Congestion Mitigation in Urban areas using Ridesharing and Street Parking Guidance Systems

BY

SANDEEP SASIDHARAN

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Civil Engineering
in the Graduate College of the
University of Illinois at Chicago, 2017

Chicago, Illinois

Defense Committee:

Professor Jane Lin, Civil and Materials Engineering, Chair and Advisor

Professor Ouri Wolfson, Computer Science, Co-advisor

Professor Bo Zou, Civil and Materials Engineering

Dedicated to my parents

ACKNOWLEDGEMENT

I would like to express my deep gratitude to my advisors, Professor Jane Lin and Professor Ouri Wolfson for their continuous support and guidance since my admission to the program. I could never accomplish this dissertation without their help. Under their guidance, I have also learnt extremely useful lessons in problem solving, analysis and presentation.

I would also like to express my sincere thanks to Prof. Bo Zou for his valuable comments and suggestions to my dissertation.

I am also grateful to my family, colleagues, and friends for their support and encouragement. Thank you to my fiancée Archana, for all her love and care. Finally, I would like to thank the Department of Civil and Materials Engineering, Department of Computer Science and National Science Foundation for their generous funding.

CONTRIBUTION OF AUTHORS

Part I represents a published manuscript (Lin et al. 2016) for which I was the primary author and developer of the simulation software, and Dr. Wolfson, Dr. Lin and Dr. Ma contributed to the writing of the manuscript, research and setting up the experiments. Part II represents a mobile software for which I was the software designer and developer. Dr. Xu and Dr. Ma helped me with providing data and parking detection software (UPDetector). Dr. Wolfson contributed to software review and field demonstrations.

SUMMARY

Congestion is a prevalent problem in almost all urban environment impacting numerous features of urban living. Increased number of vehicles and lack of parking spaces in the cities contributes to traffic congestion, fuel loss and adversely affects the sustainability. Ridesharing is a proven technique that can mitigate traffic congestion and satisfy urban commuters. Getting a taxi in highly congested areas (e.g. airports, conferences) is both time consuming and expensive. Chicago Tribune reports that wait at Chicago O'Hare International airport for taxi cabs can be as long as 45 minutes. Finding a parking space during peak time in a city is also frustrating and increases congestion in urban areas. This thesis addresses the traffic congestion problem in urban areas in two aspects: reducing the number of vehicle trips by proposing RSVP, a ridesharing system that uses walking and virtual pools, and reducing unwanted vehicle cruising (and thus vehicle miles traveled) for parking on urban streets by proposing Perfect Park, a low power smartphone application that helps cruising drivers to find and navigate to a parking space. In Part I of this thesis, RSVP ridesharing scheme is described with focus on a ridesharing model that involves walking, ridesharing algorithms, and evaluation of the model and algorithms using a database that recorded real taxi trips in NYC. In Part II of this thesis Perfect Park is introduced and its system level design, evaluation and performance are discussed.

Contents

List of Figures

List of Algorithms

Chapter 1

Introduction

(Previously published as J. Lin, S. Sasidharan, S. Ma and O. Wolfson, "A Model of Multimodal Ridesharing and Its Analysis," *2016 17th IEEE International Conference on Mobile Data Management (MDM)*, Porto, 2016, pp. 164-173)

This chapter briefly describes the background, motivation for the research, contributions and the thesis outline. Chapter 1 introduces RSVP, a ridesharing scheme (published manuscript (Lin et al. 2016)) and Perfect Park, a smartphone based parking guidance application.

1.1. Background

Congestion is a prevalent problem in almost all urban environment impacting numerous features of urban living. It is also one of the key reasons that transportation sector is the second largest contributor of U.S. greenhouse gas emissions, accounting for about 26% of total GHG emissions (Anbarani et al. 2016). (Schrank and Lomax 2002) reports that congestion in 75 major urban areas amounts to $68 billion per year in fuel and time losses to the travelling public. One of the promising techniques that fulfills people’s need in commuting and consequently reducing traffic congestion is ridesharing (Ma, Zheng, and Wolfson 2015). It has been recognized that sustainability in city logistics involves parking related activities as well (Whiteing, Browne, and Allen 2003). Modern day service industry is highly focused on ensuring enhanced mobility experience to the public not only through better service but also by providing facilities that would make the customer feel more flexible, more economical and more satisfied.

1.1.1. Ridesharing

Getting a taxi in highly congested areas (e.g. airports, conferences) is both time consuming and expensive. Chicago Tribune reports that wait at in Chicago O'Hare International airport for taxi cabs can be as long as 45 minutes (Hilkevitch 2015). While the emergence of novel Transportation Network Companies (e.g. Uber) has helped increase the supply of drivers during peak times, they have done little to reduce congestion in hubs such as airports, major stations, and stadiums. Creative on-demand transit service is needed more than ever to capture the benefits of the smartphone and health-consciousness revolutions.

This dissertation proposes RSVP (Ride Sharing by Virtual Pools), a ridesharing system based on walking and virtual-pools, aimed mainly at transportation hubs. The RSVP scheme combines in a unique way three existing mechanisms: virtual queues, slugging (i.e. walking for the purpose of ride-sharing), and multiple-drop-off ride-sharing. Assume a designated taxi ride-sharing pickup location at a hub H (e.g., airport, train station), with virtual ride-sharing demand pools associated with time-intervals. For example, a virtual pool of ride-sharing passengers will be picked up between 11:00am and 11:05am, followed by another pool to be picked up between 11:05am and 11:10am, etc. Initially, each pool consists of a number n of trips, which after merging will be reduced to m merged (or ride-sharing) trips. m should not be allowed to grow beyond the number of taxi-pickups that can occur at a specific curb location during the time-interval associated with the pool (e.g. 5 minutes).

Upon arriving at the hub H using another mode of transportation (e.g. a plane), a passenger expresses interest in taxi-ridesharing by specifying her trip and electronically enrolling it into a pool, e.g. the 11:00-11:05 pool. The trip specification indicates the destination, and the bounds on walking and delay times that the passenger is willing to tolerate in order to enable ride-sharing. It is envisioned that the passenger will register the trip in the earliest pool that allows enough time to walk from the arrival location to the ride-sharing pickup location. For example, if the passenger deplanes at 8:00am, and it takes 10 minutes to walk from her arrival gate to the ride-sharing pickup location, then the passenger will enroll her trip in the 8:10–8:15am pool. A pool closes, say, one minute before its start-time, or when it is full, whichever occurs first.

After a pool P closes, a MatchMaking (MM) system is run on the set of n trips in the pool, creating a smaller set of m merged trips, each of which will be served by a single taxi. Each merged trip may consist of multiple drop-off points of the ride-sharing passengers. The selection of drop-off points must satisfy the walking and delay time constraints specified by the passengers. Because the pick-up and drop-off points in RSVP may differ from the passenger's actual origin and destination respectively within a tolerable walking distance, RSVP incorporates slugging (Ma and Wolfson 2013).

The proposed scheme benefits travelers, businesses, and municipalities. Travelers can check in remotely, thus are freed from standing in a physical line, and can save money by ride-sharing. Businesses benefit from travelers free to spend money instead of standing in line. Municipalities benefit from reduced vehicle-miles-traveled, congestion, and emissions.

1.1.2. Parking Search

Finding an on parking space in urban areas at peak hours is often not an easy task. Therefore a well implemented parking management system becomes important in addressing the overall sustainability of the urban parking activities. A prior study (S. Mathur, T. Jin, N. Kasturirangan, J. Chandrasekaran, W. Xue and Gruteser 2010) found that in one area of Los Angeles vehicles searching for parking produced 730 tons of carbon dioxide, and burned 47,000 gallons of gasoline over one year. Fortunately, detection technologies are advancing, which makes it possible to detect the availability of certain parking spots in some cases. Solutions for fully automated indoor and outdoor car parking has been discussed in (Lan and Shih 2014; Alasaadi et al. 2013; Liu et al. 2012). This dissertation discusses the study and implementation of a low power parking guidance system in chapter 3.

1.2. Contributions

This dissertation presents the design and implementation of two systems that focus on assuaging the urban congestion.

1.2.1. Ridesharing system

The proposed ridesharing scheme differs from existing taxi ridesharing studies in two aspects. First it applies the virtual queue concept to create ride-sharing pools and efficiently manage the ride-sharing demand. Second it considers *SLuggIng-Multiple-drop-off (SLIM)*, a hybrid form of ride-sharing that combines slugging (Ma and Wolfson 2013) and multiple-drop-off ride-sharing (Gidofalvi et al. 2008),(Ma, Zheng, and Wolfson 2015),(Santi et al. 2014),(Tian et al. 2013). The research formally prove that this increases the ride-sharing opportunities.

In summary, the contributions of the proposed ridesharing scheme can be summarized as:

1. The SLIM (SLuggIng-Multiple-dropoffs) ridesharing problem is formalized and mathematically proved that some trips are shareable only if they allow slugging.
2. Efficient algorithms are proposed, including a performance-improvement technique based on Euclidean filtering, for producing a SLIM ride-sharing plan on a virtual pool.
3. The ridesharing scheme is evaluated with a database of real taxi trips in NYC, and demonstrate that it produces savings of 25-40% in terms of the total number of trips.
4. Benefits of adding walking to multiple-drop-off ride-sharing are quantified.

1.2.2. Parking guidance system

The parking navigation system is an Android based smartphone application that utilizes low energy techniques to provide turn by turn voice navigation instructions to the user upon request. This OpenStreetMap based mobile application make use of the concept of geofences (virtual boundaries) and eliminates unnecessary polling of GPS data thereby reducing battery consumption. The application is also designed to require minimum user interaction.

1.3. Thesis Organization

The rest of thesis are presented as follows: In Part I of this thesis, RSVP ridesharing scheme is described with focus on a ridesharing model that involves walking, ridesharing algorithms, and evaluation of the model and algorithms (Chapters 2 to 5). In Part II of this thesis, Perfect Park smartphone application for parking guidance is introduced and its system level design, evaluation and performance are discussed (Chapter 6).

Chapter two presents the literature review on ridesharing techniques

Chapter three explains the theoretical and mathematical background of the systems developed for ridesharing and the efficiency assessment of the system.

Chapter four describes the ridesharing system experimentation and evaluation process

Chapter five discusses the various results and performance of the proposed techniques.

Chapter six studies and discuss the implementation of parking guidance system.

Chapter seven concludes the thesis and outlines the future improvements for the proposed ridesharing and parking guidance systems.

Part I: Mitigating urban traffic congestion via ridesharing

Chapter 2

Literature Review - Ridesharing

(Previously published as J. Lin, S. Sasidharan, S. Ma and O. Wolfson, "A Model of Multimodal Ridesharing and Its Analysis," *2016 17th IEEE International Conference on Mobile Data Management (MDM)*, Porto, 2016, pp. 164-173)

This chapter briefly describes research already carried out in the area of taxi ridesharing.

2.1. Taxi Ridesharing

There have been several studies on wait line management for taxi cabs (Curry, De Vany, and Feldman 1978; Anwar, Volkov, and Rus 2013) and attempts to enhance the taxi cab operations (da Costa and de Neufville 2012; Yazici, Kamga, and Singhal 2013) at various service stations. However, these techniques fall short at eliminating physical queues at the taxi cab service stations. Taxi cab demand prediction engines (Anwar, Volkov, and Rus 2013) and decision making systems (Yazici, Kamga, and Singhal 2013) may help in better taxi cab operations, but do not guarantee service on demand without entering a physical queue.

There has been extensive research on traditional ridesharing, where driving is the only mode of transportation. Detailed overviews of this research can be found in surveys on vehicle routing problem (Laporte 2009), and ridesharing (Agatz et al. 2012). Few works have studied multimodal ridesharing where other mode of transport (especially walking or biking) are allowed. In (Ma and Wolfson 2013) the authors studied the slugging form of ridesharing, where passengers walk to the origin of the driver to get on, then get off at the destination of the driver, and finally walk back to their original destination. The challenge there is to assign the role of driver and passenger to ridesharing participants, and group passengers to ridesharing plans. Therefore, the problem of choosing pickup/drop-off points for passengers is not tackled in (Ma and Wolfson 2013). Sester et.al. studied ridesharing with walking in a setting where the role of drivers and passengers are known as input, and each driver is assigned with passengers with the same destination (Rudnicki, Anders, and Sester 2008; Czioska, Mattfeld, and Sester 2016). The main problems in both (Czioska, Mattfeld, and Sester 2016; Rudnicki, Anders, and Sester 2008) is to determine a rendezvous point for each passenger to be picked up by the assigned driver. In (Rudnicki, Anders, and Sester 2008) each driver is matched with only one driver, whereas a driver is matched with multiple passengers using Integer Linear Programming (ILP) in (Czioska, Mattfeld, and Sester 2016); and subsequently the passenger pickup order is determined for each driver. ILP is NP-hard and thus not applicable to large problem instances. Neither (Rudnicki, Anders, and Sester 2008) nor (Czioska, Mattfeld, and Sester 2016) provides a formal model in which to determine whether trips are shareable.

