and contains a total of 165646 nodes representing the intersections and 201145 edges representing the road segments (The data can be obtained by contacting the authors).

A. System Architecture

The proposed parking guidance system is implemented in python and is composed of three modules. The first module deals with generating the graph $G(V, E)$ based on finding all the nodes and edges that are within a limited distance around a particular point of interest that is specified using GPS coordinates. In our experimental testing, we consider a maximum distance of 500 meters. The user thus specifies the GPS location of the desired final destination which is then mapped to the nearest node in the OpenStreetMaps data which is designated as the source node for the ant search algorithm.

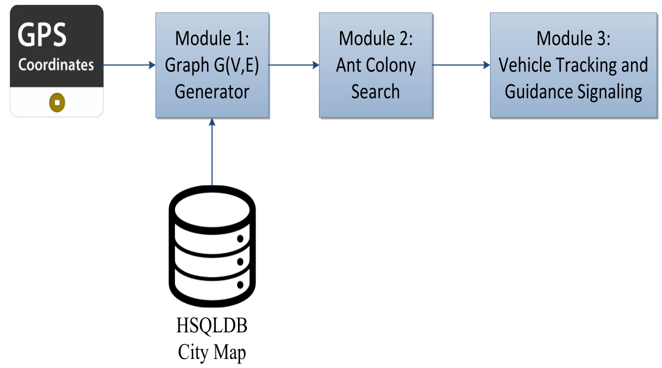


Fig. 1. Schematic diagram of the proposed system architecture.

A depth first search is then executed on the OpenStreetMaps data starting from the source location to find all the nodes that are within 500 meters from the source node. Those nodes are then the set of nodes V. All the edges that connect the nodes in V then constitute the edge set E of the graph $G(V, E)$. The second and main module of the system is the ant search algorithm (Algorithm 1) which is called after the generation of the graph $G(V, E)$.

In our implementation the ant search algorithm is set to run for 30 seconds of CPU time which we believe is adequate for ensuring a good user experience and thus the need to limit the delay between the request for parking and the start of the guidance instructions. After running Algorithm 1 and obtaining the pheromone levels which are translated to probabilities as discussed in Section III-C, Module 3 of the system tracks the user location and provides the guidance instructions. In the actual system implementation, once the a guidance signal is provided to the user, the user location and moving directions are tracked and mapped to the next node on route and Algorithm 1 is rerun to compute new probabilities for the next intersection which will then be used if a parking spot is not found on the current edge. The system architecture is shown in Fig. 1. The main architecture requirements are graph computation, fast data management, and easy deployment and integration. For that, the relational database HSQLDB was chosen since it offers small fast multithreaded and transactional database engine. The process starts when the user requests a parking spot around a particular location. Module 1 then reads the city map from the database and generates the search area and the associated graph $G(V, E)$ which is then passed to Module 2 which computes the attractiveness levels of the roads and the associated probabilities that are then passed to Module 3. Module 3 then tracks the user location and recommends a particular street to follow.

V. SUMO Simulations

In this section we discuss our system implementation in a dynamic simulation environment using a traffic simulator SUMO [20]. SUMO is an open source, microscopic road traffic simulation software package developed by the institute of transportation systems at the German Aerospace Centre (DLR) [20]. We use SUMO to evaluate the performance of our system in different scenarios.

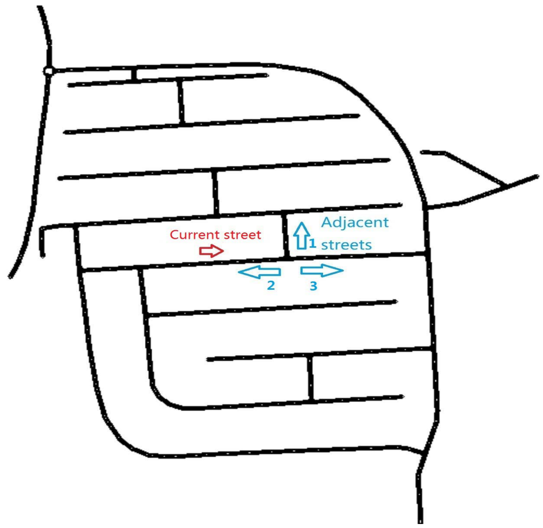


Fig. 2. Tested road network in Dublin city, Ireland.

