AN APPROACH TO DETERMINE OPTIMAL PICKUP AND DROP-OFF POINTS FOR URBAN RIDESHARING

JUNHUI MAO
June, 2020

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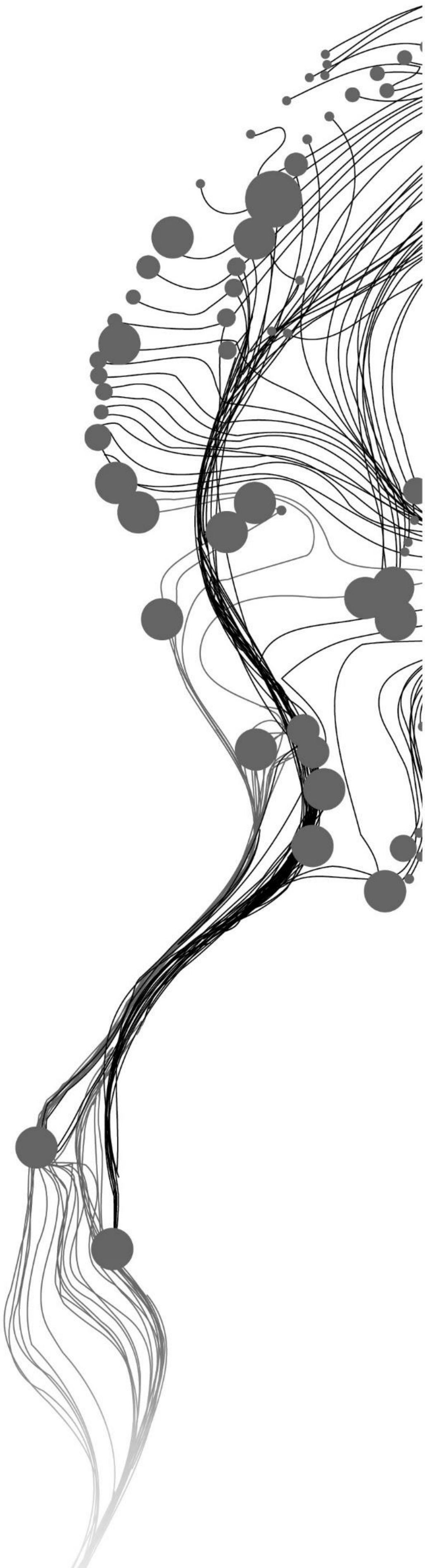

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JUNHUI MAO
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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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ABSTRACT

Recently ridesharing has been widely adopted as a way of daily travel and commuting, which is regarded as a good example of the shared economy. Taking the advantage of reducing transport emissions and relieving urban traffic congestions, the ridesharing still confronts some challenges, one of which is that the driver needs to make extra detours while the location of passenger is with lower spatial accessibility. And when it comes to multiple passengers in a single ride, the cost of the extra detours which is supposed to bring about time wasting and negative impact, would become less acceptable. To solve this problem, the flexibility characteristic of ridesharing can be the breakthrough point.

Therefore, this work aims to find out an approach to determine the optimal pickup and drop-off points (PDPs) which can effectively improve the driving rout in the urban ridesharing. It is assumed that the approach possesses both flexibility and practicality, implying that the PDPs vary with the changing circumstances of practical world. After investigating the indicators that affect the driving rout of the shared ride, the determination of possible and optimal alternative pickup and drop-off points was conducted adopting Amap-API as the implementing tool. The result demonstrated that the time cost, distance, number of traffic lights and turns, as well as the clearness of a shared ride had reduced by adopting the proposed approach to choose a alternative pickup or drop-off point while taking a rideshare.

Keywords: ridesharing, pickup point

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1. INTRODUCTION

1.1. Motivation and Problem Statement

Ridesharing, a formal or informal sharing of rides among driver and more than one or one group of passengers with similar origin-destination pairings (SAE International, 2018), has been widely adopted as a way of daily travel and commuting. It is also regarded as a good example of the shared economy. With the rapid development of Internet technologies, a fair amount of Transportation Network Companies (TNC) such appears, which attract an increasing number of customers in recent years. Like Uber, the well-known ride-hailing company and the market leader in ridesharing, announced that they had 91 million monthly active platform consumers, 3.9 million drivers and 14 million trips completed each day by December 2018[1].

Ridesharing has experienced several peaks of popularity in the past, the first time was during World War Ⅱ when the US government organized the Car-sharing clubs in order to conserve resources for the war. The second peak period was in 1970s as a consequence of energy crises(Chan & Shaheen, 2012) and the third one was in 2000s when the widespread use of Internet and cell phones made it easy to request a shared ride. And then in present day, the ridesharing is encouraged by many governments and environmental organizations as one of the carbon-efficient means, like public transportation, to achieve the targets of reducing transport emissions, solving oil-dependence problems (Sovacool, 2007) and relieving urban traffic congestions. Furthermore, ridesharing also shared the advantage of private car traveling such as the flexibility, convenience and comfortable (Sirisena, 1997; Amirkiaee & Evangelopoulos, 2018).

In spite of the benefits, there are challenges associated with time gain, transportation anxiety and participation intention (Amirkiaee & Evangelopoulos, 2018) to further develop urban ridesharing. One of the problems that drivers and passengers face in practice is that the driver needs to make extra detours while the location of passenger is with lower spatial accessibility. And when it comes to multiple passengers in a single ride, the cost of the extra detours would become less acceptable. To solve this problem, the flexibility characteristic of ridesharing can be the breakthrough point.

Compared with fixed points such as bus stops, the flexible pickup and drop-off points are able to reduce time cost and transportation anxiety by avoiding detours and heavy traffic sections. An example was provided to show how a ride can be benefited if the pickup point of the passenger was relocated in a nearby intersection. See figure 1-1, the Location 1 is the origin of the passenger when he requested a ride while Location2 is the relocated position, and compared with the rout of vehicle before coordination (blue line), the rout after coordination(red line) visibly reduces a long distance of detour (Zhao, Yin, An, Wang, & Feng, 2018). Besides, it can be assumed that taking a alternative pickup and drop-off points contributes to a possible time gain because of less detours and an increase of participation intention as a result of having more choices and information interaction between drivers and passengers.

[1] https://www.uber.com/newsroom/company-info/

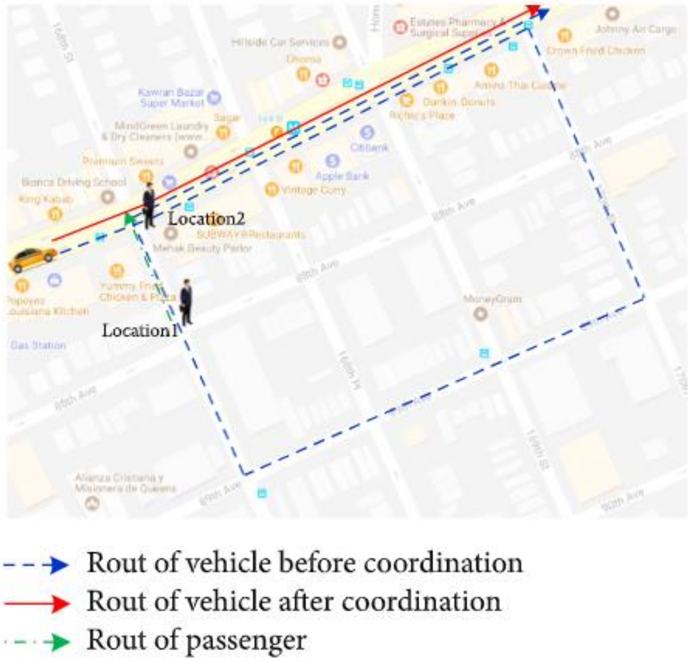


Figure 1-1 Illustration of pickup and delivery locations repositioning detour (Zhao et al., 2018)

Not all the nearby locations can have positive effects on driving routs. Hence, how to choose an alternative pickup or drop-off points remains a problem. Generally, the passengers who would try to relocate their pickup points are familiar with the surroundings, based on the experience they know the locations where drivers can avoid some predictable detour and easily find them. Also, the feature developed by some ridesharing platforms can provide suggested meeting points, which can be regarded as a kind of alternative location recommendation for passengers. However, these choices are unable to ensure an optimization on rout.

Most investigations which have been conducted on flexible pickup and drop-off points that can optimize routs, focused on theoretical models such the mathematical methods like hybrid algorithm (Balardino, 2015) and model based on Lagrangian relaxation detour (Zhao et al., 2018) instead of considering practical factors and reality. Although there are approaches which took practical conditions into account such as GIS-based identification method (Czioska, Mattfeld, & Sester, 2017), they tended to propose solutions to determine a fixed location as the pickup and drop-off point, running counter to the flexibility.

Therefore, this work aims to find out an approach to determine the optimal pickup and drop-off points (PDPs) which can effectively improve the driving rout in the urban ridesharing. It is assumed that the approach possesses both flexibility and practicality, implying that the PDPs vary with the changing circumstances of practical world.

1.2. Research Objectives and Questions

The main research objective is formulated as follow:

> To design a reality-based approach of determining the optimal pickup and drop-off points that can effectively improve the driving rout in urban ridesharing.