(Aissat and Oulamara 2015; Stiglic et al. 2015) also studied the benefit of meeting points (i.e. middle points for pickup/dropoff) for ridesharing systems. In (Aissat and Oulamara 2015) the match is between a single driver and a single rider. And the (Aissat and Oulamara 2015) model provides constraints in terms of time windows instead of maximum walking time. (Stiglic et al. 2015) provides a solution in which sources, destinations, and intermediate points are in the Euclidean plane rather than networks. From a computational perspective, similar to our approach here, both (Aissat and

Oulamara 2015; Stiglic et al. 2015) devise and apply heuristics to reduce the search space for meeting points thus speed-up computation. However, note that the heuristics used in this paper prune the search space without compromising optimality of the solution. Furthermore, in (Rudnicki, Anders, and Sester 2008; Czioska, Mattfeld, and Sester 2016; Aissat and Oulamara 2015) each driver has its own destination. In contrast, in our model a driver does not have an individual destination.

This work is also relevant to existing work on taxi ridesharing(Ma, Zheng, and Wolfson 2015; Tian et al. 2013). Those works differ from our paper in: 1) they do not consider walking as a second mode; 2) they do not build a ridesharing plan from a time windowed pool of requests. That is, in those papers, whenever a ride request arrives, all taxis are considered for matching the new query. Thus, they focus on quickly finding candidate taxis for ridesharing based on spatial indexing. In terms of savings, (Ma, Zheng, and Wolfson 2015) reports about 25%~35% more taxi requests can be served if ridesharing with at most two passengers is allowed (depending on taxi shortage, modeled by parameter Δ). This is similar to our results here.

Similar to the work here, both (Ma and Wolfson 2013; Santi et al. 2014) consider matching trips in a small time window. (Ma and Wolfson 2013) does not consider multiple drop-offs, and as a result, it requires a higher similarity between trips that can be merged. Unlike this paper, where trips are bounded within New York City, all trips in (Santi et al. 2014) are bounded within Manhattan. Thus all the destinations are in a denser area than NYC as a whole, thus ridesharing is more probable. In terms of savings, (Santi et al. 2014) reports a 50% reduction in # of trips with ridesharing allowing at most one more passenger and maximum delay of 5 minutes, using a 3 minute pool size. In contrast, our study finds a 28% ~ 35% (depending on the pool size) reduction in the number of trips, with ridesharing allowed between at most two trips, and maximum 10% travel time delay. The difference between the savings in the two papers are attribute to multiple factors: 1) aforementioned denser destinations in (Santi et al. 2014); 2) requests with different origin locations are merged as well in (Santi et al. 2014); 3) the impact of walking on the total travel time delay. Furthermore, (Santi et al. 2014) performs an offline analysis and does not address issues of real-time algorithm efficiency.

While the hybrid walking-and-driving mode in SLIM ridesharing provide flexibility for ridesharing opportunities, it also greatly complicates the ridesharing algorithm, especially for pairwise shareability determination (see Chapter 3 for more details), the process of determining whether or not two trips are sharable (i.e. mergeable to form one ride-sharing trip). Since in SLIM passengers can be dropped off at intersections away from their respective final destinations, the search space for ridesharing paths is dramatically expanded. For example, given a walking time of five minutes, we find that a destination in New York can have 20~30 candidate drop-off points on average. There have been some works on calculating shortest path for multimodal networks, especially for transit networks (Abbaspour and Samadzadegan 2010)(Lozano and Storchi 2001), however, these do not consider ride-sharing. In this paper we describe the shareability determination procedure only for trip pairs. It can be extended to combining more than two trips. In this case, after the ride-sharing plan is obtained, a variant of the Traveling Salesman Problem (TSP) with 3 or more stops needs to be solved to determine the rote of each vehicle. Existing TSP solvers (David Applegate, Ribert Bixby, Vasek Chvatal 2006)(Dubois-lacoste, Hoos, and Stützle 2015) obtain the optimal solution for large instances of TSP problems, e.g. the Concorde TSP solver can solve optimally an instance consisting of more than eighty-five thousands stops.

Chapter 3

Multimodal Ridesharing Model

(Previously published as J. Lin, S. Sasidharan, S. Ma and O. Wolfson, "A Model of Multimodal Ridesharing and Its Analysis," *2016 17th IEEE International Conference on Mobile Data Management (MDM)*, Porto, 2016, pp. 164-173)

This chapter briefly reviews the theoretical and mathematical background required for the multimodal ridesharing scheme. The chapter discuss the road network structure, definition of trips, trip constrains and shareability in the context of ridesharing. It also presents the algorithms and theoretical proofs required for the ridesharing scheme.

3.1. The Road Network and Multimodal Paths

A *road network* is a directed graph; the vertices are the intersections of the roads, and the edges are the road segments connecting the intersections. Assume that there are n vertices in the road network, denoted v_i, where i =1,2,…,n, and let edge e_{ij} be the edge from vertex v_i to vertex v_j. Each edge e in the network has a length $L(e)$. We assume that there is a walking speed which is the same for all edges (e.g. 3 mi/hr) and is denoted WS. The *walking time* of e, denoted $WT(e)$, is $L(e)/WS$. Additionally, each edge e has a maximum driving speed $mDS(e)$, e.g. 60mi/hr on a highway edge. To compute the drive time on an edge e we use a *congestion fraction* denoted cf, where $0<cf<1$. This is a fraction used to compute the driving-time on each edge e by assuming that the driving speed on e is $mDS(e)*cf$. In other words, we assume that cf is the same for all edges. In practice, cf is determined by the time of day, e.g., at rush hour all maximum speeds are cut in half. Of course, this fraction can be adapted to the type of road, but we ignore this refinement here.

Thus the *driving time* on an edge *e,* denoted *DT*(*e*), is *L(e)/*(*mDS(e)**cf*). Intuitively, *DT*(*e*) is the time it takes to traverse the edge at a speed reflected by the congestion *cf*; if driving (in the direction of the edge) is not allowed, then the speed is 0 and the driving time is infinity.

Consequently, for every path *p* in the road network, the *walking time* on *p,* denoted *WT*(*p*), is the sum of the walking times of edges of *p*, i.e.,

$$WT(p) = \sum_{\forall e_{ij} \in p} WT(e_{ij})$$

the *driving time* on *p* denoted *DT*(*p*) is the sum of the driving times of edges of *p*, i.e.,

$$DT(p) = \sum_{\forall e_{ij} \in p} DT(e_{ij})$$

In this paper we consider paths that are unimodal, i.e. consist of a single mode, either walking or driving. Consequently, the time of a path *p* is either its walking time or its driving time. If *p* is the shortest (in terms of walking- or driving-time) path between two vertices *v* and *w*, then *WT*(*p*) and *DT*(*p*) are also denoted *WT*(*v,w*) and *DT*(*v,w*) respectively. The pickup intersection is called the *hub*, denoted by *H*. For a vertex *v*, for conciseness we denote by *SP(v)* the time *DT(H,v)*, i.e. the drive-time on the fastest-drive path from *H* to *v*.

3.2. Trips and Their Constraints

A trip *A* is a triplet: <*destination-address dest*(*A*)*, number-of-travelers-in-party, constraints*>. We assume that *dest(A)* is a vertex, i.e. intersection, and a trip starts at time 0. Denote *SP(dest(A))* by *SP(A)*. Namely, *SP(A)* is the drive-time on the fastest-drive path from *H* to *dest(A)*. The constraints are:

(1) Maximum walking time, denoted *W*(*A*), from the drop-off point, denoted *d*(*A*), to the final destination *dest*(*A*), and

(2) Maximum delay (including the walking time from *d*(*A*) to *dest*(*A*)) denoted *D*(*A*). In other words, *D(A)* is the maximum difference between the total travel time to *dest(A)* in a ride-share (including driving and walking), denoted *TT(A)*, and *SP(dest(A))*; i.e., $TT(A)-SP(A) \leq D(A)$.

The number of travelers is used in match-making. For example, two trips, each of which has two travelers, cannot be combined in a taxi with 3 passenger seats.

3.3. Shareability of Trips

A trip pair (*A*,*B*) is *shareable with A first* if there exist:

(1) a driving path *dp*(*A*,*B*) starting at *H*, and having two dropoff vertices, *d*(*A*) and *d*(*B*), where *d*(*B*) is the last vertex of *dp*(*A*,*B*), (see Fig.1), and

(2) at most two walking paths *wp*(*A*) and *wp*(*B*), from *d*(*A*) to *dest*(*A*) and from *d*(*B*) to *dest*(*B*), respectively,

that satisfy the following 2 conditions:

(1) If *d*(*A*) is the same vertex as *dest*(*A*), then *wp*(*A*) is empty (this means that the dropoff point of *A* is its destination); otherwise there is a walking path *wp*(*A*) from *d*(*A*) to *dest*(*A*) that satisfies the following conditions:

$$WT(wp(A)) \leq W(A) \tag{1}$$

$$DT(q) + WT(wp(A)) \leq SP(A) + D(A) \tag{2}$$

Equation (1) says the walking time on the path *wp*(*A*) is no greater than the maximum walking time limit on *A*, i.e., $W(A)$. In (2), *q* is the prefix of the path *dp*(*A,B*) from *H* to *d*(*A*). Then (2) indicates that the total travel time from *H* to *dest*(*A*) is no greater than the sum of the shortest path from *H* to *dest*(*A*) and the maximum tolerable delay. This, to comply with constraint (2) of the trip definition because

$$DT(q) + WT\big(wp(A)\big) = TT(A) \tag{3}$$

(2) Similarly, if *d*(*B*) is the same vertex as *dest*(*B*), then *wp*(*B*) is empty (this means that the dropoff point of *B* is its destination) and $DT(dp(A,B)) - SP(\mathrm{B}) \leq D(B)$; otherwise there is a walking path *wp*(*B*) from *d*(*B*) to *dest*(*B*) that satisfies the following conditions:

$$WT(wp(B)) \leq W(B) \tag{4}$$

$$DT(dp(A,B)) + WT(wp(B)) \leq SP(B) + D(B) \tag{5}$$

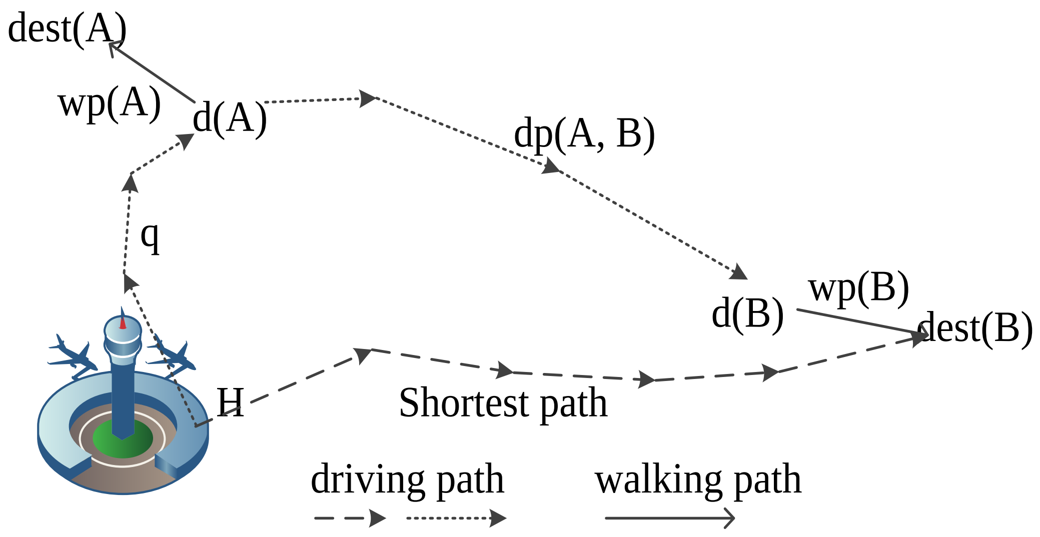


Figure 1: Illustration of shareability of trip pair (A,B)

The following proposition indicates that adding walking times enriches ride-sharing possibilities.