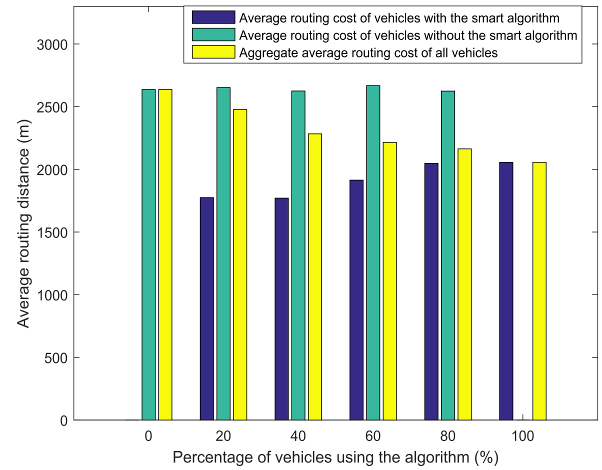


Fig. 3. Averaged routing distance of vehicles with different percentage of vehicles running the algorithm.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Maximum Parking Distance from Destination	500m
Number of vehicle	200
Probability of a vehicle looking for parking	0.5
Number of available parking spots	10 to 50
Simulation Time	10,000s

A. Simulation Setup in SUMO

In this part we evaluate the performance of our algorithm in a realistic traffic scenario in Dublin city, where the mobility of all vehicles is simulated in SUMO. The road network of interest was chosen from an area in the south of Dublin and the network was imported from OpenStreetMap and loaded in SUMO for further simulation and analysis. The diagram of our tested road network is shown in Fig. 2. The Current Street refers to the street that a vehicle is currently traveling while the Adjacent Streets denote the streets that a vehicle can take after arriving to the end of the current street. We note that on some streets it might be possible to go back in the opposite direction as illustrated in Fig. 2 where the current street leads to three adjacent streets. A summary of the simulation parameters is provided in Table I. In the simulations, we assumed that there are 200 vehicles in the area looking for free parking spaces with probability $q = 0.5$. The total number of available parking spaces facilitated in the network is varied between 10 and 50 representing different scenarios. In each scenario, the locations of the free parking spaces are randomly distributed on the road segments at the beginning of the simulation. We also assume that once a vehicle finds a parking space it will be removed from the network, and at the same time a previously occupied parking space is chosen at random and is released (i.e., becomes a free parking space). Additionally a new vehicle is then generated into the network, and we assume that the new vehicle starts from the same starting position of the vehicle that just parked. Accordingly, the number of free parking spaces in the network and the number of vehicles that are searching for a parking spot is always constant. Using this approach, we can easily evaluate the statistical performance of the system based on all the vehicles' trips.

B. Simulation Results in SUMO

In this section we discuss our simulation results. For comparison, we consider four different setups: 1). All vehicles implementing the proposed smart parking algorithm; 2). All vehicles are randomly routed without using the smart parking algorithm; 3). A fraction of vehicles implementing the smart parking algorithm (i.e., the rest are randomly routed); and 4). All vehicles implementing the smart parking algorithm but without congestion signaling (i.e. the vehicles are all routed on the street with highest q_{ij}). The performance of the system is evaluated in terms of the vehicles' travel distance and the environmental impact. In our study, the simulation time of each scenario is set to 10000 time steps (each time step is 1 second).

The simulation results are presented in Figs. 3 - 5. Fig. 3 shows the average travel distance with respect to different percentage of vehicles running the smart parking algorithm with 10 parking spaces available. We notice that, the travel distance is significantly higher for the vehicles that are not running the smart parking algorithm (green bar) compared to those that are using the proposed approach (blue bar). Particularly, when 20% of the vehicles are using the proposed smart parking, the average travel distance is 33% less. When all the vehicles are searching randomly, the average travel distance is 2637 meters while this distance decreases to 2056 meters when all the vehicles use the proposed smart parking approach (22% less). Fig. 3 also shows that the average distance travelled by the vehicles using the smart parking approach increases as the fraction of these vehicles increases. This is rather expected since more vehicles will lead to increased competition for parking. However this increase is still far smaller than the overall gain in distance travelled,

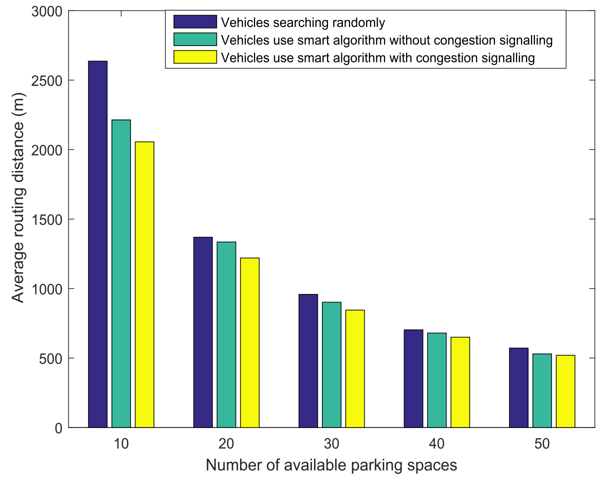


Fig. 4. Averaged routing distance of vehicles with different number of available parking spaces in different setups.