Sub-objectives and their respective research questions are listed below:

To identify the indicators that affect pickup and drop-off points determination based on existing

RQ1. Which kinds of indicators will affect pickup and drop-off points in ridesharing?

RQ2. How do these indicators affect the identification of possible pickup and drop-of points?

To determine the possible and optimal alternative pickup and drop-off points

RQ3. What is the application scope of the proposed approach?

RQ4. Which tools are used in the alternative pickup and drop-off point determination and why?

RQ5. How to determine all possible alternative pickup and drop-off points of passengers?

RQ6. How to determine the optimal pickup and drop-off points among all the possible alternative points?

To implement the approach

RQ7. What are the metrics to define whether the driving rout is effectively improved?

To evaluate the implementation

RQ8. How does this approach perform in practice?

1.3. Structure of the Thesis

This work was divided in to 5 Chapters.

In Chapter 1, the motivation and problem statement were described, followed by the research objectives and their respective research questions. Chapter 2 started with the ridesharing overview, and then introduced related works and knowledge of pickup and drop-off point, as well as the route planning. Next the Chapter 3 defined the research design involving the implementation tool and presupposition, and elaborated on the specific methods for identifying the indicators, determining the PDPs and evaluating the proposed approach. Chapter 4 described the process of implementation and discussed the results. Finally, Chapter 5 covered the conclusion, answers to research questions, limitation and future work of this research.

2. RELATIVE WORK

2.1. Ridesharing Overview

Shared mobility is defined as the short-term access to shared vehicles according to needs and convenience of different users (Shaheen, Chan, Bansal, & Cohen, 2015) vehicle sharing, on-demand ride services, ridesharing and so on. It is considered as an effective transport mode which can ease traffic congestion, having multiple shared one vehicle to reduce a massive number of private vehicles while remaining advantages of personal cars such as flexible, comfort and availability (Martinez & Viegas, 2017)

Ridesharing is one of the shared mobility modes, with features including dynamic, cost-sharing, non-recurring and independent (Agatz, Erera, Savelsbergh, & Wang, 2012). And it is defined as "the formal or informal sharing of rides between drivers and passengers with similar origin-destination pairings" by J3163™ standard (SAE International, 2018). Ridesharing is showing the potential to benefit the environment and society, which can reduce the transport emissions and congestion (Caulfield, 2009). The reduction can be reflected in many fields such as journey time, traveling distance, fuel costs and car occupancy (Fellows & Pitfield, 2000). The International Energy Agency reports that about 7.7 % fuel consumption and 12.5% vehicle miles could be reduced if there is one more passenger added in a shared journey (Birol, 2005). Meanwhile ridesharing is also affected by various factors such as sharing intention of drivers(Cheng, Su, & Yang, 2020) and effects of policy.

Various kinds of dilemmas start appearing in different fields such as environment, society and economy. An increasing number of articles claim that the ridesharing service is not ecological as people expected and it is the one to blame for growing urban pollution issues. A social-economic problem can be a cost-sharing problem, as there are multiple participants in a ride including drivers and more than one/one group of passengers, how to fairly and responsibly share all the related costs such as fuel-cost and time-cost remains a problem (Rapoport, Qi, Mak, & Gisches, 2019). One of the social reasons could be the sharing intention of drivers, which is affected by the interaction of passengers exemplified by paying on time, online review and driving expenses (Cheng et al., 2020). Also, an experimental study reports reveals some factors of choosing ridesharing such as time benefit, transportation anxiety and ridesharing participation intention (Amirkiaee & Evangelopoulos, 2018).

There are several hotspots in the ridesharing field such as matching system and routing problems while there are less discussions of pickup points. Matching systems are widely studied by different methods exemplified by the mathematical model of high-capacity (Alonso-Mora, Samaranayake, Wallar, Frazzoli, & Rus, 2017) and the equilibrium model for morning commute problem (Fu & Wang, 2018). The popular method to address the routing problem of ridesharing is investigating the historical traces such as GPS trajectories mining (W. He, Hwang, & Li, 2014). For pickup point selection existing studies tend to determine a fixed meeting point (Stiglic, Agatz, Savelsbergh, & Gradisar, 2015) instead of making good use of the flexible nature of ridesharing.

2.2. Pickup and Drop-off Point

Previous research on pickup and drop-off points tend to focus on public transport and taxi. For public transport it can be regarded as the stop/station allocation problem, which is analysed more likely based on static data and demands, considering the factors such as stop spacing and population density (Ibeas, dell'Olio, Alonso, & Sainz, 2010). For the taxi, the original-destination (OD) trip data are analysed for optimal dispatching system, the patterns of distribution and relationship between the pickup and drop off point can reveal interesting urban phenomena in different cities(Zhou et al., 2019). Also, the patterns of pickup points can provide useful suggestions for empty taxis to increase their utilization (Lee, Shin, & Park, 2008). There is very few study focused on the pickup and drop-off for shared mobility, especially for urban ridesharing, the one that discussed the optimal pickup point for ridesharing proposed a method to determine a fixed location for dynamic ridesharing which aims at protect privacy and safety of users (Goel, Kulik, & Ramamohanarao, 2016).

Various indicators should be taken into account when determining an efficient pickup and drop off location for ridesharing such as travel time, turn cost and behaviour of passengers. According to different scenarios and realistic conditions, the priority of indicators will vary, and interaction with passengers can play an important role. Related works that determine indicators of optimizing pickup and drop off location for a ridesharing journey are detour, walking distance (including walking length and walking speed, traffic signals and pedestrian navigation etc.) and passenger preference.

2.2.1. Meeting Point

The study about meeting points can be discussed by different conditions: Fixed route with fixed point, fixed route with flexible point, flexible route with fixed point and flexible route with flexible point. The first situation is common in public transport planning, since the bus/tram routes and stops were already decided in a planning stage and will not be changed. For the flexible route and fixed point it is a familiar mode of traditional airport express service or long-distance ridesharing service such as blabla car , the meeting points are fixed which are always located at the hotels or stations and the express routes will change depending on the ride request. Also the fixed meeting point is regarded as a privacy-preserving method in ridesharing under the big data background (Aïvodji, Gambs, Huguet, & Killijian, 2016), and various approaches such as agent-based (Rudnicki, Anders, & Sester, 2008) and GIS-based methods (O'Sullivan, Morrison, & Shearer, 2000) are studied in this field.

2.2.2. Detour

Detour is an important issue of ridesharing in reality. Traditional taxi mode allows drivers to go directly from one pick up to one destination, which is different from ridesharing which needs to consider multiple passengers. Not all the routes of different groups of passengers can overlap well so that detour is inevitable. Recent research showed that delay and detour could be the reason for a low percentage of ridesharing in China, while the extra delay was explained as the result of pickups, drop-offs and detours (Li, Pu, Li, & (Jeff) Ban, 2019).

The related concept is turn cost or turn penalties. Turn cost is the risk and time associated with turn, since vehicles tend to slow down when taking turns or some turns are forbidden, which is an important issue that needs to be addressed (Bräysy, Martínez, Nagata, & Soler, 2011). Turn penalties is a term discussed in vehicle routing problems and pedestrian routing issues. The indirect left-turn (or right-turn problem in left-hand traffic countries) is considered as a solution to congestion, since in a practical driving situation the direct left turn is supposed to cause delay in at-grade intersection and or accidents (Tao & Wei, 2009). In a given scenario the application of indirect turn can effectively decrease the journey time and increase the traffic output (Ahmed, 2011). From a pedestrian view it can be considered that there is zero cost when making a right turn in an intersection but non-zero cost while going in other directions due to the traffic lights and the demand of crossing the road (Bräysy et al., 2011).

2.2.3. Walking Distance

Walking distance is a significant consideration in transit planning, which was widely discussed in location selection problems. Related research showed that many spatial and personal characteristics are the factors affecting the determination of walking distance (Maghelal, 2011). These characteristics can be population density, sidewalk availability (El-Geneidy et al., 2014), and individual characteristics such as age (Alshalalfah and Shalaby, 2007). Besides, the total length of ride will have an important impact, which means that passengers would like to walk a long distance if they expected a longer journey (El-Geneidy et al., 2014). For a public transport which is supposed to have fixed routes and stops, spatial features of larger scale, like land use, are important to be taken into account (Tao & Wei, 2009).

Walking length and walking time can be used to measure walking distance according to different requirements such as less walking or less time-cost. Walking length is simpler to determine since it can depend on people's willingness in most cases, while there are more complicated factors contributing to walking time. For instance, walking speed, pedestrian navigation, traffic signals and walking-friendly level will have an important effect on walking.

Pedestrian walking speed can be divided into sidewalk speed and crossing speed, and vary from different regions, age and gender (Chandra & Bharti, 2013). Pace of life project (2006) announced a result of different walking speed around the world in which people in Singapore walk fastest among the 32 cities and Dutch people in Utrecht rank 9th fastest who took 12.04 seconds to walk 60ft. It is observed that male is walking faster than female (Fruin, 1971; Polus et al., 1983) and elderly pedestrians will have an obvious slower walking speed, for instance a research shows that in Northern America the proper walking can be 1.0 m/sec while 1.0 and 1.2 m/sec at crosswalk and signalized intersections (Coffin & Morrall, 1995).