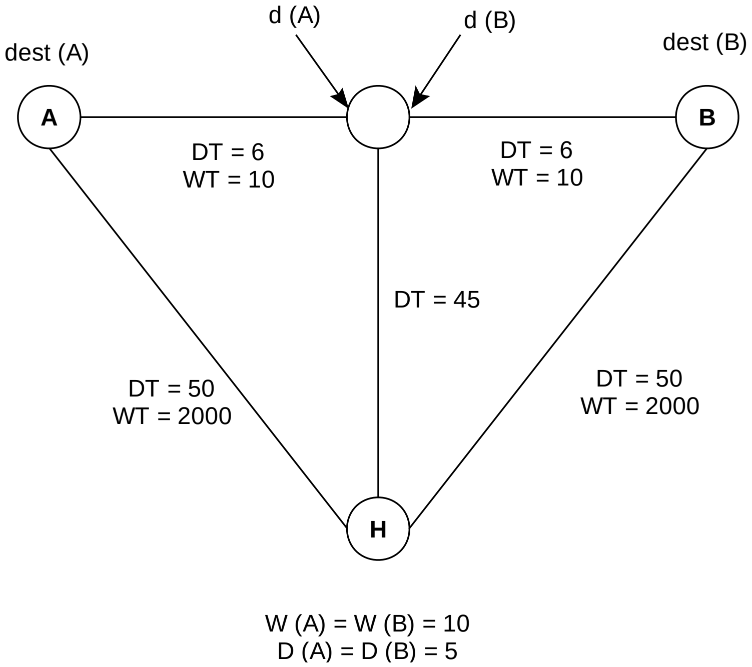


Figure 2: Trips A and B that are shareable if walking is allowed, but not otherwise

Proposition 1: There exist trips *A* and *B* that are shareable if their maximum walking times, *W*(*A*) and *W*(*B*), are greater than 0, but not otherwise. This is true even if the walking time is slower than the driving time for each edge.

Proof: Consider the road network of Fig. 2, giving the driving time and walking time on each edge. And consider trips A and B starting at H with maximum delays *D*(*A*)=*D*(*B*)=5 and destinations *dest*(*A*) and *dest*(*B*) respectively. If the maximum walking times are *W*(*A*)=*W*(*B*)=10, then the two trips are shareable with either A first or B first. In either case, both travelers are driven to vertex *d*(*A*)=*d*(*B*) and are dropped off there, from which they walk, each to their respective destination. The total shared trip time for A is the driving time, 45, plus the walking time, 10, i.e. 55 in total. Since the driving time directly from H to *dest*(*A*) along the shortest path is 50, the maximum walking and delay constraints are satisfied for A. And similarly for B.

Now, it is easy to see that if the maximum delays are kept at 5, but the maximum walking times are reduced to 0 for both trips, then A and B are not shareable with A first, nor with B first. The reason is that the drive from H to *dest*(*A*) is 50, and from *dest*(*A*) to *dest*(*B*) is 12, exceeding the maximum delay for B. Thus the trips are not shareable with A first. Similarly for B first.

3.4. The MatchMaking (MM) System

In this section we describe the MM system. We first give an overview of the approach (A), then devise the PST algorithm that produces the shareability graph and analyze its complexity (B); finally we discuss Euclidean filtering, a step executed before a pool of trips is fed into the PST algorithm to eliminate in constant time pairs of trips that are not shareable (C).

3.4.1. The Approach

After a pool P closes, a MatchMaking (MM) system is run on the set of *n* trips in the pool, creating a smaller set of *m* merged trips, each of which will be served by a taxi. Obviously, among the *m* trips there will be some that have not been merged. This will be the case for a trip A in which the constraints do not allow its merging with any other trip. For example, if all the trips in A's pool allow a delay of at most 5 minutes, and any other destination in the same pool is at least 10 miles away from the shortest path to A's destination, then A cannot be merged with any other trip.

The output of the MM system is a set of merged trips. For each merged trip T, MM produces the route to be taken by the taxi servicing T and the drop-off points, such that the constraints of all the individual trips merged into T are satisfied. If some drop-off point is not a destination, then MM will also produce the walking path that the passenger has to follow to reach her destination.

Now we discuss the approach used by the MM system. MM consists of two stages: (1) construction of a shareability graph (SG), and (2) finding the maximum matching of SG. The first stage finds all the possible pairs that can be merged in a way that satisfies the constraints of the two trips. In other words, it constructs a graph in which the nodes are the trips, and each edge indicates that the two connected trips can be merged.

To see the need for the second stage, suppose a pool initially consists of 4 trips, and that at the end of the first stage we have a graph of 4 nodes A, B, C, D and 3 edges A-B, B-C, and C-D. If B and C are merged, then no more trips can be merged, and the total number of resulting trips in the pool is 3. If, on the other hand, A and B are merged, and C and D are merged, the resulting number of trips is two, which is superior to the first option.

Thus, the second stage finds, for an arbitrary graph, the merging of pairs which results in the minimum number of merged trips in the pool. For finding the maximum matching we use a standard existing algorithm (Galil 1986).

3.4.1.1. Building the Shareability Graph

A shareability graph is a graph in which the vertices are trips and the edges indicate that the trip pair connected by the edge is shareable. The shareability graph is constructed as follows.

First, to speed up the graph-building process, we perform following precomputations: (assuming that drop-off points and trip destinations are always intersections). For each intersection P, we precompute only once the following:

a) $\mathbf{I}(P) = \{i | WT(P,i) \leq C\}$, i.e., the set of the neighboring intersections, from which the walking time to intersection P is no greater than C. Intuitively, these are candidate drop-off points for trips that have P as a destination assuming that the maximum walking time of any trip is C (say 10 minutes).

b) $DT(H,P)$, i.e. the driving time from the hub H to intersection P, using the speed limits of road segments.

Second, the following pairwise shareability test (PST), which uses the above precomputations, is applied to check whether or not trip a pair (*A,B*) is *shareable with A first*.

Discussion of the PST Algorithm: Line 1 checks whether the route driving from H to dest(A) (along the shortest path), and from there to dest(B), satisfies the maximum delay of B. If so, then this route satisfies the delay constraints of both trips, thus they are shareable.

Otherwise, the rest of the PST algorithm checks for every pair of feasible drop-off points, one of A and the other of B, whether they satisfy the delay constraints of A and B.

Line 4 checks whether the drop-off point satisfies the delay constraint of A, and if not the drop-off point is abandoned. Line 11 checks the same condition for the delay constraint of B, with a lower bound given by the Euclidean distance. Lines 4, 9, and 11 use calculations that involve only constants and precomputed values[1]. They serve as defenses, to avoid the expensive shortest path calculations executed by Line 13.

Line 13 calls *PathSearch* function, which tries to find a path from a drop-off point *i* of dest(A) to some drop-off point *j* of dest(B) within a given travel time budget that satisfies the delay constraint of B. This is expensive because the drive-time between i and j is not precomputed (the table giving the shortest drive-path between every pair of intersections would be too large to search efficiently). And executing the shortest path computation between every pair of feasible drop-off points, one of A and the other of B, involves hundreds of shortest-path computations (we find out that each destination usually have 20~30 drop-off points for a 5 minutes walk). The Path Search Algorithm (PSA, Algorithm 2) improves the efficiency by using the following idea. First, do a single-source shortest path computation from a drop-off point of *A* to all the feasible drop-off points of *B*. The resulting shortest-path tree *T* may contain multiple drop-off points of *A*; and if for any pair of drop-off points in *T*, one for *A* and the other for *B*, the $budget_{left}$ is not exceeded, then *A* and *B* are shareable with *A* first. Otherwise, the single-source-shortest-path computation is repeated for other feasible drop-off points of *A*, with the following cutoff improvement. If a vertex v that was "seen" in previous single-source-shortest-path computations is reached, and if the shortest path to *v* is not improved, then *v* is "cutoff", i.e. not expanded. In other words, PSA combines multiple single-source-shortest-path computations. Specifically, PSA is executed at most once for each drop-off point of *A*.

---

[1] the precomputed driving times are multiplied by the congestion fraction (*cf)* parameter.

Algorithm 1: Pairwise Sharability Test (PST), i.e. determine whether or not trip pair (A, B) is sharable with A first

```
   Data:
   $A$, $B$, given trip pair;
   $I(dest(A))$, precomputed drop-off points within the maximum walking time $W(A)$ from $dest(A)$;
   $I(dest(B))$, precomputed drop-off points within the maximum walking time $W(A)$ from $dest(B)$;
   $WT(i, P), i \in I(P)$, precomputed walking time from a drop-off point $i$ of intersection $P$ to $P$;
   $DT(H, P)$, precomputed driving time from hub $H$ to any intersection $P$ using speed limits;
   $S_{max}$, maximum speed limit for driving;
   $G = (V, E)$, graph representing the road network
   $cf$, congestion fraction (of maximum speed);
   Result: True or False
   /* if shareable using destinations as drop-off points */
1  if $DT(H, dest(A)) + SP(dest(A), dest(B)) - DT(H, dest(B)) \leq D(B)$ then
2      return True
3  for vertex $v \in V$ do /* budget array is to be used in Line 13 */
4      $budget[v] \leftarrow 0$
5  for drop-off point $i \in I(dest(A))$ do
       /* delay for $A$ exceeds the delay threshold */
6      if $DT(H, i) + WT(i, dest(A)) - DT(H, dest(A)) > D(A)$ then
7          continue to Line 3
8      for drop-off point $j \in I(dest(B))$ do
9          $budget_{left} \leftarrow DT(H, dest(B)) + D(B) - DT(H, i) - WT(j, dest(B))$

10         $E(i, j) \leftarrow$ Euclidean distance from $i$ to $j$
           /* delay for $B$ exceeds the delay threshold with lower
              bound approximation for travel time from $i$ to $j$ */
11         if $budget_{left} < E(i, j)/(S_{max} * cf)$ then
12             continue to Line 8
           /* $PathSearch$ excutes at most once for each $i$ */
13         $feasibility \leftarrow PathSearch(i, j, G, budget_{left} + WT(j, dest(B)), budget)$
14         if $feasibility == True$ then
15             return True
16 return False
```

Algorithm 1: Pairwise Sharability Test (PST)

```
Algorithm 2: Path Search Algorithm, based on Dijkstra's Algorithm
   Data:
   $i \in I(dest(A))$;
   $I(dest(B))$, precomputed drop-off points of trip $B$;
   $WT(u, dest(B))$, precomputed walking time from a drop-off point $u$ of $dest(B)$ to $dest(B)$;
   $G = (V, E)$, graph representing the road network (edge values represent driving time under speed limits);
   $budget_{left}$, total travel time budget left for vertex $i$;
   $budget[]$, an array which keeps track of the maximum budget for each vertex that has been explored (global varible, modifications to it are reflected in the caller function);
   Result: True or False
   /* initial budget is not greater than the maximum budget that has been seen for vertex $i$ */
 1 if $budget_{left} \leq budget[i]$ then
 2     return False
 3 for $vertex\ v \in V$ do                    /* distance initialization */
 4     $dist[v] \leftarrow \infty$
 5 $dist[i] \leftarrow 0$
 6 $budget[i] \leftarrow budget_{left}$
 7 $Q \leftarrow$ empty priority queue
 8 add $i$ to $Q$
 9 while $Q$ is not empty do
10     $v \leftarrow$ pop vertex with min $dist[v]$ from $Q$
11     for each neighbor $u$ of $v$ do
12         $tmp \leftarrow budget[v] - e_{vu}$
13         if $tmp \leq budget[u]$ && $budget[u] > 0$ then  /* cut the branch if budget left for $u$ is not greater than the max budget has been seen for $u$ */
14             continue to Line 11
15         $budget[u] \leftarrow tmp$
16         if $u \in I(dest(B))$ && $WT(u, dest(B)) \leq budget[u])$ then
17             return True
18         $dist[u] \leftarrow min(dist[u], dist[v] + e_{vu})$
19         add $u$ to queue $Q$
20 return False
```

Algorithm 2: Path Search Algorithm

Complexity of Constructing the Shareability Graph: In the worst case, the PST Algorithm constructs a shortest-path tree for each drop-off point of A. This takes $O(|E| + |V|log|V|)$. Since the number of drop-off points that are at most C time-units (e.g. C = 10 minutes) away from any destination is a constant, this is also the complexity of the PST algorithm. Since A and B are shareable if and only if they are shareable with A first or with B first, and since the number of trips in a pool is bounded by a constant (in our experiments the average number of trips ranges between 25 and 40 depending on the length of the time interval), the above is the asymptotic complexity of constructing the shareability graph.

Complexity of finding the Maximum Matching of the Shareability Graph: The maximum matching can be found in $O(|E||V|^{1/2})$, where |V| is the number of trips, and |E| is the number of edges in the shareability graph (see (Galil 1986)). Since the number of trips is a constant, finding the maximum matching can be done in a negligibly small constant time.

Incremental updating the Shareability Graph: After the shareablity graph is built, a maximal matching M is computed on the graph. Then all nodes and links that are included in M are removed from the graph, and each pair boards a vehicle. At this point there are 2 possibility for the unmatched trips. They can remain in the pool and board at the same time-interval as single-trips, or drop back to the next pool, attempting to be matched there. If the second option is selected, the remaining part of the graph can be incrementally reused for constructing the new shareability graph. That is, given a pool of trips consisting of c old trips and d new trips, to build the new sharability graph, we only need to run the PST algorithm $d(d+c)$ times instead of $(d+c)^2$ times.