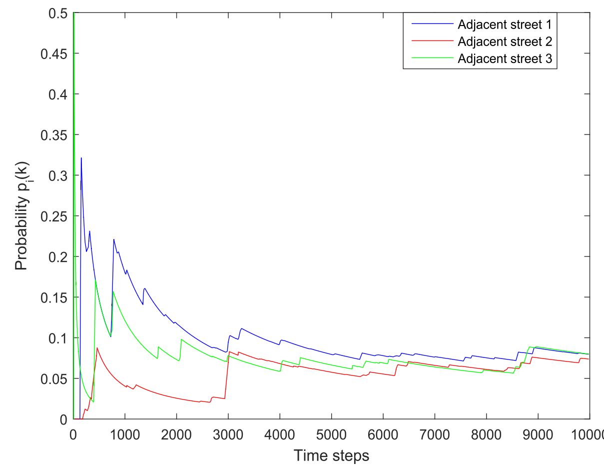


Fig. 5. Evolution of $p_i(k)$ for all connected adjacent streets of a street in centre.

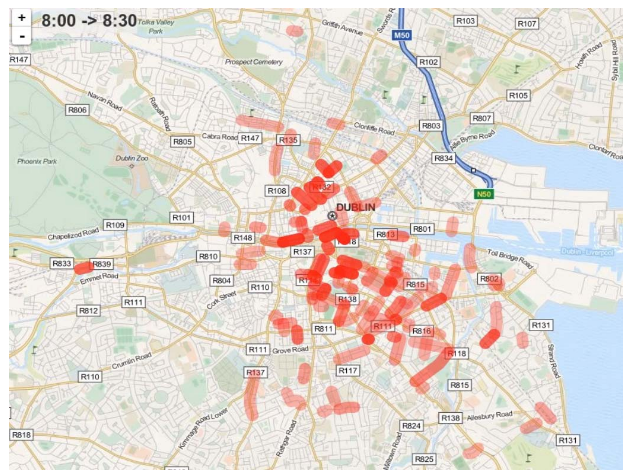


Fig. 6. Parking occupancy heat maps at 7:00-7:30.

and the aggregate average travel distance decreases as more vehicles use the proposed smart parking approach (yellow bar).

For the results that are shown in Fig.4, we conduct three different simulations with different parking search algorithms. In the first (blue bar), all the 200 vehicles are randomly searching for a free parking spot. In the second (green bar), all the vehicles are using the smart algorithm without congestion signaling and finally in the third scenario (yellow bar), all the vehicles are using the smart algorithm with congestion signaling. Fig.4 shows the change in average distance travelled as the number of available parking spaces increases from 10 to 50 and illustrates the value of congestion signaling. While the distance travelled decreases when the smart algorithm is used by the vehicles, we notice that congestion signaling where the vehicles are randomly routed according to the probabilities that are calculated by the ACO algorithm leads to a decrease in travel distance compared to the cases where the vehicles are always routed to the street with the highest probability. This is indeed expected since the vehicles are missing on the parking spaces that are available on the streets with lower probabilities and thus accordingly balancing the routing of vehicles leads to better performance. Finally, as expected, Fig.4 shows that the benefit of using the smart parking approach decreases as the number of available parking spaces increases thus the need for smart parking systems in highly congested cities. The proposed smart parking algorithm also balances the probability of finding a parking space on the street of the networks. To illustrate this, we compute the probability of finding a parking space according to Eq. (1) for the three adjacent streets that are the center of the map (see Fig. 2). The evolution of these probabilities with the simulation time is shown in Fig. 5. We notice that the probabilities for the three streets converge to similar values as the simulation progresses and thus showing the value of the proposed congestion balancing approach.

VI. Historical Parking Data

The previous sections illustrated the efficacy of our algorithm. To further illustrate the value of the proposed smart parking approach, we use real data obtained from smart parking meters from the City of Dublin [21] to further evaluate the proposed approach.

In the area of interest there are 365 smart parking meters that report detailed transaction records that include time of transaction, parking duration, and the total number of parking spaces. We thus obtained the transaction records for the months of October and November 2015 and only used weekday data from 7:00 until 17:00 during which the parking meters are active. The time horizon is then split into 30 minutes time periods and the average number of parked cars during each of the 30 minutes time periods is calculated. Figs. 6 - 9 show snapshots of the number of parked cars in Dublin city at different time of the day. The darker color indicates the higher number of occupied parking spaces. It is evident that the busiest areas of Dublin city are in the city center as shown in the coverage maps.

A. Experimental Testing

To demonstrate the proposed parking guidance, we consider a case where a vehicle is looking for a parking space around its current location at 17 Wellington Road in Dublin.

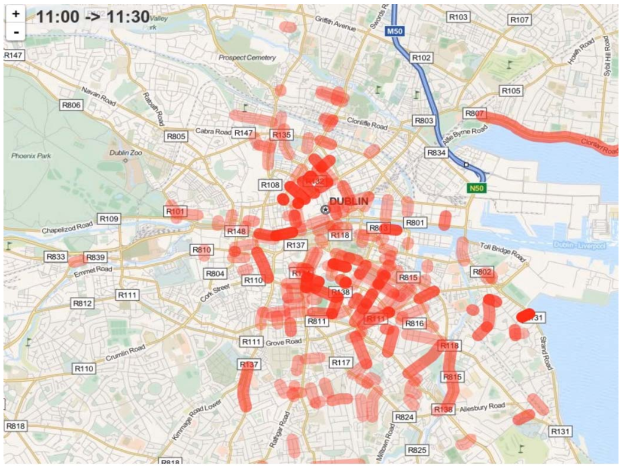


Fig. 7. Parking occupancy heat maps at 11:00-11:30.