Also, walking time will be different because of pedestrian navigation, in some situations it may take more time for pedestrians to find their way to the pickup or drop-off point. The walking environment and passengers' cognition of geographic space are the important factors that affect the wayfinding. For example, landmarks are frequently used in urban pedestrian navigation due to the wide range of landmark categories including traffic lights, restaurants, parks and other buildings, etc. (May, Ross, Bayer, & Tarkiainen, 2003). It can be inferred that it may take less time to get to the point if there are recognizable landmarks pickup and drop-off points on the pedestrian route.

Other factors that cause a walking time delay can be traffic signals. If there are traffic lights on the route, then the waiting time should be taken into account. According to various traffic conditions of different streets and sessions, the traffic light schedule will be different, furthermore some cities may have a real-time traffic lights schedule which will make the walking time cost become more difficult to predict (Zhou., 2010).

2.3. Route Planning

2.3.1. Route Planning Overview

An optimal route choice of driver can not only contribute to travel efficiency but also help improve the traffic condition and utilization of road networks(Zheng, Wang, Wangling, & Kuang, 2008). Since route planning is a hotspot, there is plenty of research that has studied this field. Major works focus on the shortest route planning, while popular routing based on history trajectories is getting more and more attraction (Liu, Jin, & Zhou, 2016). Moreover, because of the increase of different demands and available information support, various optimizations of route planning have been discussed and implemented such as the ease of transfer, carbon footprint and calorie consumption.

Many attributes will affect route planning such as the turn cost, driving direction and traffic condition. Turn cost is one of the important indicators affecting route planning, works have been done for investigating such as the model based on a pseudo-dual graph proposed by Winter (2002). Driving direction is considered in a more detailed route planning solution instead of a simple model, which will lead to significant problems in performance (Delling, Goldberg, Pajor, & Werneck, 2017). Traffic condition is related to the dynamic route planning since the traffic varies from different time and the traffic aware routing can support better driving decision making (Xu, Guo, Ding, Sun, & Liu, 2012).

There are a large number of existing route planning algorithms. Most route planning applications use the shortest path computation, and Dijkstra's algorithm, which is to find the shortest paths between nodes in graph, is the basis of these state-of-the-art algorithms. Related to the multimodal transport modal, Lozano and Storchi (2001) studied an algorithm for finding a set of nondominated shortest viable path, Zografos and Androutsopoulos (2008) proposed an algorithm was proposed for solving itinerary planning problems based on dynamic programming, Kheirikharzar (2010) discussed the resulting k-optimum paths between two predefined points on a network by exploiting label setting. Also, time-dependent shortest path algorithm based on Euclidean distance considering "closeness" to the target node as heuristic was studied (Idri, Oukarfi, Boulmakoul, Zeitouni, & Masri, 2017).

Routing contributes to the point selection in ridesharing since they are interacting with each other. Different points will conduct to different possible routes in the ridesharing journey, and the routes can help to decide the optimal pickup and drop-off points. In this work, the routing problem is regarded as the vehicle routing problem with pickup and delivery (VRPPD) and with passenger capacity constraints, integrating the ride matching system. The order of processing the routing is that first the matching system will allocate the driver to the passenger, and then the routing will start.

The classic vehicle routing problem is formulated by Dantzig and Ramser (1959), which is one of the NP-hard tasks and set up with assumption such as demands are deterministic, orders are carried by one vehicle and all the vehicles have same carrying capacity (Barnhart, 2007). According to different tasks, the vehicle routing problems have a further classification. These tasks can be the number of depots and consumers, types of vehicles and products, constraints on the goods or time and other particular conditions, and correspondingly there are various kinds of vehicle routing problems such as MDVRP (multidepot VRP), VRPB (VRP with backhauls), VRPPD (VRP with pickup and delivery), SDVRP (Split-delivery VRP) and VRP with risks etc. (Guzairov, Yusupova, Smetanina, & Rassadnikova, 2016). In this case, ridesharing routing problems can be simplified as VRPPD with carrying capacity constraints.

2.3.2. Matching system.

Matching problem is one of the most popular hotspots in ridesharing study, a number of models and algorithms are proposed for dynamic matching, and based on various demands or optimizations, these approaches may have many differences. The different demands can be length of journey or security, for example traditional ridesharing methods are designed for long distance journey, which is less flexibility for the urban range travel (Schreieck et al., 2016), and the method considering gender preference is assumed to have higher safety (He, Cheng, Chen, & Hang, 2018). For different optimizations, examples can be the methods that aim to reduce travel distance or increase system stability, which are exemplified by a method applying undirected weighted graphs is proved to save 23% to 35% overall travel distance of targeting passengers (Shi, 2017) and a heuristic algorithm introduced a notion of two-sided matching to build stable matching system (Ma, Yao, Song, & Jin, 2019). Besides there are other kinds of approaches with different aims, such as a real time algorithm which is mainly considered flexibility of the ridesharing (Masoud & Jayakrishnan, 2017), and PTRider which is with awareness of travel cost such as price and time (Chen et al., 2018).

2.3.3. Real-time Traffic

Real-time traffic shows the current traffic situation which is helpful in route planning, many previous works discuss optimal routing exploiting the real time traffic information, such as the procedure for determining the routes and departure time (Kim, Lewis, & White, 2005) and a system for eco-routing with multisource real-time traffic information and simulated traffic data (Boriboonsomsin, Barth, Zhu, & Vu, 2012). Real time traffic involves various types of specific information such as the travel speed, travel time, traffic incidents, road maintenance and construction etc. Traffic speed can be measured based on GPS traced data from the vehicles equipped with record devices (De Fabritiis, Ragona, & Valenti, 2008), traffic incidents information can be detected by automatically using artificial neural network (Srinivasan, Loo, & Cheu, 2003) or social media data (Gu, Qian, & Chen, 2016).

3. RESEARCH DESIGN AND METHODS

This chapter introduces the general design of the proposed approach and the methods that were used to conduct the research and answer the research questions. As reminder the involved research questions are listed as follow:

To identify the indicators that affect pickup and drop-off points determination based on existing

RQ1. Which kinds of indicators will affect pickup and drop-off points in ridesharing?

RQ2. How do these indicators affect the identification of possible pickup and drop-of points?

To determine the possible and optimal alternative pickup and drop-off points

RQ3. What is the application scope of the proposed approach?

RQ4. Which tools are used in the alternative pickup and drop-off point determination and why?

RQ5. How to determine all possible alternative pickup and drop-off points of passengers?

RQ6. How to determine the optimal pickup and drop-off points among all the possible alternative points?

3.1. Research Design Overview

3.1.1. General Research Design

The purpose of this research is to design an approach for determining the optimal alternative pickup and drop-off point (PDP) for urban ridesharing, to achieve the goal the design will be divided into three stages, including indicators investigation of PDPs, pickup and drop-off point analysis consisting of possible alternative PDP determination and alternative PDP optimization, and evaluation.

In the first stage the indicators were investigated by the literature reviews, and the ones which are applicable to the proposed approach were determined to provide foundations for building up a location set of candidate alternative PDP in the second stage. After conducting route planning on each candidate PDPs and comparing their time-cost in the third stage, the one with minimum time-cost was chosen as the optimal PDP. The second stages were done by the method of adopting the map API. And finally, the approach was evaluated by comparing and analysing the results and performances of different routes.