3.4.2. Euclidean Filtering

In order to eliminate the infeasible pairs of trips quickly, rather than feeding them through the PST algorithm directly, the MM method uses the principles of Euclidian geometry. We call this Euclidean filtering. More specifically, in this subsection we present an inequality, (9), which, if not satisfied, for a pair of trips, then the trip-pair cannot be shareable; thus the pair does not need to be fed to the PST algorithm. Furthermore, (9) can be computed using only the precomputed tables, but independently of the road network, i.e. in constant time.

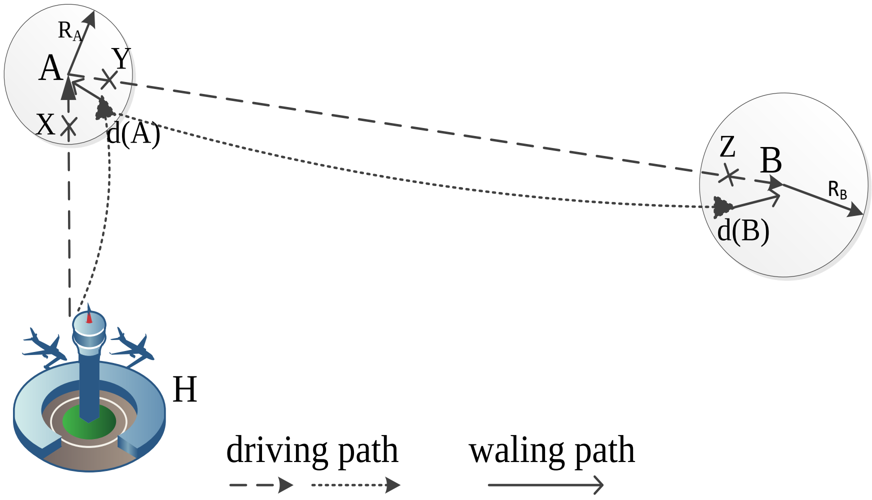


Figure 3: Demonstration of the proof of Theorem 2

Denote by S_{max} the maximum driving speed among all edges (e.g. 60 mi/hr) without congestion, i.e. when $cf=1$. We trivially assume that $(S_{max} * cf) > WS$ (Otherwise, walking from H to the destination would be faster than driving).

Given two points X and Y in the Euclidean space, denote by by $D_{X,Y}$ the Euclidean distance between two points X and Y, and by $T_{X,Y}$ the time to cover $D_{X,Y}$ at speed $(S_{max} * cf)$.

Theorem 2: If *A* and *B* are two trips that are shareable with *A* first, then:

$$T_{H,dest(A)} + T_{dest(A),dest(B)} - 2 * W(A) < SP(B) + D(B) \qquad (9)$$

Proof: Consider the two shareable trips *A* and *B* with drop-off points *d(A)* and *d(B),* as represented in Fig 3. *A*, *B* represent the destination locations of the two trips respectively, and R_A, R_B represent the maximum distances that can be covered in times $W(A)$ and $W(B)$, respectively, at a walking speed of WS.

We will prove that:

$$T_{H,dest(A)} - W(A) < SP(d(A)) \qquad (10)$$

and,

$$T_{dest(A),dest(B)} - W(A) < DT(d(A), d(B)) + T(wp(B)) \qquad (11)$$

Recall from sec. III.A that $SP(d(\mathrm{A}))$ is the shortest drive-time from *H* to the *d(A)*, and $DT(d(\mathrm{A}), d(\mathrm{B}))$ is the shortest driving-time from the drop-off point of *A* to that of *B*.

Thus, combining (10) and (11), we have

$$T_{H,dest(A)} + T_{dest(A),dest(B)} - 2 * W(A) < SP(d(A)) + DT(d(A), d(B)) + WT(wp(B)) \quad (12)$$

where the right side of (12) is the total travel time for B in any ridesharing plan with A first, thus not larger than $SP(B) + D(B)$; the theorem follows.

Now we prove (10). Denote by X the point on the straight line from H to *dest(A)* such that $D_{X,dest(A)} = D_{d(A),dest(A)}$. In other words, X is the point on the straight line whose Euclidean distance from *dest(A)* is the same as the Euclidean distance between *d(A)* and *dest(A).*

Since a straight line is the shortest distance between two points in Euclidean space, then $D_{HX} \le D_{H,d(A)} \le D(d(A))$, where $D(d(A))$is the distance of the shortest-time driving path from H to $d(A)$. Thus we have $T_{H,X} \le T_{H,d(A)} \le \frac{D(d(A))}{S_{max} * cf} \le SP(d(A))$. Also, since $(S_{max} * cf) > WS$, $T_{X,dest(A)} < WT(D_{X,dest(A)}) \le W(A)$. Thus: $T_{H,dest(A)} = T_{H,X} + T_{X,dest(A)} < SP(d(A)) + W(A)$, giving (10).

Now we prove (11). Denote by Y the point on the straight line between *dest*(A) and *dest*(B) such that $D_{dest(A),Y} = D_{dest(A),d(A)}$, and by Z the point on the same line such that $D_{Z,dest(B)} = D_{d(B),dest(B)}$. Since $(S_{max} * cf) > WS$, $T_{dest(A),Y} < W(A)$ and$T_{Z,dest(B)} < WT(D_{d(B),dest(B)})$, then$T_{dest(A),dest(B)} \le T_{dest(A),Y} + T_{YZ} + T_{Z,dest(B)} < T_{YZ} + W(A) + WT(D_{d(B),dest(B)})$.

Since a straight line is the shortest distance between two points in Euclidean space, $D_{YZ} \le fp(d(A), d(B))$ where $fp(d(A), d(B))$ is the length of the path that gives the shortest driving-time between *d(A)* and *d(B).* Since S_{max} is maximum speed of all road segments along the shortest path between *d(A)* and *d(B)*, we have $T_{YZ} \leq DT(d(A), d(B))$. Thus:$T_{dest(A),dest(B)} - W(A) < DT(d(A), d(B)) + WT(wp(B))$, which is (11).

If between every pair of intersections driving is faster than walking, then the lower bound of Th. 2 can be improved by replacing $T_{H,dest(A)}$ by the higher *SP(A)*. Precisely:

Theorem 3: If A and B are two trips that are shareable with A first, and between every pair of intersections the driving time is shorter than the walking time, then:

$$SP(A) + T_{dest(A),dest(B)} - 2 * W(A) < SP(B) + D(B) \qquad (13)$$

Proof: In this case the proof of Th. 2 can be repeated verbatim, except that (10) is: $SP(A) - W(A) \leq SP(d(A))$; and it holds for the following reason. If $SP(A) - W(A) > SP(d(A))$, then $SP(A)$ can be shortened as follows: drive from H to $d(A)$ along the shortest path (which will take less than $SP(A) - W(A)$) and then drive from $d(A)$ to $dest(A)$ (which will take less than $W(A)$).

Chapter 4

Evaluation of RSVP

(Previously published as J. Lin, S. Sasidharan, S. Ma and O. Wolfson, "A Model of Multimodal Ridesharing and Its Analysis," *2016 17th IEEE International Conference on Mobile Data Management (MDM)*, Porto, 2016, pp. 164-173)

This chapter briefly describes the methodology adopted for evaluating the proposed ridesharing scheme. The experiment set up and the data set used for evaluation is discussed in this chapter.

4.1. Databases

The first database used in the evaluation of the MM system is the NYC taxi trip database (see((DOITT) 2015),(Donovan and Work 2014)). This database records over four years of taxi operations in New York City (NYC) and includes nearly 700 million trips. The database is stored in CSV format, organized by year and month. In each file, each row represents a single taxi trip described by fields such as taxi ID, timestamped origin and destination, travel time and distance, and passengers count. The database does not provide GPS sequences for a trip. Reference (Swoboda 2015) provides a detailed description of the NYC taxi data.

4.2. Experiment

The experiment was conducted on randomly selected pools formed from 1.8 million trips. These trips originated from LaGuardia airport with destinations in NYC, during 261 weekdays in 2013 between 10am and 10pm. The pools were created based on the departure time. So, if the pool size is 5 minutes, the input (before merging) trips in the Jan. 15th, 10:00-10:05a pool are all the trips that departed on that date between 10:00 and 10:05, as reflected in the dataset. As Fig. 8 indicates, the average number of input trips ranges from 20 (for a 5 minute pool) to 40 (for a 10 minute pool), assuming that 90% of the trips can be shared. Observe that this method of generating the pools is conservative in the sense that it does not model unsatisfied demand. More precisely, it is possible that many passengers faced with a taxi line have decided to, for example, take the bus. A less conservative approach would have inflated the actual demand reflected in the database to model this unsatisfied demand, leading to a higher number of trips per pool, and thus to higher savings resulting from ride-sharing.

In this paper, the results presented in section D are based on a hundred pools randomly chosen from the above trip database. We observe that a hundred random pools yield an acceptable confidence level of the statistics to be presented in Section D. For example, consider 100 random 5-minute pools extracted for the following experimental setup: percentage of willingness to ride share = 90%, Max Delay = 10% of the individual shortest path trip time, and Maximum Walk Time = 5 min (see Fig. 4). The result indicates that the average number of trips saved per pool is 6.25 with a standard deviation of 5.29. If a normal distribution is assumed, then there is at least 88% confidence level that the average number of trips saved per pool is not lower than 90% of the mean value.

The second database used in the experiments is the road network. For creating the street network of New York City, the data from openstreetmap.org was used, consisting 486,746 road links and 261,187 intersections (i.e. vertices).

4.3. Metrics

RSVP is evaluated according to the following performance metrics.

- *Computation time.* Since ride-sharing plans must be computed continuously as customers arrive and depart the virtual queue, efficient computation is important.
- *Reduction in total number of trips in RSVP.* It is expected that trip reduction is related to a number of factors including the willingness to ride share by passengers, the pool size, maximum walking time tolerated, maximum total delay tolerated, and traffic condition (reflected by traffic speed). We examine the trip savings with respect to each of those key input parameters in the experiment.

4.4. Setup of Experiment

The congestion fraction: For determining the shareability of trips A and B, travel time was assigned to each road segment based on the road type, its maximum travel-speed (e.g. 40mi/hr on an arterial road), and a congestion fraction *cf* computed as follows. Denote by cf_1 the fraction = (travel-time from the hub to *dest*(*A*) at maximum speed allowed by each edge)/(actual travel time of trip A from the hub to *dest*(*A*)). And denote by cf_2 the fraction = travel-time from the hub to *dest*(*B*) at maximum speed allowed by each edge)/(actual travel time of trip B from the hub to *dest*(*B*)). Then the congestion fraction $cf=(cf_1+cf_2)/2$. In other words, *cf* is the average of the congestions reflected by trips A and B.

Destinations: The trip destinations were matched to the nearest intersections on the road map, using a kd-tree based KNN search. Intersections from the openstreetmap data were computed using QGIS. For each intersection a collection of neighboring intersections within *10* minutes walking distance (at 3mi/hr) were precomputed using Breadth-First-Search.

Taxi capacity: We assume that each taxi cab has 4 passenger seats. Therefore trip combinations with a total passenger count of at most four can be merged. For example, a trip with 2 passengers can be merged with another trip with 2 passengers but not with a 3-passenger trip.

Chapter 5

Results and Discussions

(Previously published as J. Lin, S. Sasidharan, S. Ma and O. Wolfson, "A Model of Multimodal Ridesharing and Its Analysis," *2016 17th IEEE International Conference on Mobile Data Management (MDM)*, Porto, 2016, pp. 164-173)

This chapter presents the results of the evaluation of ridesharing scheme described in the previous chapter 5.

5.1. Trip Reduction vs. Passengers' willingness to Rideshare

Figure 10 shows the percentage of trip reduction by percentage of passengers' willingness to ride share starting at 10%. It is assumed the maximum walking time is 5 minutes, pool size is in a 5-minute interval, and the maximum delay tolerated is 10% of the individual shortest path trip time. As expected, as more passengers are willing to ride share, the percent trip reduction increases.

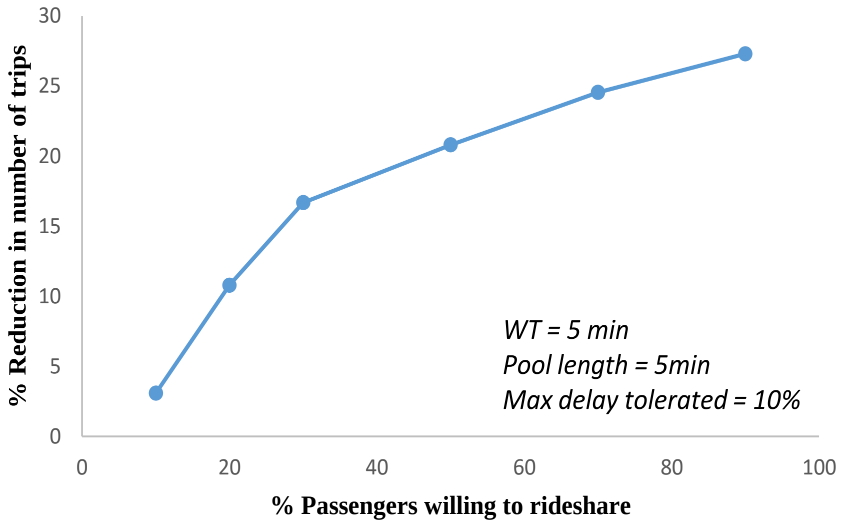


Figure 4: % trips reduction by willingness to ride share

5.2. Trip Reduction vs. Driving Speed

Figure 11 gives the percent trip reduction as a function of the driving speed.