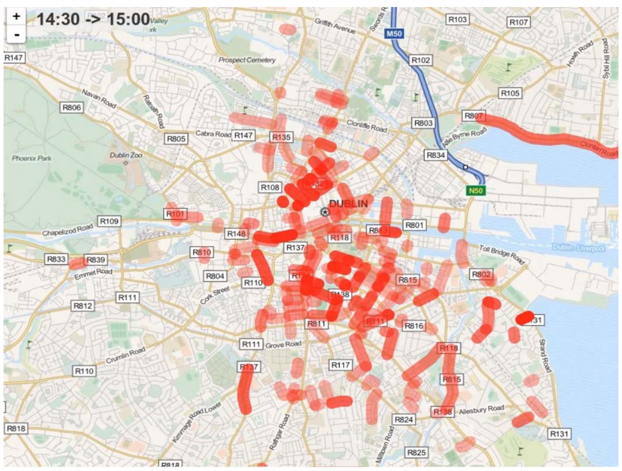


Fig. 8. Parking occupancy heat maps at 14:30-15:00.

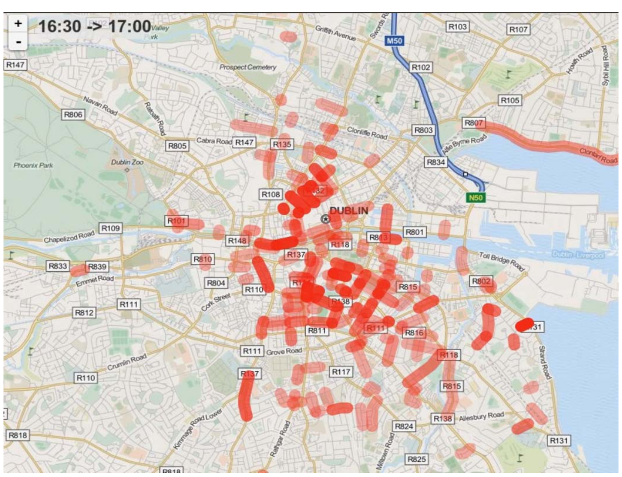


Fig. 9. Parking occupancy heat maps at 16:30-17:00.

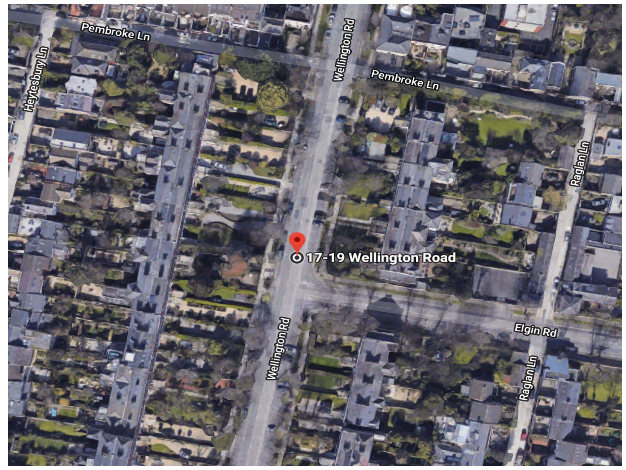


Fig. 10. Parking search example: roads map.

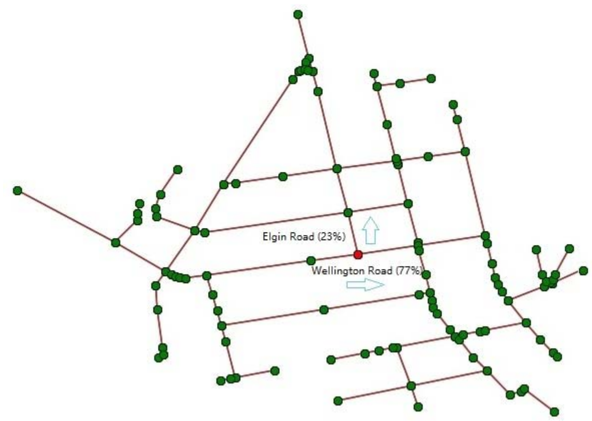


Fig. 11. Parking search example: corresponding graph.

The exact location is shown in Fig. 10. The corresponding graph $G(V, E)$, which indicates the streets that are within the desired distance, is constructed as discussed in Section IV-A and is shown in Fig. 11. Given the vehicle's current location, two options are possible, either continue on Wellington Road or turn on Elgin Road. After running the Ant Search algorithm proceeding on Wellington Road has a probability of 77% while Elgin Road has a probability of 23%. Thus to balance the congestion, the driver will be instructed to proceed on Wellington Road with a probability of 77% and to proceed on Elgin Road with a probability of 23%.