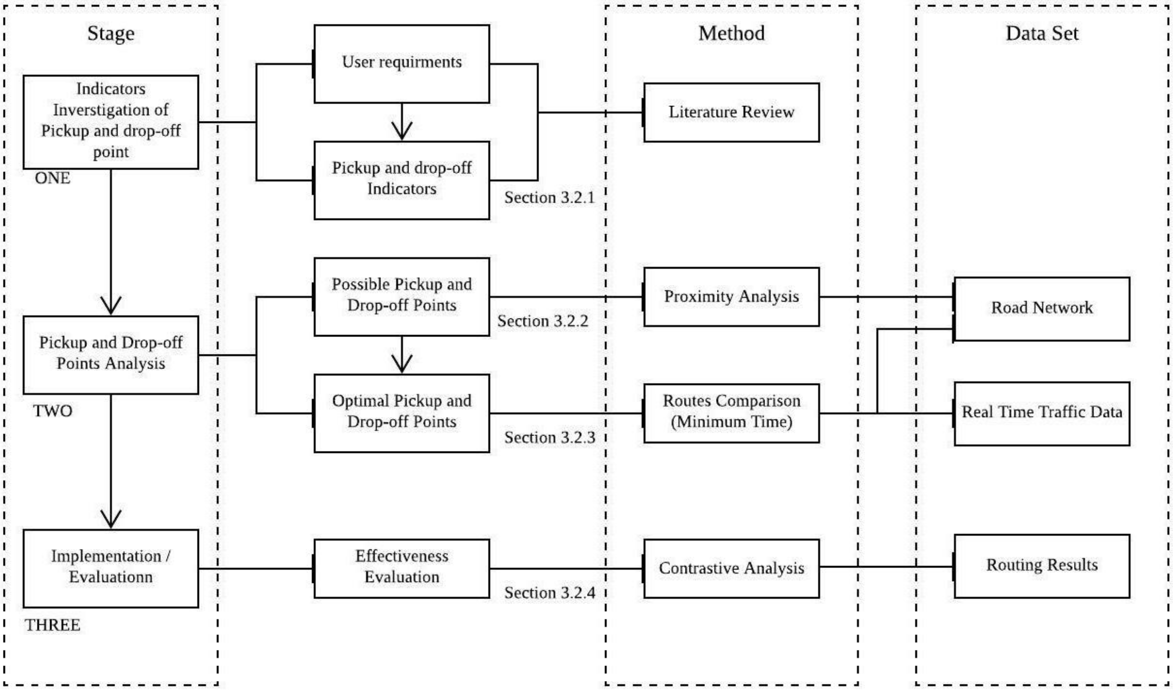


Figure 3-1 Workflow of General Research Design

3.1.2. Implementation Tool: Amap API

Map API is an application program interface of online map services, and there are multiple Map APIs available for the implementation such as Google map API, Mapbox API and TomTom API. This work adopted the Amap-API[2] which is independently developed, owned, operated and made available by AutoNavi for the reason that it provides a batch request interface and relatively comprehensive content for intersection information. Another reason is that the real time traffic status will affect the analysis and evaluation of the proposed approach, therefore the case study area was finally changed to the city in China where the traffic situation came back to normal after the pandemic the Amap is more applicable. The specific reasons why Shenzhen was chosen as the study area were described in Section 4.2.1.

Amap provides various services such as positioning, location search, route planning, public transport inquiry and road condition display. Also, it enables other operations like store, search, manage and display different kinds of data. Almost 90% of domestic travel applications such as DiDi which is the most popular ride sharing platform in China, use the map, navigation, route planning and automobile matching services provided by Amap.

Web Service API was adopted in this work for implementation in the second and third stages of the design, which included Geocoding and Reverse Geocoding API, routing planning API, places API and Cloud layer service API. JS API was adopted in the fourth stage of the design, including map display, routing display and cloud layer display functions for evaluation.

In this thesis, the programming language in working on Web Service API is Python 3.7 and on JS API is JavaScript.

[2] https://lbs.amap.com/api

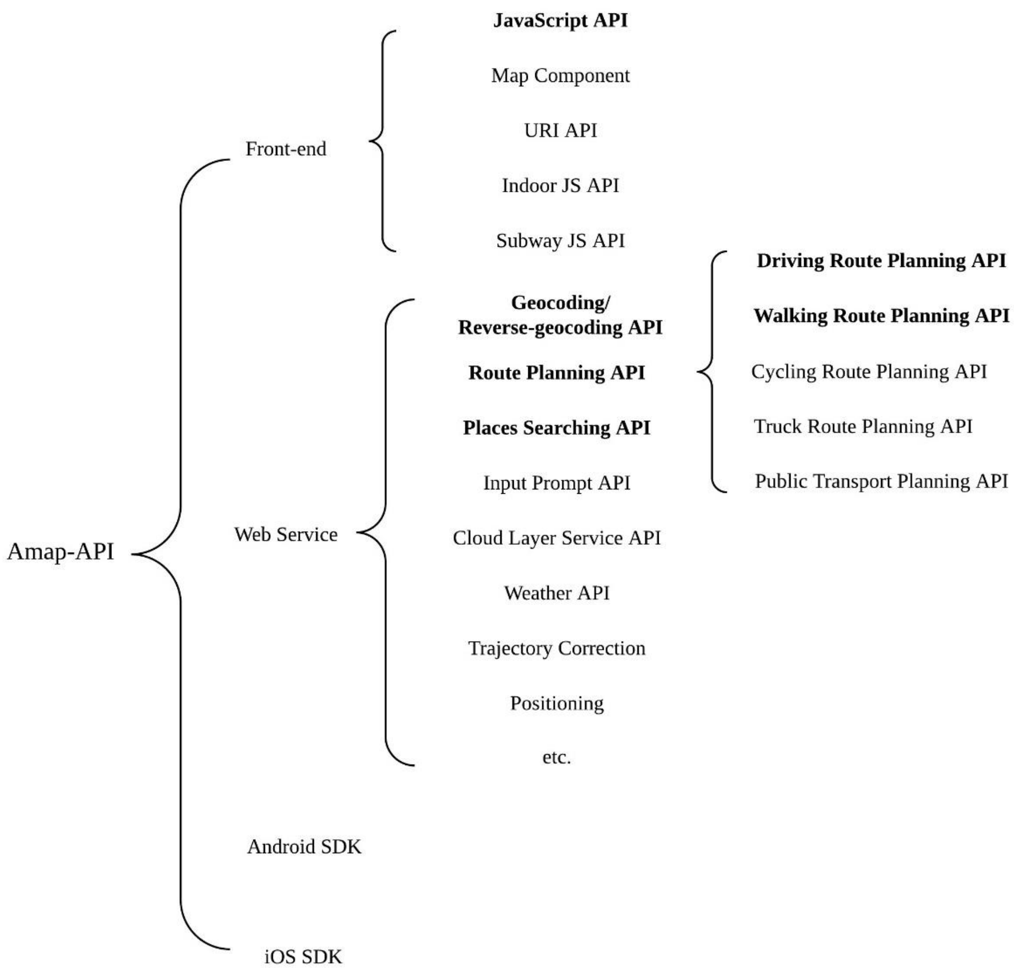


Figure 3-2 Category of Amap-API

3.1.3. Presupposition

The approach was design in the specific context following several presuppositions:

- The reservation of passengers and the driver (automobile) in a shared ride were predetermined, which implied that the dynamic matching system and time windows were not parts of the approach.
- Each shared ride had three passengers and the reasons why there were three passengers were explained in section 3.2.2.2.
- The driver was initially located nearby one of the passenger's departure point.
- The starting point of the shared ride was the driver's location and the ending point was the destination of the final passenger.
- Temporarily cancellations of reservations were not considered.

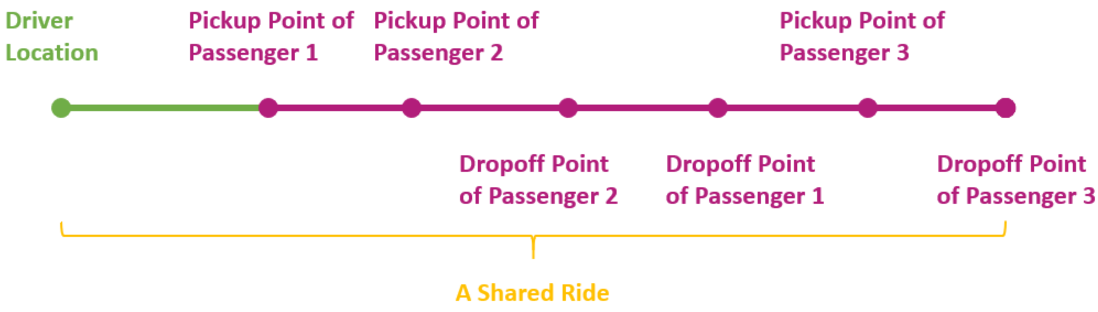


Figure 3-3 Example of A Shared Ride

3.2. Research Methods

3.2.1. Indicators of Pickup and Drop-off Point selection

Literature review is the main method to determine indicators of PDP selection. The indicators are supposed to be extracted from the user requirements. The users of ridesharing are passengers who want to request a shared ride, and drivers who provide a ride for passengers.

3.2.1.1. Requirements of Passengers and Drivers

For the passengers, the main reason for choosing ridesharing is the time-cost, fee and convenience. Compared with the traditional dial-a-ride service, ride sharing is the more affordable one since the fee can be shared by multiple co-passengers, but it is also at the expense of more time-cost. Compared with the public transport, the passengers can request a ride without restriction of regular time schedule and locations that the public transport cannot reach. Although the locations are flexible to be changed, the deviation of location is limited since there is maximum tolerable walking distance which could be varied from different passengers. Hence the alternative location decision depends on how far each passenger are willing to walk.

For the drivers, the main concern is to pick up as many as possible passengers in a ride, hence two important requirements for them are reducing the distance and detour which is common in ridesharing, and one of the solutions to these is choosing intersections as PDPs.

3.2.1.2. Real time traffic information

Real-time traffic information also has an impact on PDP selection especially in the practice. The status of roads will affect the choice of routes, like the optimal route provided in a simulation may be different from the one in reality due to some traffic jams. It can be supposed that in peak hours the routes that avoid heavy traffic sections result in less time-cost. DiDi provides a route planning strategy of congestion avoidance which takes the real time traffic flow and speed into consideration, and there is feedback that when this strategy is chosen the navigation system always shows a route passing through narrower lower level roads, in this case the time-cost would be reduced but more turns would be made.