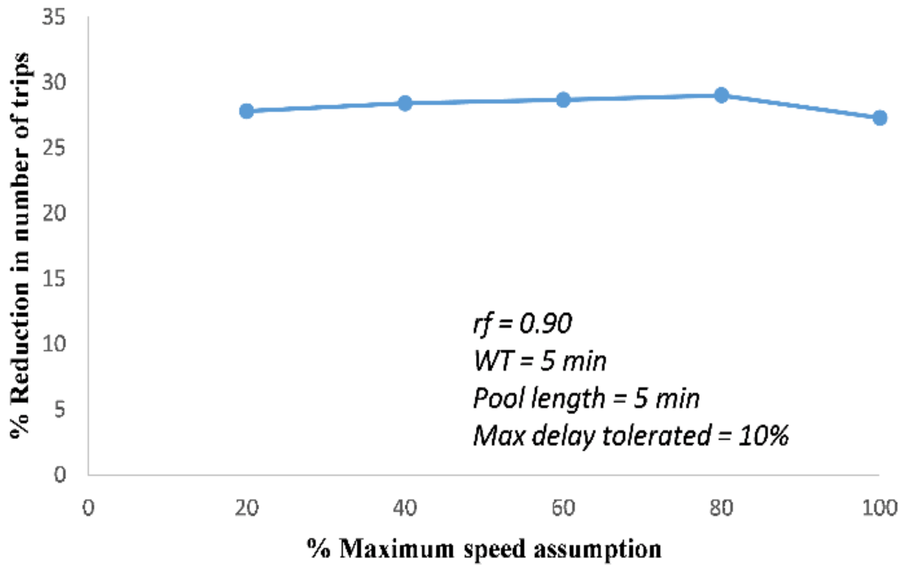


Figure 5: % trips reduction by congestion fraction

This speed is given as a percentage of the corresponding maximum speed, depending on the road type. So for example, 50% indicates that on a highway the average speed is 30mi/hr, and on an arterial road (where the maximum speed without traffic is 40mi/hr) is 20mi/hr. It is assumed here that the percent passenger willingness to ride share (*rf*) is 90%, the maximum walking time is 5 minutes, pool size is in a 5-minute interval, and the max delay tolerated is 10% of the individual shortest path trip time. It is interesting to see that the % trip reduction remains at about 28% regardless of the network driving speed. In other words, RSVP will consistently deliver a significant trip reduction regardless of the network traffic condition. That is an encouraging finding.

5.3. Trip Reduction vs. Average Maximum Delay

When the average maximum delay tolerated varies from 5% to 20% of the travel time, percent trip reduction goes up from 18% to 36% accordingly (Figure 12). That should come as no surprise - as passengers are more flexible with their travel time budget more trips can be shared and thus the total number of trips is further reduced.

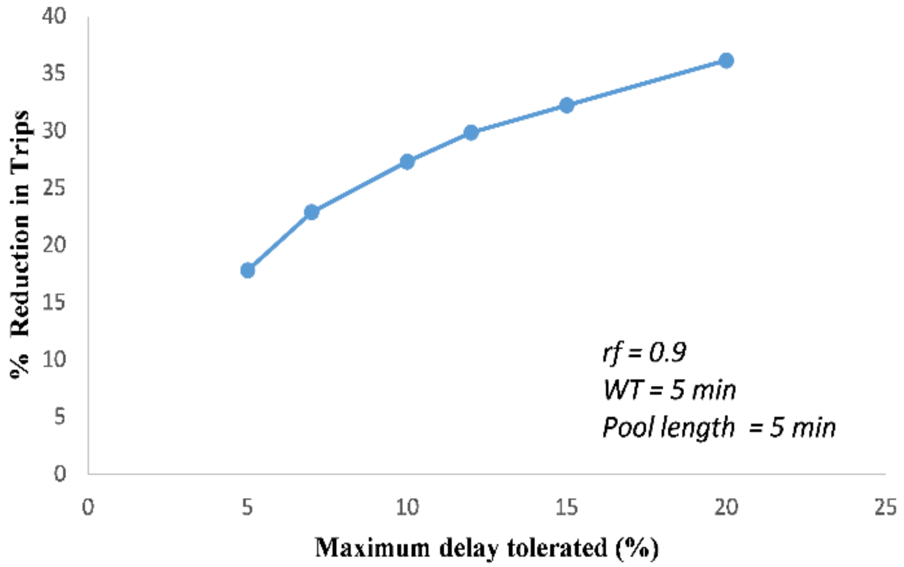


Figure 6: % trips reduction by average maximum delay

5.4. Trip Reduction vs. Maximum Walk Time Tolerated

One of the important features of RSVP is the incorporation of walking option from the drop-off point to the final destination by allowing passengers to specify the maximum tolerable walk time to their destinations after drop-off. It was hypothesized that RSVP would increase ride-sharing by incorporating this feature. Figure 13 confirms the hypothesis. Moreover, when the maximum walk time goes from zero to a mere 3-minute bound, it results in 15% additional trip reduction, which is a significant reduction.

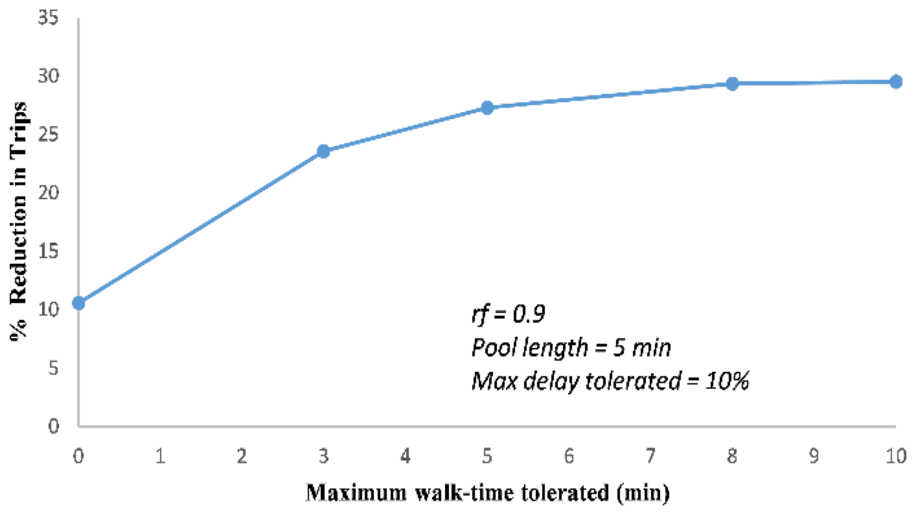


Figure 7: % trip reduction by maximum walk time

Notice that the % trip reduction levels off after 5 minutes, which suggests a 5-minute walk time tolerance would be a good cut-off point in practice.

5.5. Trip Reduction vs. Pool Size

Another interesting feature to observe is that percent trip reduction seemingly has little to do with the pool size (Figure 14). This is a desirable feature because it implies that the similar ride sharing result will be obtained regardless of how the trips are pooled. Therefore, in practice the pool size should be 6 minutes, the point at which the savings levels off. The reason for this is as follows. In a pool of size n minutes, the average wait to board is n/2 minutes. Thus, to minimize this wait, the pool size should be the smallest such that beyond it the savings is marginal.

Figure 14 also gives the actual numbers of trips before and after MatchMaking, for each pool-size.

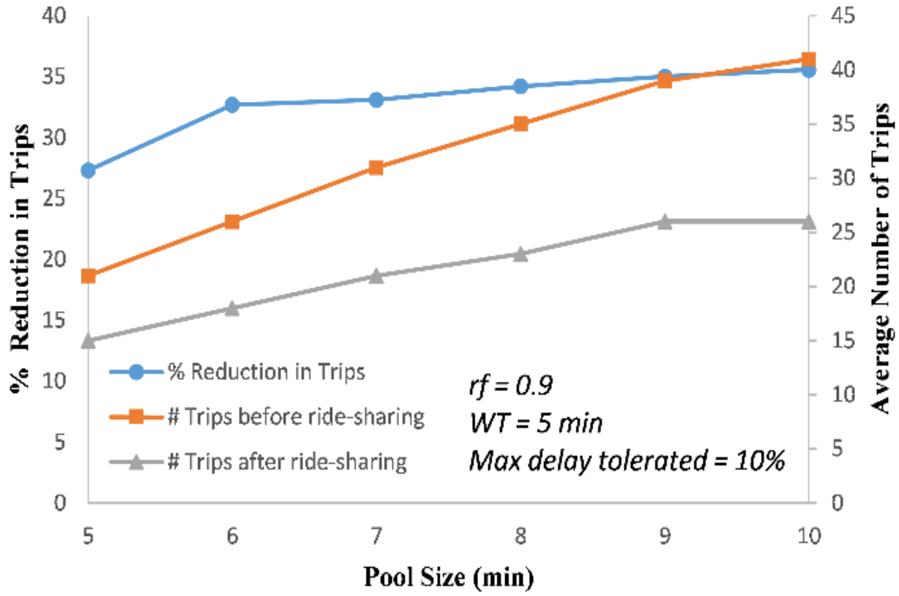


Figure 8: % trip reduction by pool size

5.6. Computation time vs. Pool Size

Computation time of the MM system is investigated as a function of the pool size.

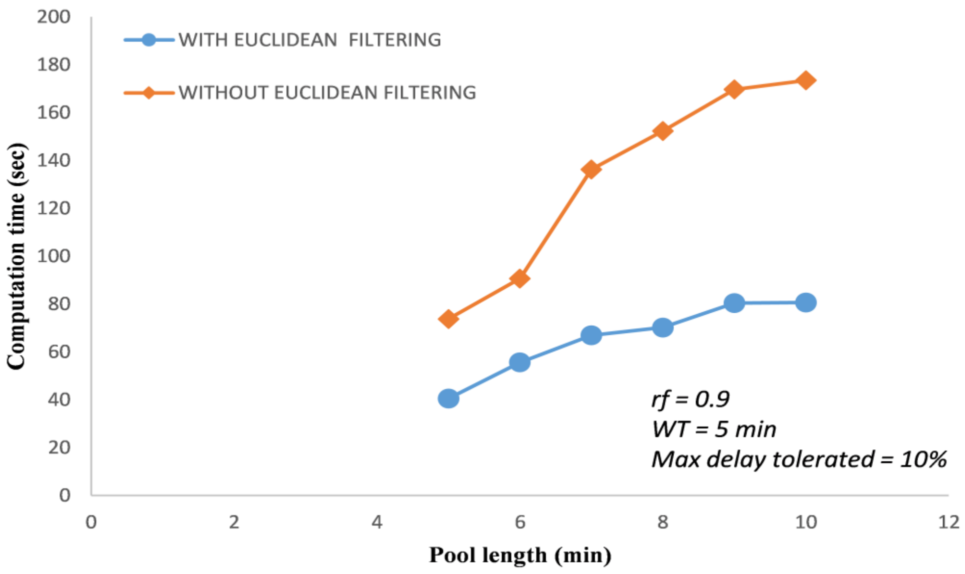


Figure 9: Computation time by pool size

The MM system was implemented in Java, and run on a single system equipped with 2.5 GHz CPU and 16 GB RAM using a single thread. Two cases were analyzed – with and without Euclidean filtering. Figure 15 shows the result, assuming a 90% willingness to ride share (*rf*), a 5-min maximum walking time, and a 10% max delay tolerated. The Euclidean filtering algorithm is proved to be effective in reducing the computation time by a factor ranging from 33% to over 50%. Without the Euclidean elimination algorithm, the computation time escalates 2.5 times when the pool size increases from 5 minutes to 10 minutes.

Part II: Reducing vehicle cruising for parking via Perfect Park

Chapter 6

Parking Navigation System

This chapter introduces Perfect Park, the parking navigation system designed for users searching for parking near to their destination. The chapter starts with a brief introduction of the application and proceeds with the implementation details and the advantages of the system for sustainable parking solutions.

6.1. Introduction

Finding parking slots in urban areas is considered as a major transportation challenge. (Shoup 2006) concludes that 30% of city road traffic is searching for available parking spots. Putting this in aggregate, parking space search in the city of Chicago resulted in 63 million vehicle-miles-traveled, 3.1 million gallons of gasoline consumption, and 48,000 tons of CO2 emissions per year (Ayala et al. 2011). Fortunately, with the advancement of sensor based detection technologies it is possible to detect the availability of certain parking spots in some cases (e.g. SFPark project in San Francisco). But the implementation and maintenance cost of such systems are expensive. Solutions for fully automated indoor and outdoor car parking has been discussed in (Lan and Shih 2014; Alasaadi et al. 2013; Liu et al. 2012).