Using a 50 randomly selected locations in Dublin, Fig. 12 and Fig. 13 illustrates the impact of the search area radius and the time limit of Algorithm 1. Fig. 12 reveals an exponential increase in the average CPU time that is required by the depth first search algorithm to construct graph $G(V, E)$ as a function of an increase in the radius of the search area. Nonetheless, a search radius of up to 1000 meters requires less than 1 second of CPU time. The search area radius can thus be a parameter that is set by the vehicle drivers to indicate how far from the final destination they would be willing to park. Finally, Fig. 13 shows that the majority of the change in the probabilities of the routing recommendations are due to the first 30 seconds of computations of Algorithm 1. Increasing the time limit from 5 seconds to 30 seconds leads to an average change of 42% in the probabilities while increasing the time limit from 30 seconds to 35 seconds leads to an average change of less than 3% on average. Thus the recommendation is to set the

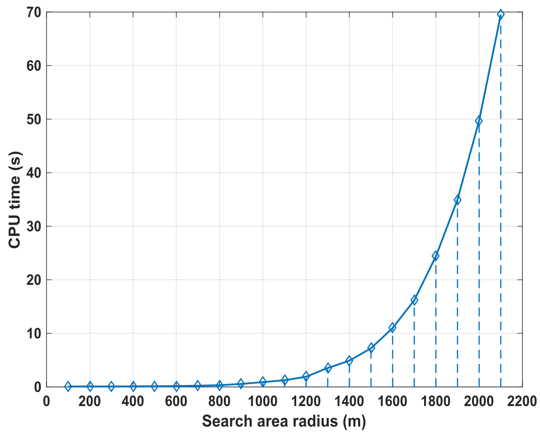


Fig. 12. Computational performance of the depth-first search as a function of the search area radius.

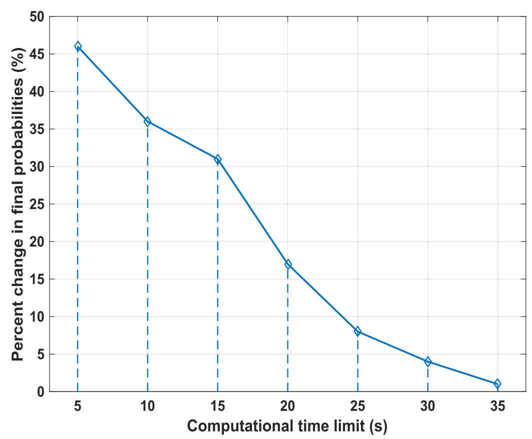


Fig. 13. Percentage change in the guidance probabilities as a function of the time limit of Algorithm 1.

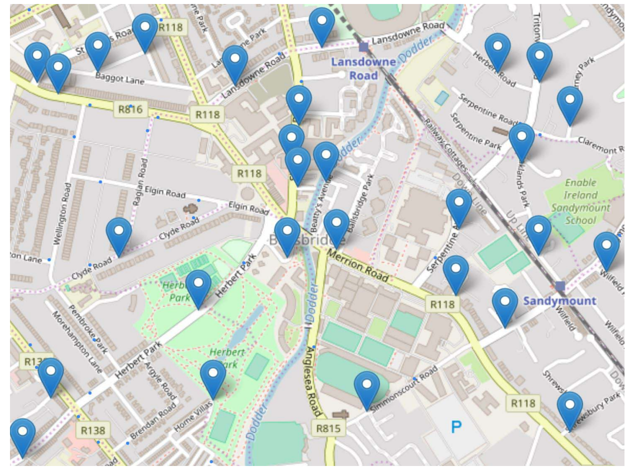


Fig. 14. Map of balls bridge area in dublin with the locations of smart parking meters.

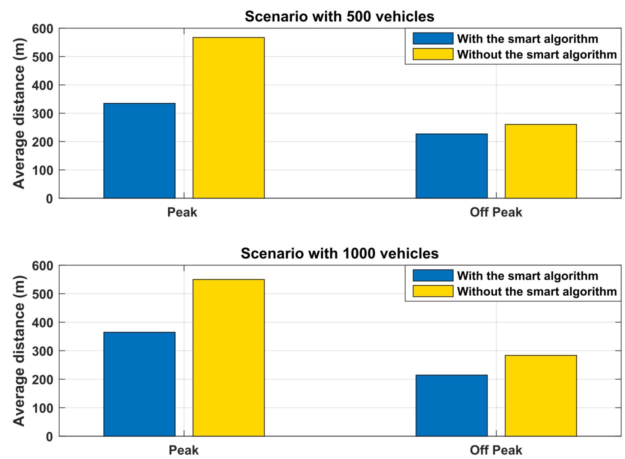


Fig. 15. Comparison of distance travelled to find a parking spot.

search area of the proposed parking guidance system to less than 1000 meters and a 30 seconds time limit for Algorithm 1.