3.2.1.3. POIs or Landmarks

Another problem that users are facing is that they find it hard to find each other. This is induced by several reasons such as the GPS positioning problem and the unfamiliarity of the roads. Many companies such as Uber and DiDi have designed a solution which is providing the suggested pickup points for users by mining the historical data and suggesting the POIs. POIs can be one of the indicators that reducing the time-cost of a shared ride, however the saving time is hard to be measured. Even though according to ride sharing service companies choosing POIs (or landmarks, here defined as a POI that is easy to find) are an effective way to let drivers and passengers find each other easier, there is no quantified evidence for proving it, hence the POIs were not determined as one of the indicators that affect the PDP selections.

In summary, the indicators considered for determining PDPs in this work are walking distance, intersections which are for less detours and distance, and real-time traffic.

3.2.2. Method of Alternative Pickup and Drop-off Points Selection

In this work an individual trip of passengers is divided into three sections: Original departure to Pick up point, pick up point to drop-off point, and drop-off point to original destination, see figure 3-4. Original departure and destination are collectively referred to as original points. A brief workflow of selecting alternative PDPs involves two sections: identifying the original positions of passengers and searching for all possible PDP with certain constraints.

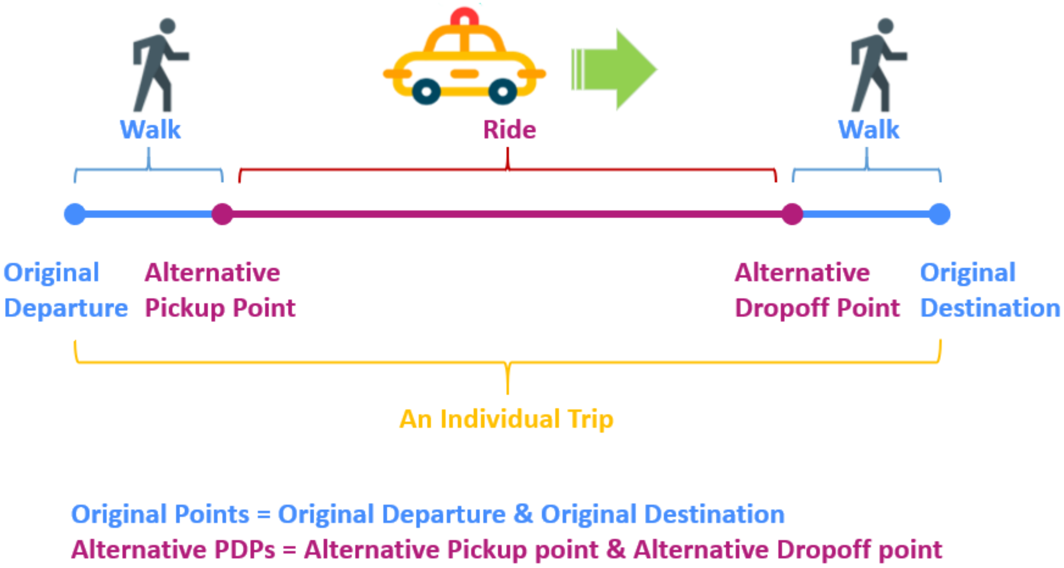


Figure 3-4 Example of An Individual Trip

3.2.2.1. Identify the original position of passenger

In general, the original position is defined as the location where a passenger currently is. Suppose that a passenger is planning to request a shared ride via mobile phone, the GPS coordinates of the phone are the current position of the passenger, also the original location of his/her trip. However, it is true only with conditions. For example, when the passengers are alongside the street where the automobile can easily pick them up, their GPS coordinates can be regarded as the original point; when the passengers are inside a building, then the original points should be reconsidered as the entry or exit of the building which the passengers need to pass through before accessing the automobile, and in this case the reverse geocoding is required.

Reverse Geocoding

Reverse geocoding is to convert the point coordinates to a readable address or place name. When a coordinate is provided near the midpoint of a segment, reverse geocoding will return an approximate address, for instance, if you are inside a park or a building, then the name and other information of the park or building will be returned.

Amap reverse geocoding API provides formatted address and various address component information like road intersections as output but excluding entry or exit information, therefore Places API needs to be introduced for that.

Table 3-1 URL of Reverse Geocoding API

URL	https://restapi.amap.com/v3/geocode/regeo?parameters
Request Method	GET

Table 3-2 Parameters of Reverse Geocoding API

Parameter	Description	Required or Optional	Default Value
key	Amap-API Key	Required	None
location	Latitude and longitude coordinates	Required	None
poitype	Type of return nearby poi	Optional	None
radius	Searching radius	Optional	1000
extensions	Result control	Optional	base
batch	Batch query control	Optional	false
roadlevel	Road level	Optional	None
sig	Digital signature	Optional	None
output	Output format	Optional	JSON
callback	Callback	Optional	None
homeorcorp	Optimize poi order	Optional	0

```
https://restapi.amap.com/v3/geocode/regeo?
  output=xml&
  location=113.899168,22.563713&
  key=daee36485ea08ec6e9871a4d4bcf5a46&
  radius=1000&
  roadlevel=1&
  extensions=all
```

Figure 3-5 Example of an Execute Request of Reverse Geocoding API

Places searching

Formatted address and the first point of interest (POI) from reverse geocoding API output can be used as the request parameters of places searching API, which also return poi information but including the entry and exit location. The input poi and the first poi of the outputs of places searching API are the same one with identical poi ID if there is only one available entry, whose coordinate will be the original location of the passenger. If there are multiple entries, the nearest entry will be returned in the first poi entry information, and other entries will become individual pois in the following list.

Table 3-3 URL of Places Searching API

URL	https://restapi.amap.com/v3/place/text?parameters
Request Method	GET

Table 3-4 Parameters of Places Searching API

Parameter	Description	Required or Optional	Default Value
key	Amap-API authorization ID	Required	None
keywords	Query keywords	Required	None
types	Query POI type	Required	None
city	Query city	Optional	None
citylimit	Only return data for specified cities	Optional	False
children	Display subclass poi data or not	Optional	0
extensions	Output control	Optional	Base
sig	Digital signature	Optional	None
output	Output format	Optional	JSON
callback	Callback	Optional	None

```
https://restapi.amap.com/v3/place/text?
  key=daee36485ea08ec6e9871a4d4bcf5a46&
  keywords=保利文化广场&
  types=190302&
  city=shenzhen&
  output=xml&
  extensions=all
```

Figure 3-6 Example of an Execute Request of Places Searching API

In short, the original location of passengers is the starting point of their trip and depending on different situations the identification involves two steps: reverse geocoding and places searching.

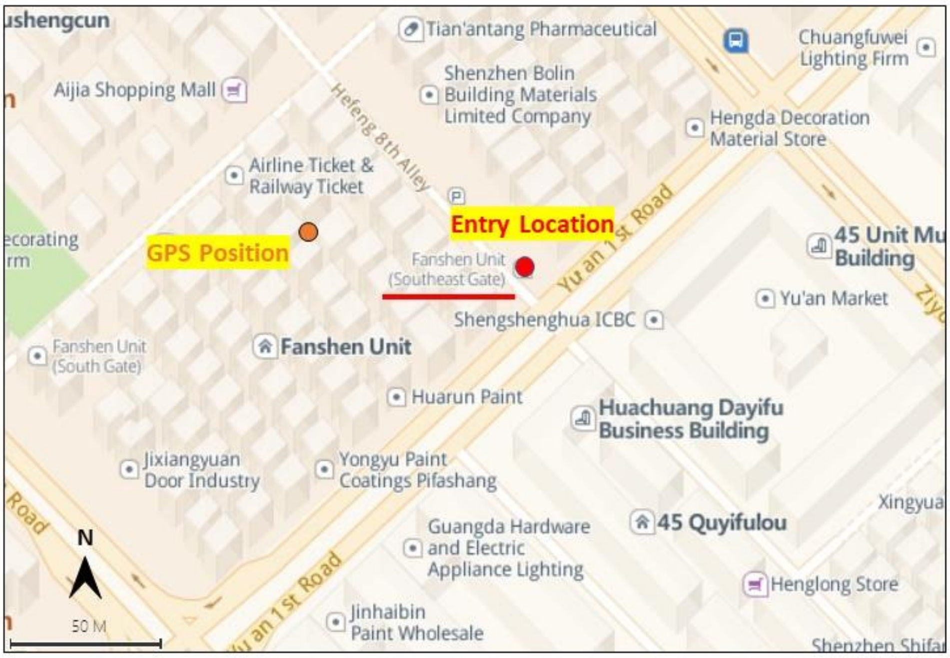


Figure 3-7 Example of Original Point Determination

1 Identify the Original Position of Passengers

Input: GPS Coordinates

Output: Original Location

```
OriginalLocation ← string
if GPS Coordinates are inside a POI then
    function REGEOCODE(GPS Coordinates)
        Url = Reverse geocoding URL + GPS Coordinates (as parameter)
        Data = request.urlopen(Url)
        Address ← Data['Address']
        return Address
    end function
    function GETENTRY(Address)
        Url = Reverse PlacesSearch Txet URL + Address (as parameter)
        Data = request.urlopen(Url)
        EntryCoordinates ← Data['EntryPoint']
        return EntryCoordinates
    end function
    OriginalLocation ← EntryCoordinates
else
    OriginalLocation ← GPSCoordinates
end if
```

Figure 3-8 Pseudocode of Original Position of Passengers Identification

3.2.2.2. Determine possible PDPs

Possible PDPs were determined depending on the original points and constraints. The number of candidate PDPs is set as three. It is related to the number of passengers in each shared ride, time and space complexity. The common automobiles for ridesharing are cars with 5-7 seats which means that 4-6 available seats for passengers, it is feasible to assume that there are up to 3 groups of passengers in a shared ride. Each group has one departure and one destination, there are 6 locations that can be replaced by alternative PDP. Supposed that the number of candidate PDP is n, in total n6 operation is needed for each shared ride routing. Hence n = 3 is sufficient for both time and space complexity.