Perfect Park mobile application discussed in this dissertation is capable of providing turn by turn route guidance to the users while they approach their destination. The application solves the problem of unwanted cruising for parking in urban areas. The Perfect Park software is designed focusing on two key aspects: (1) Minimum user intervention (2) Minimum smartphone battery usage during the trip. Traditional smartphone navigation applications are less useful when it comes to navigating in parking lots since many outdoor and indoor parking areas and approach roads are unmapped. High power consumption of GPS sensors in smartphone is a disadvantage for most smartphone navigation applications. The proposed system solves these problems by benefiting from the capabilities of Android platform to localize the vehicles using low power localization techniques and it smooth integration with OpenStreetMap APIs.

6.2. System Architecture

The Perfect Park parking guidance system has two modules – the Android client module and a web server module that performs computations and stores information on a database server. The client navigation system is an OpenStreetMap (OSM) based application that runs on Android platform. The Android client application is carefully designed to reduce the overall power consumption. The parking related information is stored in the server so that it can be accessed real time by the Android client application.

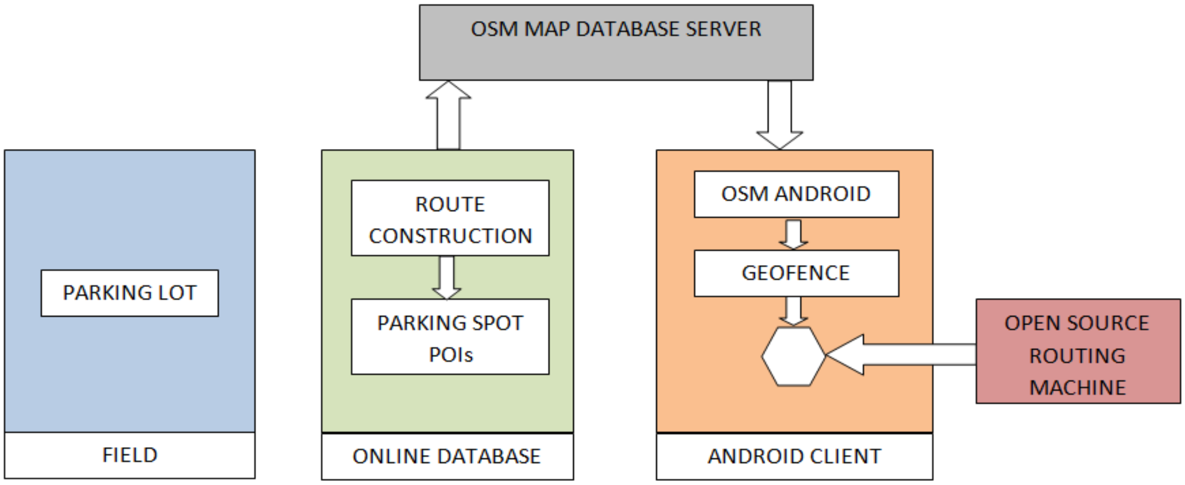


Figure 10: Android Client Subsystem

6.2.1. Database Server

The Perfect Park relies on the data collected by UPDetector application (Ma, Wolfson, and Xu 2014). Perfect Park tracks the parking and deparking activities detected by the UPDetector background process and send it to the database server. The database server consists of several tables that stores the real time parking status and the historic information. The techniques used to compute the parking availability at street level is discussed in (Xu et al. 2013).

A Jetty web server is implemented using Spark web framework and RESTful API services is used to establish client – server communication. The webserver is provided with SQL interfaces to push and retrieve real time and historic data from a MYSQL database server when required. The street blocks with parking availability, parking restrictions, real time and historic parking information are stored in the database server.

6.2.2. Android Client

The smartphone navigation application is designed to utilize low energy techniques such as Wi-Fi Localization and Geofencing. The system is most useful in the areas where the GNSS satellite visibility is poor (in cities due to urban canyon effect, indoor structures etc.) and the GPS system often fail to resolve position coordinates precisely. The application depend on hybrid localization technique for high accuracy and low power consumption. Hybrid positioning uses a combination of several positioning technologies such as assisted GPS (A-GPS), Wi-Fi positioning etc. for localization. The location monitoring is set to run as a background service and GPS is used only for navigation purpose once the user is closer to his destination thereby reducing the smartphone battery consumption which is a very critical for GPS based apps. This also minimizes the user intervention while driving. Once the destination is set, the application exits and will automatically starts once the user crosses the geofence. A geofence is a virtual barrier that can trigger events when the client enters or exits the virtual fence. In case the access of GPS is restricted, Wi-Fi localization is predominantly used for localization. The application is also capable of providing turn by turn instructions with voice to the user to navigate within the parking space.

Android powered by Google location Services are capable of providing a powerful high level frame work that promises automatic handling of location providers such as assisted GPS and Wi-Fi localization with minimum power usage ("Google and Open Handset Alliance N.d. Android API Guide.," n.d.). This application primarily make use of Android's Fused Location API and Geofencing API to provide a low power navigation solution.

The client subsystem diagram is presented in Figure 4.

For displaying interactive map, Perfect Park application uses OpenStreetMap API. The user can select his destination interactively using the map user interface. Once the destination is selected, the mobile client application queries the webserver to gather information on the nearest parking blocks. The server acknowledges by sending the parking space recommendations near the desired destination. The client application logic then automatically creates a Geofence of half mile radius around the selected parking location and exits the Perfect Park application. Once the user crosses the Geofence, a notification is generated and it internally triggers the Perfect Park application. At this point, the mode of operation will be switched to high accuracy mode while navigating inside the Geofence i.e. closer to the recommended parking space. Open Source Routing Machine (OSRM) computes the navigation route from the current user location to the recommended parking space.

6.2.3. Digital Map and Localization

The Perfect Park supports street parking, indoor parking structures with sufficient Wi-Fi access points (for hybrid positioning in case GPS is unavailable) and open parking spaces. Unmapped parking spaces need to be mapped manually and uploaded using OpenStreetMap editor. For indoor parking structure, floor plan blue prints can be uploaded using JOSM OpenStreetMap editor. The floor plans will be available on the OSM Map server after moderation. The street parking information is collected from various 3rd party sources and stored in the database server. Inside the geofence, the GPS values are read every 5 millisecond.

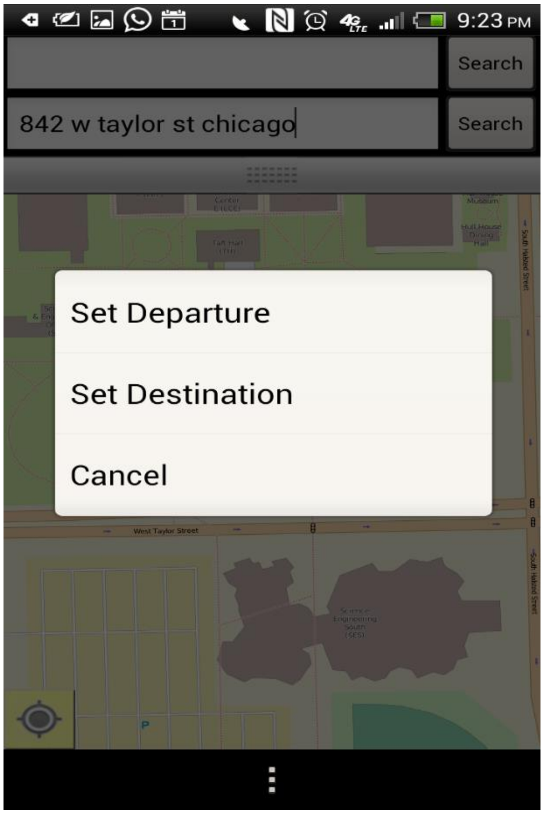


Figure 11: Perfect Park Screen Shots: Destination selection

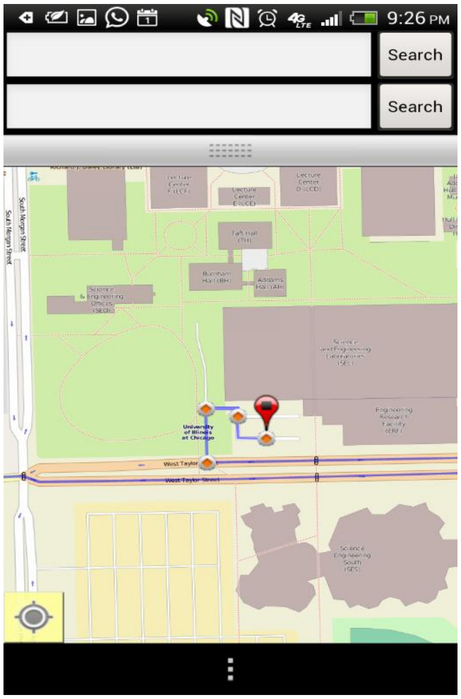
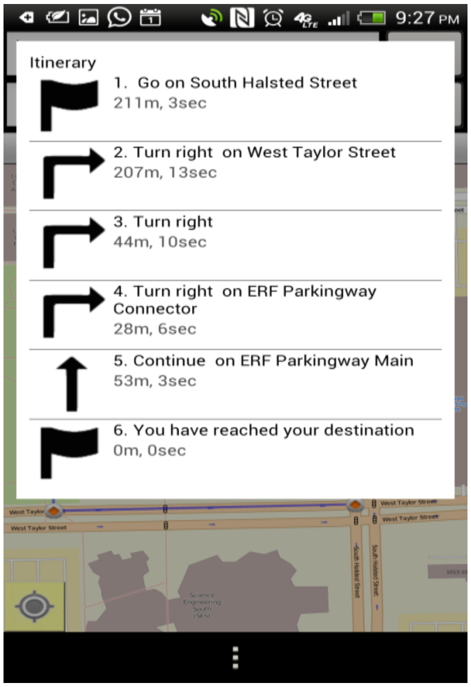