It is important to note that the study presented in this section is based on static parking information. Such a study is valid only if we assume a decoupling from the parking density and the operation of the vehicles; namely if only very few vehicles are operating the algorithm. We note again that the objective in presenting this data is to illustrate the computational complexities of the algorithm and that the algorithm can be implemented using readily available coarse-grained information. Of course in any real implementation the algorithm would operate based on dynamically changing parking information. The effect of communication and routing delays on the algorithm are beyond the scope of the present paper.

B. Simulations Based on Historical Data From Dublin

To further evaluate the impact of the proposed parking guidance system, this section presents comprehensive simulation results using the historical parking occupancy data from the City of Dublin. Particularly, we evaluate the performance of the proposed parking guidance system using two traffic density patterns. The first is a low traffic density with 500 vehicles while the second is a high traffic density with 1000 vehicles. Furthermore, we consider that 10% of the vehicles are searching for a parking spot while the remaining vehicles are just driving through the area. For the vehicles that are searching for a parking spot, 50% are using the proposed smart parking guidance system. Futhermore, for each traffic density scenario, we consider two parking occupancy levels: off-peak which indicates a low parking occupancy based on the historical data from the City of Dublin and peak time which indicates high parking occupancy. The area in Dublin that is considered along with the actual locations of the smart traffic meters is shown in Fig. 14. Finally, we assume that once a vehicle parks, that vehicle will remain parked for the rest of the simulation and no other parking spot is released. The simulation time is fixed to 1000 seconds.

The results that are shown in Fig. 15 show that the vehicles that use the smart parking guidance system travel significantly less to find a parking spot compared to the remaining vehicles. Particularly, this difference is larger for the peak hours which is rather expected since as parking spots become scarce, the smart guidance leads to increasing benefits while when several parking spots are available, less guidance is needed to find a free parking spot. We also note that in both cases of high and low traffic densities, the reduction in travel distance

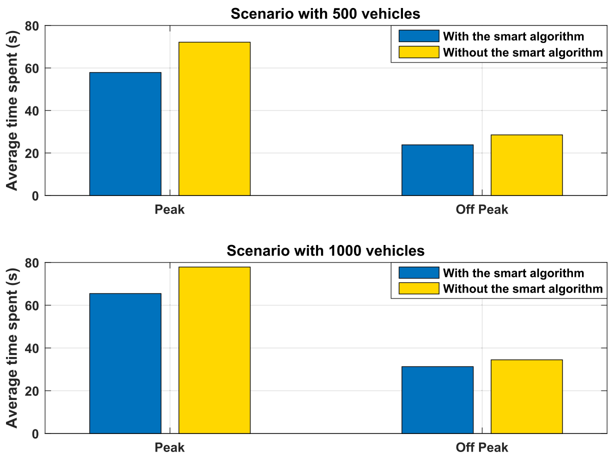


Fig. 16. Comparison of time spent to find a parking spot.

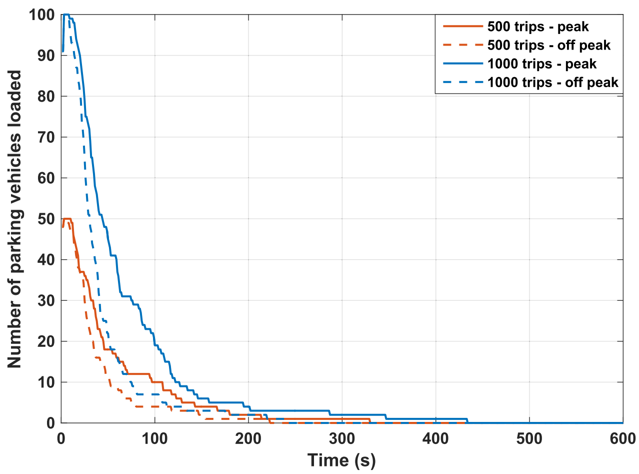


Fig. 17. Number of vehicles looking for parking in peak vs off-peak hours.

is significant when smart guidance is employed with a small increase in benefit for the case of high traffic density which is expected due to the increasing demand for parking.

Similar to travel distance, Fig. 16 shows a significant difference in the amount of time spent to find a free parking spot between the vehicles that use the smart guidance and others with the advantage for the guided vehicles. These results illustrate the value of the proposed guidance system in reducing travel time and distance which potentially leads to several societal and environmental benefits.

Finally to illustrate the impact of the proposed guidance system in peak vs. off-peak hours, Fig. 17 shows the evolution of the number of vehicles that still did not find a parking spot after a certain point in time. As shown in Fig. 17, in both cases of traffic densities, the vehicles that are looking for a parking spot drops quickly and a majority of the vehicles find a parking spot in less than 100 seconds with very few vehicles remaining after 300 seconds of search time. This is a consistent for both peak and off-peak hours and as expected, vehicles park faster in off-peak hours.