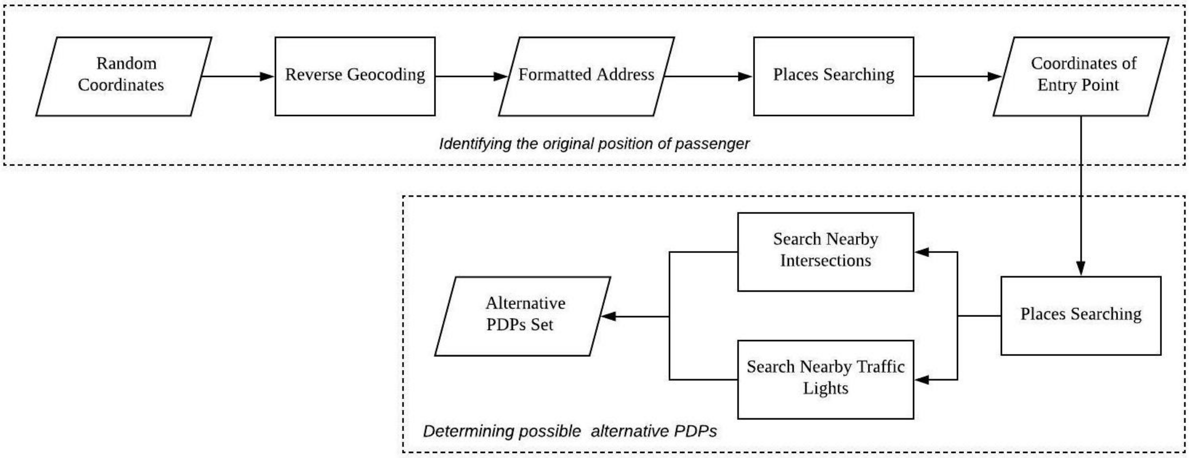


Figure 3-9 Workflow of identifying the original position of passengers and selecting alternative PDPs

Constraints

It is supposed that passengers will walk in the first and final sections (original departure to pick up point and drop-off point to original destination) of their individual trips, the constraints here will be considered in the situation of walking. Based on indicators of PDPs selection, simply the constraints consist of road intersections, walking duration and distance, and the types of road.

Due to the road hierarchy, there are also different levels of road intersection. For the purpose that the automobile is able to avoid unnecessary turns, the intersections involving non-motorway roads were not part of the calculation. Besides, in hypothesis the intersections of main carriageways or with traffic lights are considered as a prior choice for PDPs selection because it will have a greater influence on altering the planned routes.

Some types of roads are considered less suitable for passengers or expecting more time for walking. Usual road types can be sidewalk, crosswalk, underpass, overpass and so on, among them the crosswalk and underpass through subway stations should be taken into account as special cases that would cost extra time because of traffic signals and complex indoor pedestrian navigation.

Distance and time are important constraints to determine the PDPs, generally there is no certain limits for all the passengers but accordingly to individuals depending on various conditions. Different kinds of passengers, different individuals, same passenger in different situations would have their own bearable distance and time for walking to the PDPs. Also making the time and distance as less as possible is inappropriate for the reason that it will be insufficient to reach the effective intersections. Hence instead of giving limited walking distance or time, this work will choose the three nearby intersections with least walking time as the candidate PDP, and at least one is the intersection of main carriageways or with traffic lights.

Figure 3-10 Example of Possible PDPs Determination

Reverse geocoding API was adopted again for determining nearby intersections with the entry coordinates as input. Two poi types including intersection (poicode:190302) and traffic lights (poicode: 180400) were used as request parameters. Random check was made to inspect the quality of these intersections, here poor quality is defined as the location deviation or insufficient intersection which will not alter the routes. Walking route planning API was adopted for constraints of road type, walking distance and time.

Table 3-5 URL of Walking Route Planning API

URL	https://restapi.amap.com/v3/direction/walking?
Request Method	GET

Table 3-6 Parameters of Walking Route Planning API

Parameter	Description	Required or Optional	Default Value
key	Amap-API authorization ID	Required	None
origin	Starting point	Required	None
destination	Destination	Required	None
sig	Digital signature	Optional	None
output	Output format	Optional	JSON
callback	Callback	Optional	None

```
https://restapi.amap.com/v3/direction/walking?
  key=daee36485ea08ec6e9871a4d4bcf5a46&
  origin=113.899168,22.563713&
  destination=113.901947,22.561756&
  output=XML
```

Figure 3-12 Example of an Execute Request of Walking Route Planning API

2 Determine Possible PDPs

Input: Original Location
Output: Alternative PDPs

```
function GetPDPs(Original Location)
    Url = Reverse PlacesSearch Around URL + Original Location (as parameter)
    Data = request.urlopen(Url)
    PDP1 ← Data['Intersection'][0]
    PDP2 ← Data['Intersection'][1]
    PDP3 ← Data['Intersection'][2]
    AlternativePDPs ← [PDP1, PDP2, PDP3]
    return AlternativePDPs
end function
```

Figure 3-11 Pseudocode of Possible PDPs determination

3.2.3. Method of Optimal Pickup and Drop-off Points Selection

A shared ride is defined as a trip of a ridesharing automobile which starts with the automobile location and ends with a drop-off location of one of co-passengers. As mentioned before there are totally 3 (groups of) passengers and 6 original points in one shared ride and each original point has 2-3 candidate PDPs, which means that there will be 729 combinations of PDPs in a ride. Here an alternative route is defined as the routing result of a combination. The optimization of PDPs is achieved by calculating and comparing all possible alternative routes, and among them the one with least time-cost is the optimal route consisting of optimal PDPs. Without considering the situation that some passengers broke the appointment, each route consists of 7 locations, the starting point is the location of the automobile, the waypoints and ending points are the locations of co-passengers.

3.2.3.1. Dispatch system

Dispatch system is one of the most important parts in ridesharing which has a great impact on route planning. Different ridesharing platforms have their own dispatch system, but most of them share a common principle of proximity. For example, in DiDi, when passengers request a ride the platform will search for nearby automobiles with the shortest distance and time to them. Also, it adopted the global optimum mode which having most people had a ride with help of predictions based on historical data. For the ridesharing the problem is more complicated due to dynamic passengers, which is called multi-vehicle dynamic Dial-A-Ride problem (DARP). The aim of this kind of problem is to determine the optimum of passenger dispatch, allocate the passengers who are requesting a ride to automobiles, meanwhile optimizing routes of each automobile. The dispatch system is not the purpose of the proposed approach but an essential prerequisite to carry on the routing for optimizing the PDPs.

This work is under the scenario of scheduling service in advance to make sure that there are three (groups of) passengers in each shared ride. It follows some presuppositions: (1) the dispatch system will assign multiple passengers to the driver each time and will assign new passengers only after all previous passengers are settled. (2) In the beginning of a trip all the passengers and their departures and destinations will be added in the passenger list. (3) during the trip no new passenger will be added, the trip and the passenger list cannot be extended and (4) recalculation only happens if there is a passenger breaking the appointment. (5) the automobile is within the distance of 5-minute drive to one or more of the co-passengers.

3.2.3.2. Sequence of PDPs

Before calculating the alternative routes, the sequence of passengers needs to be confirmed by ensuring each passenger's pickup point is ahead of the drop-off point. The permutation is based on the total time-cost of the shared ride, the one with least time cost is regarded as the optimal choice.

3.2.3.3. Routing strategy

There are several optimal routing strategies available in Amap including time-cost, expense, distance, congestion avoidance, etc. After iterations multiple developed strategies were designed such as considering a combination of shortest distance & charges avoidance & high-way preference. The driving route API provides 21 types of strategy and this work adopted the strategy #11, which follows the optimization of minimum duration, shortest distance and congestion avoidance. Among them the minimum duration, as known as the shortest time, is the highest priority of this strategy.

3.2.3.4. Real-time traffic information

Two types of real-time information can be taken into account for route planning, which are traffic flow and traffic accidents. Traffic flow is applied as a real time traffic layer where each section of the road network is with a status such clear, slow and congested. It is exploited in the proposed approach by selecting the routing strategy involving congestion avoidance, which means that the routing algorithm considers the status of each road section and tries to avoid the slow or congested ones. Traffic accidents can be used as the avoid area by extracting the locations of reported traffic accidents (or maintenance and constructions) and setting them as the avoid-polygon in the map. It can be implemented by adopting places searching API or other real time traffic accident reporting resource (in xml format) for collecting traffic accidents and the request parameter "avoidpolygons" for setting up avoid areas.