Figure 12: Perfect Park Screen Shots: Route Display



Itinerary

1. Go on South Halsted Street
211m, 3sec

2. Turn right on West Taylor Street
207m, 13sec

3. Turn right
44m, 10sec

4. Turn right on ERF Parkingway Connector
28m, 6sec

5. Continue on ERF Parkingway Main
53m, 3sec

6. You have reached your destination
0m, 0sec

Figure 13: Perfect Park Screen Shots: Turn by turn instructions

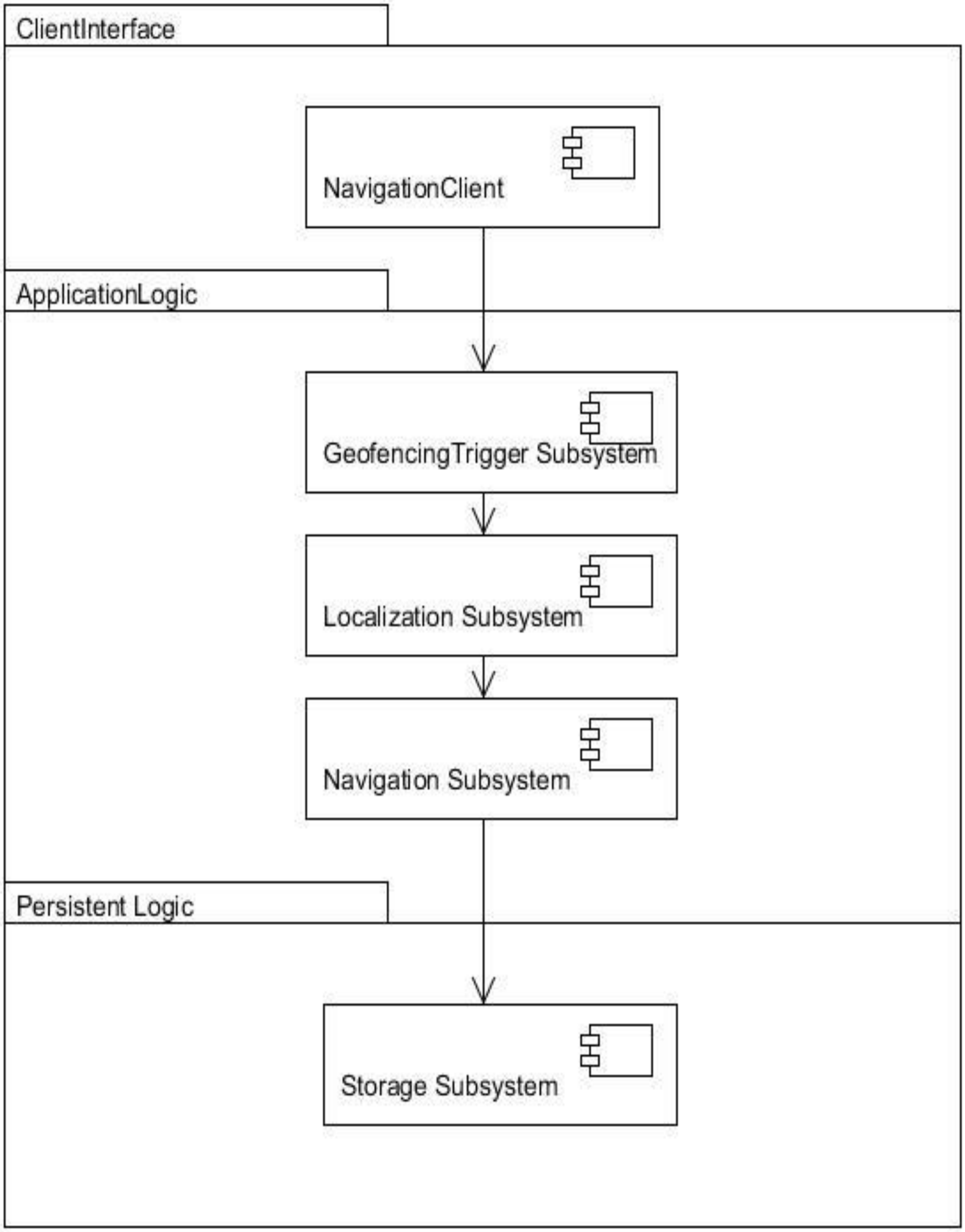


Figure 14: Subsystem Decomposition

6.3. Experiment and Observation

The experiment was conducted near University of Illinois at Chicago campus open parking lot at 1100 W Harrison Street. Since this parking lot was unmapped on OpenStreetMap, the boundaries, road segments, entrances, exits and point of interests were marked manually using OpenStreetMap Editor Software. Bing satellite image was used to match the ground features on the map data. The OpenStreetMap data is then parsed and stored in the webserver to reflect the availability information.

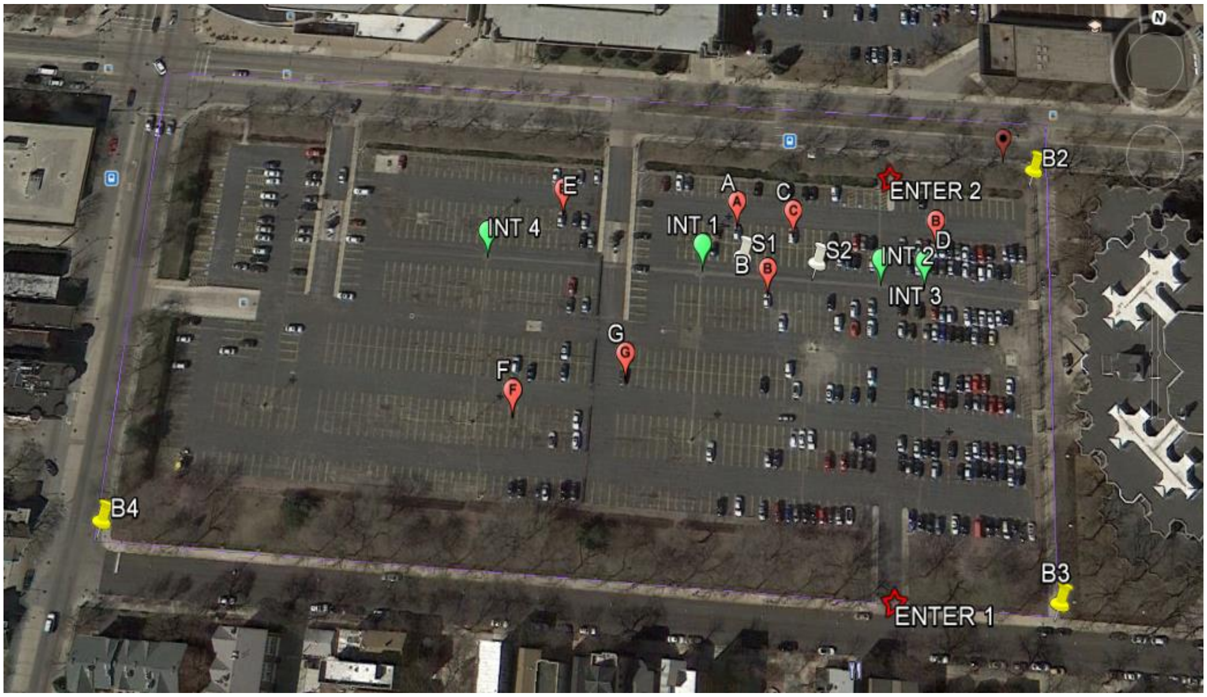


Figure 15: Parking lot mapping

Perfect Park application was tested in driving and walking mode multiple times. To evaluate the power efficiency of the designed application, a replica of the software was created that depend GPS for localization and navigation. The application power handling was approximately computed using various 3rd party power monitoring tools. A power reduction up to 40% was reported for the Perfect Park application compared to the replicated software version.

Chapter 7

Conclusion and Future Work

This chapter presents the conclusion and future work of the thesis.

7.1. Conclusion

The RSVP scheme proposed in this dissertation facilitates ride-sharing at transportation hubs. The scheme combines in a unique way three existing mechanisms: virtual queues, slugging, and multiple-drop-off ridesharing. The scheme produces pools of trips, which are then consolidated into ride-sharing plans by the MatchMaking (MM) system. Technically, the heart and novelty of the MM system is a combination of two components: (1) Euclidean filtering that uses Euclidean geometry to reduce the complexity of finding an optimal ride-sharing plan, and (2) the PST algorithm which uses a middle ground between single-source-shortest-path and all-pairs-shortest-path.

The RSVP scheme is then evaluated on 100 random pools formed from 1.8 Million trips that originated from LaGuardia Airport (LGA) in NYC. The results indicate that:

(1) The trip-savings enabled by RSVP-ride-sharing are significant, e.g., about 25% of the trips are saved if about 75% of the passengers are willing to ride-share. This is true for a modest delay of 10% of the trip time, and a maximum walk of 5 minutes.

(2) Walking is valuable in combination with multiple-drop-off ride-sharing. For example, if passengers allow a 10-minutes walk, then the trips-reduction by ride-sharing increases from about 10% to about 30%.

Considering that at airports passengers often walk for 10 minutes from the gate to the curb, this assumption seems reasonable.

(3) The computation time for a 6 minutes pool of trips is less than 1 minute.

(4) Euclidean filtering is effective, reducing the computation time by 30%-50%.

In Part II of this thesis the design, implementation and evaluation of Perfect Park, a smartphone based low power vehicle parking navigation and guidance application is presented. The application utilizes hybrid positioning and geofencing techniques to provide a low power turn by turn navigation solution with voice guidance to the users. The overall system design focus on two aspects: (1) Minimum user intervention to start the parking guidance while the user is driving (2) Minimum smartphone battery usage during the trip. The application has the capability to auto trigger itself when the user approaches his destination and the evaluation indicates that the Perfect Park behaves the same as traditional navigation applications in terms of quality and usability, while achieving around 40% energy savings.

7.2. Future Work

Much remains to be done in terms of future work for RSVP ridesharing scheme. First, the optimization criteria needs to be refined to travel-time per vehicle rather than number of trips. Second, the sharing of more than two trips needs to be investigated, although (Santi et al. 2014) determined that the additional savings from allowing the sharing of 3 trips is marginal. Third, the results need to be compared with other hubs. Finally, the RSVP schemes can be reversed to traveling to the hub, rather than from it. In other words, instead of having a single source, the passengers would have a single destination, the hub. And they would walk to pick-up locations, rather than from drop-off locations.

On the Perfect Park client side, the next step is to introduce design and algorithms for navigation in indoor parking structures. Though hybrid positioning is capable of navigating indoors, its performance is restricted by the availability of Wi-Fi access points. On the web server side, parking recommendation algorithms such as (Guo and Wolfson 2016) can be incorporated to improve resource search experience.

References

(DOITT), New York City Taxi & Limousine Comminssion (TLC) in partnership with the New York City Department of Information Technology and Telecommunications. 2015. "Big Step for Big Data: Yellow/Green Taxi Trip Records Now Available Online."

Abbaspour, Rahim A, and Farhad Samadzadegan. 2010. "An Evolutionary Solution for Multimodal Shortest Path Problem in Metropolises." *Computer Science and Information Systems* 7 (4): 1820–0214. doi:10.2298/CSIS090710024A.

Agatz, Niels, Alan Erera, Martin Savelsbergh, and Xing Wang. 2012. "Optimization for Dynamic Ride-Sharing: A Review." *European Journal of Operational Research* 223 (2): 295–303. doi:10.1016/j.ejor.2012.05.028.

Aissat, K, and A Oulamara. 2015. "Meeting Locations in Real-Time Ridesharing Problem: A Buckets Approach." *Operations Research and Enterprise Systems* 577: 71–92. doi:10.1007/978-3-319-27680-9.

Alasaadi, Abdulla, Juan Aparicio, Nazif Tas, Justinian Rosca, and Tamer Nadeem. 2013. "ParkZoom: A Parking Spot Identification System." *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, no. Itsc: 702–7. doi:10.1109/ITSC.2013.6728313.

Anbarani, Ramin, Mahmoud Javanmardi, Mehran Langerudi, and Abolfazl Mohammadian. 2016. "Analyzing Impacts of Individuals' Travel Behavior on Air Pollution: Integration of a Dynamic Activity-Based Travel Demand Model with Dynamic Traffic Assignment and Emission Models." *Proceedings of the 95th Annual Meeting of the Transportation Research*

Board (TRB), Washington, DC.

Anwar, Afian, Mikhail Volkov, and Daniela Rus. 2013. “ChangiNOW : A Mobile Application for Efficient Taxi Allocation at Airports.” *Proceedings of the 16th International IEEE Annual Conference on Intelligent Transportation Systems (ITSC 2013)*, no. Itsc: 694–701. doi:10.1109/ITSC.2013.6728312.

Ayala, Daniel, Ouri Wolfson, Bo Xu, Bhaskar Dasgupta, and Jie Lin. 2011. “Parking Slot Assignment Games.” *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - GIS ’11*, 299. doi:10.1145/2093973.2094014.

Curry, Guy L., Arthur De Vany, and Richard M. Feldman. 1978. “A Queueing Model of Airport Passenger Departures by Taxi: Competition with a Public Transportation Mode.” *Transportation Research* 12 (2): 115–20. doi:10.1016/0041-1647(78)90050-3.

Czioska, Paul, Dirk Mattfeld, and Monika Sester. 2016. “GIS-Based Identification and Assessment of Suitable Meeting Point Locations for Ride-Sharing.” *19th Euro Working Group on Transportatoin Meeting, EWGT 2016*. doi:10.1017/CBO9781107415324.004.

da Costa, David Carvalho Teixeira, and Richard de Neufville. 2012. “Designing Efficient Taxi Pickup Operations at Airports.” *Transportation Research Record: Journal of the Transportation Research Board* 2300: 91–99.

David Applegate, Ribert Bixby, Vasek Chvatal, William Cook. 2006. “Concorde TSP Solver.”

Donovan, Brian, and Daniel B. Work. 2014. "New York City Taxi Trip Data (2010-2013)." *University of Illinois at Urbana-Champaign.* http://dx.doi.org/10.13012/J8PN93H8.

Dubois-lacoste, Jérémie, Holger H Hoos, and Thomas Stützle. 2015. "On the Empirical Scaling Behaviour of State-of-the-Art Local Search Algorithms for the Euclidean TSP." *Proceedings of the 2015 on Genetic and Evolutionary Computation Conference. ACM*, 377–84. doi:10.1145/2739480.2754747.

Galil, Z. 1986. "Efficient Algorithms for Finding Maximum Matching in Graphs." *ACM Computing Surveys* 18 (1): 23–38. doi:10.1007/3-540-12727-5_4.

Gidofalvi, Gyozo, Torben Bach Pedersen, Tore Risch, and Erik Zeitler. 2008. "Highly Scalable Trip Grouping for Large-Scale Collective Transportation Systems." In *Proc. of the 11th Int. Conf. on Extending Database Technology Advances in Database Technology*, 678. EDBT '08. New York, NY, USA: ACM. doi:10.1145/1353343.1353425.

"Google and Open Handset Alliance N.d. Android API Guide." n.d.

Guo, Qing, and Ouri Wolfson. 2016. "Finding Geospatial Resources Using Uncertain Data." *Proceedings - IEEE International Conference on Mobile Data Management* 2016–July: 66–71. doi:10.1109/MDM.2016.23.

Hilkevitch, Jon. 2015. "O'Hare Taxi Passengers, Drivers Often in Holding Pattern." *Chicago Tribune*. July 12. http://www.chicagotribune.com/business/breaking/chi-taxicabs-ohare-getting-around-met-20150316-column.html#page=1.