C. Dynamic Parking Space Availability

In the previous section, we evaluated the performance of our algorithm based on static parking data. To further illustrate the efficacy of our proposed algorithm in a more realistic setting, we now take into account the dynamic changes in the parking availability during the search process at different time slots in a day and account for the dynamic changes in the parking availability during the search process.

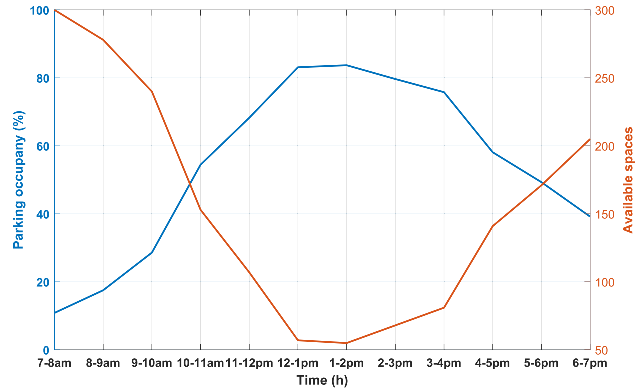


Fig. 18. Occupancy rate and parking availability at different time slots of a day.

Using the historical dataset that was obtained from the City of Dublin, we estimated the occupancy rate for parking spaces for 1 hour time periods throughout the day in the Balls Bridge area of Dublin as well as the number of available parking spaces. The occupancy rates along and the number of available parking spots that are summarized in Fig. 18 show that parking occupancy is at its lowest in morning time periods (7-8am) and then consistently increases until it peaks in the periods from 12 to 2pm and then decreases with a sharp drop after 4pm. Not surprisingly, parking occupancy rate coincides with typical business hours that often start at 8am and end at 4pm. Using this setup, we obtain statistics on the clearing times of the vehicles, i.e. the time it takes a vehicle to find a free parking spot in each interval of the day.

This setup is implemented in SUMO and we assumed that there are 100 vehicles searching for parking spaces at different time slots during a day. For each time slot, we fixed the total number of free spaces on the streets, and we implemented 20 independent simulations. Each simulation is then repeated twice, once with the vehicles using the proposed parking search algorithm and a second time with the random search for parking. Each simulation is terminated when all vehicles have found parking spots.

The results are summarized in Fig. 19 which illustrates the average parking time for all vehicles (and error interval). Fig. 19 shows that the smart parking search algorithm consistently outperforms random search for parking for all the time periods of the day. Evidently, when the occupancy rate is low (high number of available parking spaces), the difference in performance between smart parking search and random parking search is small. The value of smart parking search is when parking spots are scarce such as during 12-2pm time periods. Fig. 20 which shows the difference in average parking time between random search and smart parking search reveals that during peak hours, the difference in parking time is about 1 minute per vehicle on average.

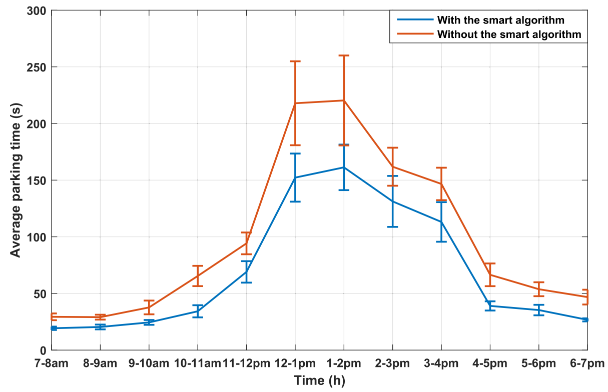


Fig. 19. Comparison of the average parking time for 100 vehicles, with/without using the smart algorithm, at different time slots of a day.

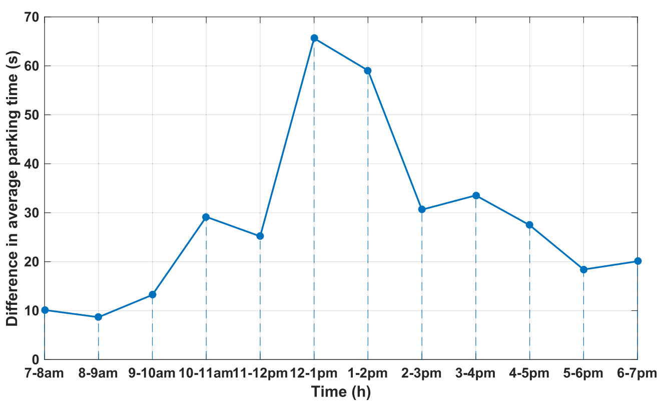


Fig. 20. Difference in average parking time with/without the smart algorithm.