Table 3-7 URL of Driving Route Planning API

URL	https://restapi.amap.com/v3/direction/driving?parameters
Request Method	GET

Table 3-8 Parameters of Driving Route Planning API

Parameter	Description	Required or Optional	Default Value
key	Amap-API authorization ID	Required	None
origin	Starting point	Required	None
destination	Destination	Required	None
strategy	Driving route optimization	Optional	0
waypoints	Waypoints	Optional	None
avoidpolygons	Avoid area	Optional	None
extensions	Output control	Required	base
sig	Digital signature	Optional	None
output	Output format	Optional	JSON
callback	Callback	Optional	None

```
https://restapi.amap.com/v3/direction/driving?
  key=daee36485ea08ec6e9871a4d4bcf5a46&
  origin=113.893932,22.567904&
  destination=113.907229,22.527346&
  waypoints=113.913696,22.540707;113.905948,22.559647&
  strategy=11&
  output=JSON&
  extensions=all
```

Figure 3-13 Example of an Execute Request of Driving Route Planning API

3 Determine Optimal PDPs

Input: Original Point Set, Alternative PDPs Set, Driver Location *the original point set includes 6 items (type:string), alternative PDPs set includes 6 items (type:list)

Output: Optimal PDPs Info

```
Calculate the optimal order of passengers with Original Point Set
    Rule: Pickup point must be before Drop off point of each passenger
Calculate the original route
    set driver location as start point, 6 original points as waypoints and destination
Calculate the optimal routes
function OptimalRouteCalculation(Alternative PDPs Set, Driver Location)
   OptimalTimeCost ← OriginalRouteTimeCost
   Departure ← DriverLocation
   loop
      i ← [0, 1, 2]
      Waypoint0 ← AlternativePDPsSet[0][i]
      loop
         j ← [0, 1, 2]
         Waypoint1 ← AlternativePDPsSet[1][j]
         loop
            k ← [0, 1, 2]
            Waypoint2 ← AlternativePDPsSet[2][k]
            loop
               l ← [0, 1, 2]
               Waypoint3 ← AlternativePDPsSet[3][l]
               loop
                  m ← [0, 1, 2]
                  Waypoint4 ← AlternativePDPsSet[4][m]
                  loop
                     n ← [0, 1, 2]
                     Waypoint5 ← AlternativePDPsSet[4][n]
                     Url = routing url + (Departure+Waypoints+Destination, as parameters)
                     Data = request.ulopen(Url)
                     TimeCost ← Data["duration"]
                     if time cost of Current route <time cost of Optimal Route then
                        OptimalRoute ← CurrentRoute
                     end if
                  end loop
               end loop
            end loop
         end loop
      end loop
   end loop
   return OptimalRoute
end function
OptimalPDPinfo ← OptimalRoute["information"]
```

Figure 3-14 Pseudocode of Optimal PDPs determination

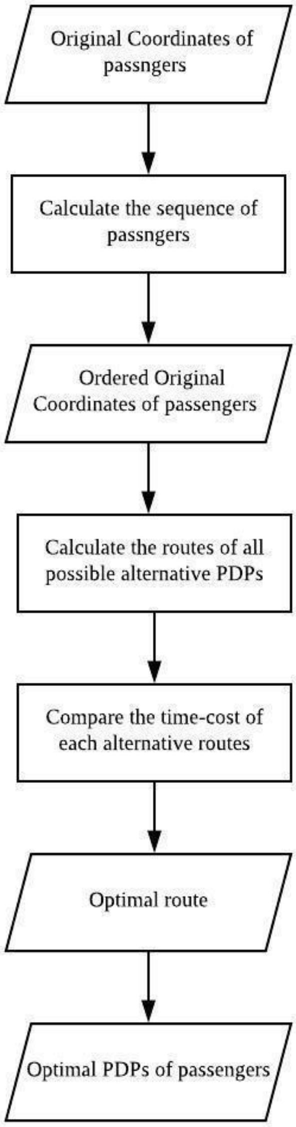


Figure 3-15 Workflow of selecting optimal PDPs

3.2.4. Evaluation

The approach was evaluated through analysing the comparisons of the original routes and alternative routes by metrics and trajectory analysis in a case study.

The metrics of a shared ride consist of distance, duration, fee, turns, passing sections and the clearness-rate. Distance involves the total distance of the automobile and the distance that passenger walks from their original departure/destination to their PDPs, the former was compared between original route and alternative route. Duration is the basis of determining the optimal alternative routes, including the total time cost of the automobile and the walking time of all co-passengers. Fee is the predicted fee that a whole shared ride will cost, which is based on the charging standards of local taxis. Turns are the number of turns including left-turns, right-turns and U-turns in the shared ride. Passing sections is all sections of roads the automobile passed through and the clear rate is the percentage of the sections with clear status.

The metrics of an individual trip consists of walking distance, walking duration, the number of crosswalks and the number of inconvenient road types including overpass, underpass, subway tunnels and stairways. Also includes the distance, duration and fee of a segment from pickup location to the drop-off location.

Finally, the trajectories of typical route comparisons such as the one that the alternative route is slower and longer than the original route were analysed.

4. EVALUATION AND DISCUSSION

This chapter introduces the evaluation of the approach, which was implemented by a case study in Shenzhen, and discusses the findings of the experimented results including the comparison of metrics and trajectories between original routes and optimal routes. It also answered the research question:

RQ7. What are the metrics to define whether the driving rout is effectively improved?

RQ8. How does this approach perform in practice?

4.1. Data

The data used for implementation are from AutoNavi (as known as the developer, owner and operator of Amap-API) in order to maintain consistency between API and experimental data, including road network, geographic data, photographic images, traffic data and address data. All these data are created by AutoNavi or licensed by third parties, which are exploited only by the method of the Amap-API in the implementation instead of being processed and stored. The geographic coordinate system is GCJ-02. Besides the content provided by Amap-API, a list of traffic lights locations is used as a complement for intersections searching.

4.2. Case Study

A case study in Shenzhen was carried out to evaluate the approach, which consists of two datasets. One dataset includes alternative PDPs which are within 5 minutes' walk to the original points, and the other includes alternative PDPs which are about 10 minutes' walk.

4.2.1. Study Area

The proposed approach was implemented in a case study in Shenzhen, a southern city in China, whose urban area is 1748 km² and urban density is up to 7400/km². Shenzhen is the first special economic zone established in China with a large number of actual populations of short-term residents, floating migrants, commuters, visitors and part-time residents; it also has the largest traffic volume in China due to favourable location.

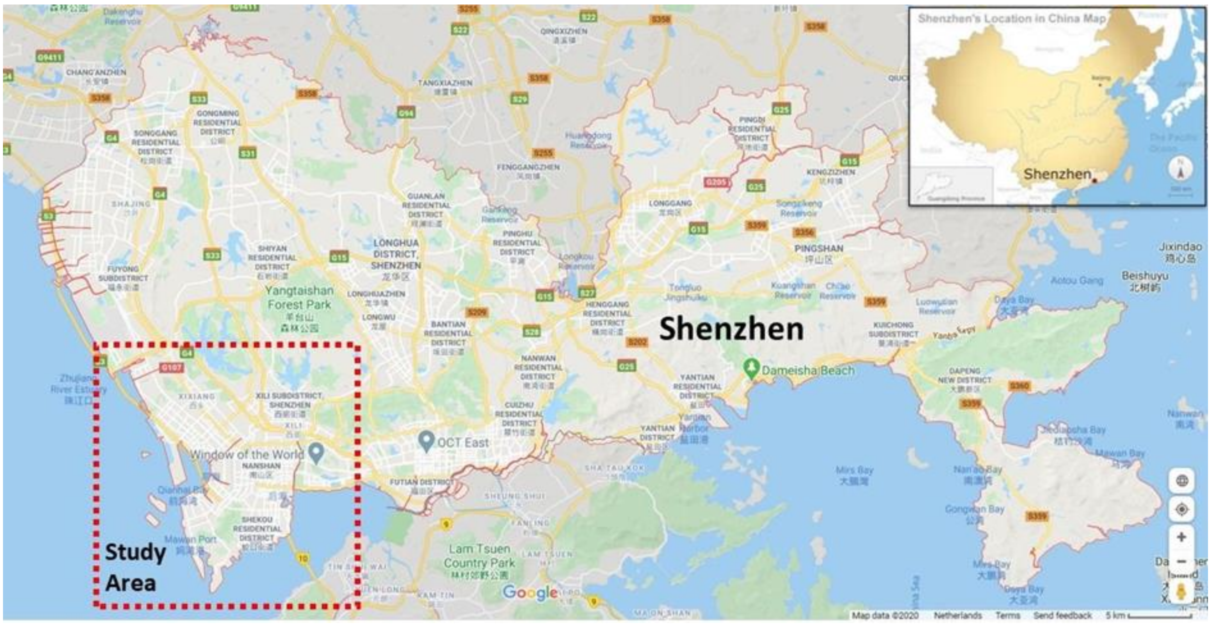


Figure 4-1 Location of Shenzhen and the Specific Study Area

There are several reasons why Shenzhen is the study area. Firstly, based on the user's statistics of DiDi which is the leading transportation platform with highest market penetration in China, Shenzhen is one of the cities with most ridesharing users, only behind Beijing, Shanghai and Chengdu. Compared with these three cities, Shenzhen has other advantages like Shenzhen is the city with the highest road network density of 9.5 km/km^2 and it is the first city in China that established a fully integrated mobility services platform for citizens.