Lan, Kun Chan, and Wen Yuah Shih. 2014. “An Intelligent Driver Location System for Smart Parking.” *Expert Systems with Applications* 41 (5). Elsevier Ltd: 2443–56. doi:10.1016/j.eswa.2013.09.044.

Laporte, Gilbert. 2009. “Fifty Years of Vehicle Routing.” *Transportation Science* 43 (4). INFORMS: 408–16. doi:10.1287/trsc.1090.0301.

Lin, Jane, Sandeep Sasidharan, Shuo Ma, and Ouri Wolfson. 2016. “A Model of Multimodal Ridesharing and Its Analysis.” In *Proceedings - IEEE International Conference on Mobile Data Management*, 2016–July:164–73. doi:10.1109/MDM.2016.34.

Liu, Jingbin, Ruizhi Chen, Yuwei Chen, Ling Pei, and Liang Chen. 2012. “iParking: An Intelligent Indoor Location-Based Smartphone Parking Service.” *Sensors (Switzerland)* 12 (11): 14612–29. doi:10.3390/s121114612.

Lozano, Angelica, and Giovanni Storchi. 2001. “Shortest Viable Path Algorithm in Multimodal Networks.” *Transportation Research Part A: Policy and Practice* 35 (3): 225–41. doi:10.1016/S0965-8564(99)00056-7.

Ma, Shuo, and Ouri Wolfson. 2013. “Analysis and Evaluation of the Slugging Form of Ridesharing.” *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - SIGSPATIAL’13*. New York, New York, USA: ACM Press, 64–73. doi:10.1145/2525314.2525365.

Ma, Shuo, Ouri Wolfson, and Bo Xu. 2014. “UPDetector: Sensing Parking/Unparking Activities Using Smartphones.” *Proceedings of the 7th ACM SIGSPATIAL International Workshop on Computational*

Transportation Science, 76–85. doi:10.1145/2674918.2674929.

Ma, Shuo, Yu Zheng, and Ouri Wolfson. 2015. “Real-Time City-Scale Taxi Ridesharing.” *IEEE Transactions on Knowledge and Data Engineering* 27: 1782–95.

Rudnicki, Radoslaw, KH Anders, and Monika Sester. 2008. “Rendezvous-Problem in Local Shared-Ride Trip Planning.” In *International Society for Photogrammetry and Remote Sensing Congress*.

S. Mathur, T. Jin, N. Kasturirangan, J. Chandrasekaran, W. Xue, M., and and W. Trappe Gruteser. 2010. “ParkNet: Drive-by Sensing of Road-Side Parking Statistics.” *ACM MobiSys,*.

Santi, Paolo, Giovanni Resta, Michael Szell, Stanislav Sobolevsky, Steven H. Strogatz, and Carlo Ratti. 2014. “Quantifying the Benefits of Vehicle Pooling with Shareability Networks.” *Proceedings of the National Academy of Sciences* 111 (37): 13290–94. doi:10.1073/pnas.1403657111.

Schrank, D., and T. Lomax. 2002. “The Urban Mobility Report.” *Texas Transportation Institute, College Station, TX*.

Shoup, Donald. 2006. “Cruising for Parking.” *Transport Policy* 13 (6): 479–486.

Stiglic, Mitja, Niels Agatz, Martin Savelsbergh, and Mirko Gradisar. 2015. “The Benefits of Meeting Points in Ride-Sharing Systems.” *Transportation Research Part B: Methodological* 82: 36–53. doi:10.1016/j.trb.2015.07.025.

Swoboda, Andrew James Touloukian. 2015. “New York City Taxicab Transportation Demand Modeling for the Analysis of Ridesharing and Autonomous Taxi Systems.” *B.S. Thesis, Department of Operations Research and Financial Engineering, Princeton University.*, no. June.

Tian, Charles, Yan Huang, Z Liu, F Bastani, and Ruoming Jin. 2013. “Noah: A Dynamic Ridesharing System.” *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data. ACM*, 985–88. doi:10.1145/2463676.2463695.

Whiteing, T, M Browne, and J Allen. 2003. “City Logistics: The Continuing Search for Sustainable Solutions.” *Global Logistics and Distribution Planning (Ed, Waters, D.)*, 308–20.

Xu, Bo, Ouri Wolfson, Jie Yang, Leon Stenneth, Philip S. Yu, and Peter C. Nelson. 2013. “Real-Time Street Parking Availability Estimation.” *Proceedings - IEEE International Conference on Mobile Data Management* 1: 16–25. doi:10.1109/MDM.2013.12.

Yazici, M Anil, Camille Kamga, and Abhishek Singhal. 2013. “A Big Data Driven Model for Taxi Drivers ’ Airport Pick-up Decisions in New York City.” *IEEE International Conference on Big Data*, 37–44. doi:10.1109/BigData.2013.6691775.

Appendix A

A.1 Perfect Park class diagram

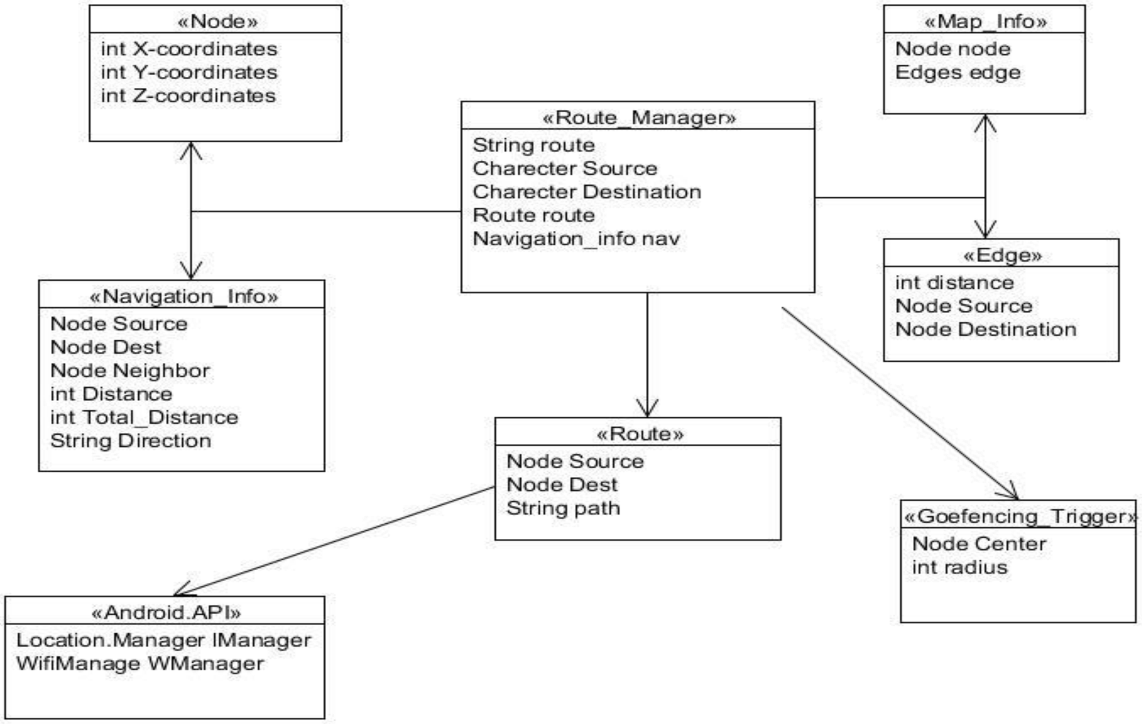


Figure 16: Perfect Park class diagram

A.2 Perfect Park sequence diagram

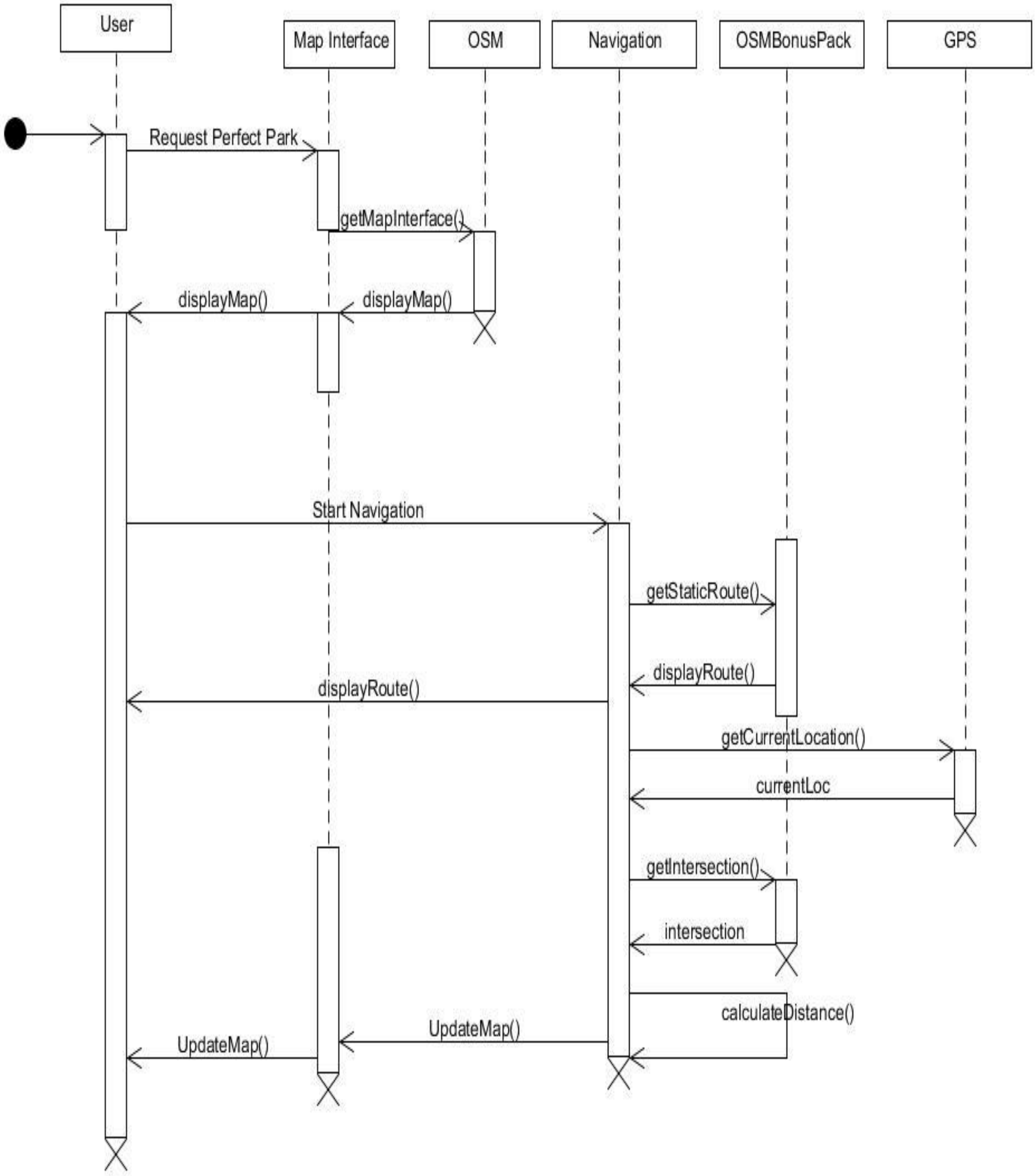


Figure 17: Perfect Park sequence diagram

Appendix B

B.1 Rightslink Terms and Conditions for IEEE Material

1) In the case of textual material (e.g., using short quotes or referring to the work within these papers) users must give full credit to the original source (author, paper, publication) followed by the IEEE copyright line � 2011 IEEE.
2) In the case of illustrations or tabular material, we require that the copyright line � [Year of original publication] IEEE appear prominently with each reprinted figure and/or table.
3) If a substantial portion of the original paper is to be used, and if you are not the senior author, also obtain the senior author�s approval.

Requirements to be followed when using an entire IEEE copyrighted paper in a thesis:

1) The following IEEE copyright/ credit notice should be placed prominently in the references: � [year of original publication] IEEE. Reprinted, with permission, from [author names, paper title, IEEE publication title, and month/year of publication]
2) Only the accepted version of an IEEE copyrighted paper can be used when posting the paper or your thesis on-line.
3) In placing the thesis on the author's university website, please display the following message in a prominent place on the website: In reference to IEEE copyrighted material which is used with permission in this thesis, the IEEE does not endorse any of [university/educational entity's name goes here]'s products or services. Internal or personal use of this material is permitted. If interested in reprinting/republishing IEEE copyrighted material for advertising or promotional purposes or for creating new collective works for resale or redistribution, please go

to http://www.ieee.org/publications_standards/publications/rights/rights_link.html to learn how to obtain a License from RightsLink.

If applicable, University Microfilms and/or ProQuest Library, or the Archives of Canada may supply single copies of the dissertation.