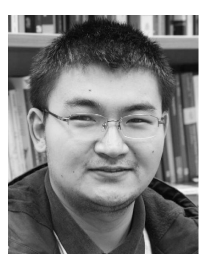
VII. Conclusion

This paper proposes a parking guidance system focusing on street side parking. As opposed to many advanced systems that require expensive infrastructure to enforce parking spaces reservations before vehicles' arriving, the proposed system only requires limited information regarding the probability of finding parking spaces on the streets. Such data can be obtained either from historical data of smart parking meters in a relatively static manner, or dynamically through real-time feedback of probabilities via the increasingly available infrastructure to vehicle communication. We discuss and present our system implementations in both cases in the paper. Finally the recommendations that are relayed to the drivers account for congestion balancing.

In future work, a spatio-temporal analysis of the various factors that impact the availability of parking spaces may improve the outcome of the proposed system in reducing the amount of time before a parking spot is found. Furthermore, multi-vehicle collaborative algorithms where a vehicle learns from the trajectory of other vehicles that are searching for parking may provide improving performance and will be enabled through the future availability of vehicle-to-vehicle communication.

References

[1] T. Lin, H. Rivano, and F. Le Mouël, "A survey of smart parking solutions," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 12, pp. 3229–3253, Dec. 2017.
[2] D. C. Shoup, "Cruising for parking," *Transp. Policy*, vol. 13, no. 6, pp. 479–486, 2006.
[3] W. Elfrink and R. Kirkland, *The Smart-City Solution*. New York, NY, USA: McKinsey, 2012.
[4] M. Caliskan, A. Barthels, B. Scheuermann, and M. Mauve, "Predicting parking lot occupancy in vehicular ad hoc networks," in *Proc. IEEE 65th Veh. Technol. Conf. (VTC-Spring)*, Apr. 2007, pp. 277–281.
[5] M. Dohler, I. Vilajosana, X. Vilajosana, and J. LLosa, "Smart cities: An action plan," in *Proc. Smart Cities Congr.*, Barcelona, Spain, 2011, pp. 1–6.
[6] X. Chen, E. Santos-Neto, and M. Ripeanu, "Crowdsourcing for on-street smart parking," in *Proc. 2nd ACM Int. Symp. Design Anal. Intell. Veh. Netw. Appl.*, 2012, pp. 1–8.
[7] J. Kopecký and J. Domingue, "ParkJamJAM: Crowdsourcing parking availability information with linked data," in *Proc. Extended Semantic Web Conf.* Berlin, Germany: Springer, 2012, pp. 381–386.
[8] F. Caicedo, C. Blazquez, and P. Miranda, "Prediction of parking space availability in real time," *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7281–7290, 2012.
[9] R. G. Thompson, K. Takada, and S. Kobayakawa, "Optimisation of parking guidance and information systems display configurations," *Transp. Res. C, Emerg. Technol.*, vol. 9, no. 1, pp. 69–85, 2001.
[10] D. Teodorović and P. Lučić, "Intelligent parking systems," *Eur. J. Oper. Res.*, vol. 175, no. 3, pp. 1666–1681, 2006.
[11] F. Caicedo, "The use of space availability information in 'PARC' systems to reduce search times in parking facilities," *Transp. Res. C, Emerg. Technol.*, vol. 17, no. 1, pp. 56–68, 2009.
[12] F. Caiced, "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, 2010.
[13] B. J. Waterson, N. B. Hounsell, and K. Chatterjee, "Quantifying the potential savings in travel time resulting from parking guidance systems—A simulation case study," *J. Oper. Res. Soc.*, vol. 52, no. 10, pp. 1067–1077, 2001.
[14] J. H. Shin and H. B. Jun, "A study on smart parking guidance algorithm," *Transp. Res. C, Emerg. Technol.*, vol. 44, pp. 299–317, Jul. 2014.
[15] P. Bonsall and I. Palmer, "Modelling drivers' car parking behaviour using data from a travel choice simulator," *Transp. Res. C, Emerg. Technol.*, vol. 12, no. 5, pp. 321–347, 2004.
[16] H. Ceylan, O. Baskan, C. Ozan, and G. Gulhan, "Determining on-street parking places in urban road networks using meta-heuristic harmony search algorithm," in *Computer-Based Modelling and Optimization in Transportation*. Cham, Switzerland: Springer, 2014, pp. 163–174.
[17] M. Dorigo, "Optimization, learning and natural algorithms," Ph.D. dissertation, Dept. Electron., Polytech. Univ. Milan, Milan, Italy, 1992.
[18] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theor. Comput. Sci.*, vol. 344, nos. 2–3, pp. 243–278, 2005.
[19] M. Haklay and P. Weber, "OpenStreetMap: User-generated street maps," *IEEE Pervasive Comput.*, vol. 7, no. 4, pp. 12–18, Oct. 2008.
[20] *Simulation of Urban Mobility*. Accessed: Apr. 1, 2015. [Online]. Available: http://www.sumo-sim.org
[21] R. Cogill *et al.*, "Parked cars as a service delivery platform," in *Proc. IEEE Int. Conf. Connected Vehicles Expo (ICCVE)*, Nov. 2014, pp. 138–143.



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