Another important reason is that Shenzhen structure of road network is more suitable to focus on part of the city. Shenzhen has an urban form of diverse functional groups with multiple city centres while Shanghai Chengdu and Beijing have a ring and radial pattern based on the old city as the only centre. Figure 4-2 showed the traffic flow of Shenzhen, Shanghai, Chengdu, and Beijing, which depicted the structures of the cities. Since these cities cover a large area and few shared rides would have such a long distance, the study area will not be the whole city-wide but focus on part of it. Refer to the traffic flow map of these four cities, Shenzhen and Chengdu both showed a multiple groups structure by the traffic flow, however it should be noted that the surround groups in Chengdu are the residential area, which can be regarded as satellite towns that all connecting to the city centre, therefore they are not the functional groups that can be separated into a individual part as the study area. While Shenzhen has a better structure of road network to split the city into different small parts.

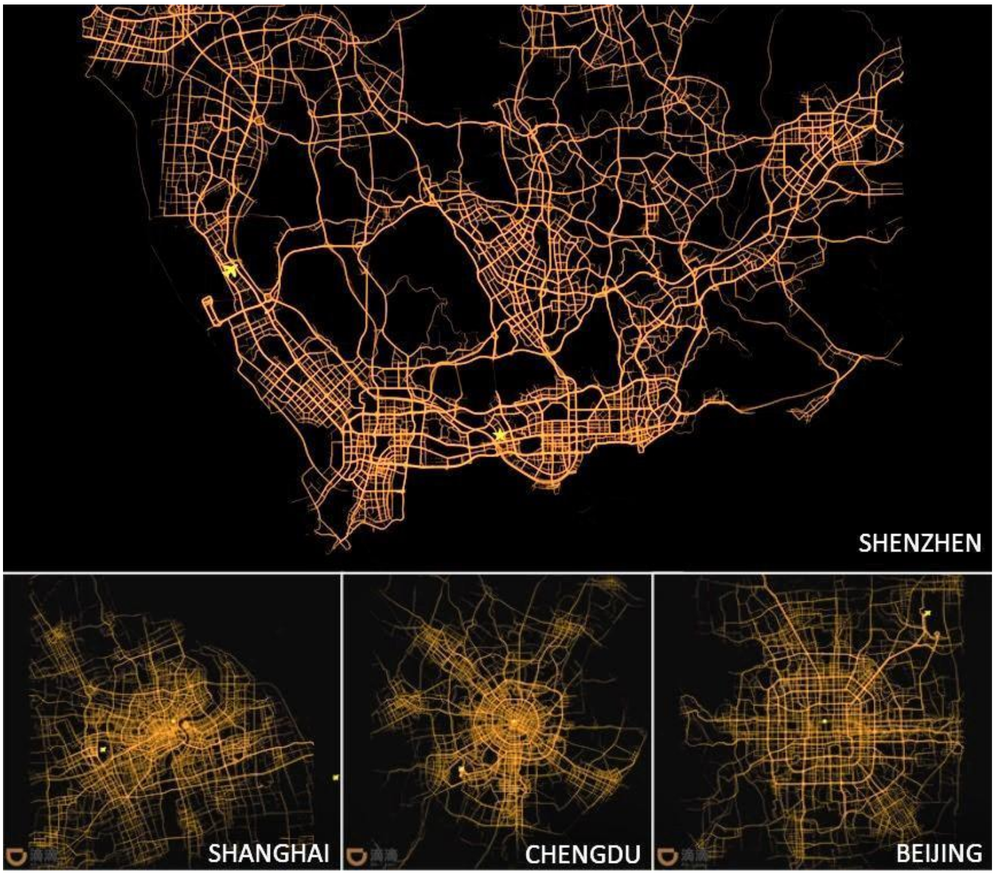


Figure 4-2 Traffic Flow Maps of Shenzhen, Shanghai, Chengdu and Beijing

4.2.2. Two Datasets

Different cities have their own characteristics and structures of road network and form, which will affect the determination of alternative PDPs, hence in this case two candidate datasets were used for the implementation.

The first dataset, in which the distances between original points and two corresponding PDPs are limited within 5 minutes walks, and PDPs are located at the closest intersections near the original points.

The second dataset was created as the extension of the first dataset. Candidate PDPs were added to three including two intersections from the first dataset and one newly added point with around 10 minutes (no maximum or minimum limited) walking distance to original points.

For instance, see figure 4-3, the first dataset consists of the original point (red point) and two nearer alternative PDPs (blue points), while the second dataset consists of all three points in the first dataset and an additional further PDP (purple point).

Figure 4-3 Example of Original point and PDPs of two datasets

4.3. Implementation

The implementation consisted of three technical steps, which includes building up the location sets, calculating the optimal routes and extracting the PDP information.

4.3.1. Building Location Set

The location set contains the information of passengers and automobiles' coordinates, which were collected to simulate a shared ride, consisting of 20 tuples and 5 attributes. Based on the attributes which were shown in Table 4-2, the location set can be divided into three part, the original point, the PDPs and the driver location.

Table 4-1 Attributes of Location Set

Attribute	Description
Original Point	The coordinates of original point of the passenger
PDP 1	The coordinates of the first PDP of the passenger
PDP 2	The coordinates of the second PDP of the passenger
PDP 3	The coordinates of the third PDP of the passenger
Driver Location	The coordinates of a nearby automobile

The first part was related to original position of passenger identification, the theory was discussed in Section 3.2.2.1. In implementation, 20 coordinates were randomly selected from Amap as the input of "GetLocations.py", where the coordinates of original point would be calculated by applying reverse geocoding and places search APIs. Figure 4-4 showed the distribution of the original points visualized in Amap.

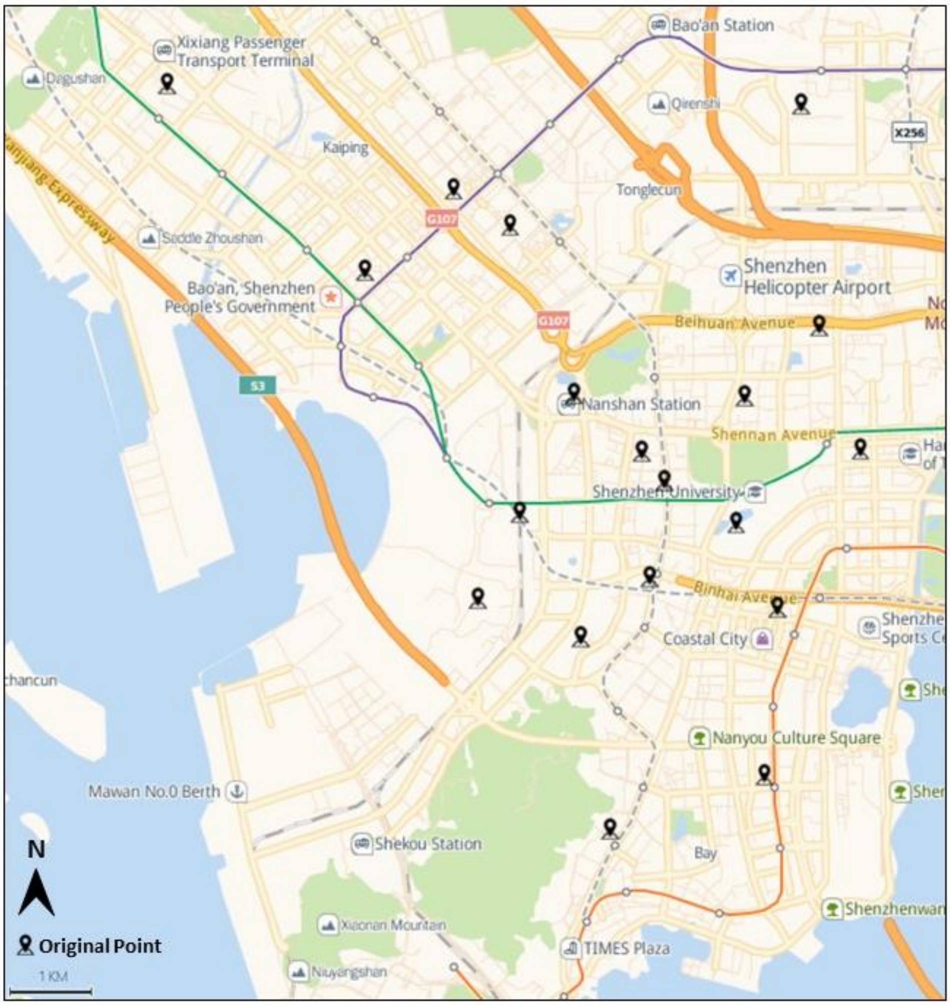


Figure 4-4 Original Points Distribution

The second part was related to alternative PDPs determination, whose method was discussed in Section 3.2.2.2. Also, in file "GetLocations.py", the calculated original points were used to determine alternative PDPs with places search API supplemented with external dataset of traffic lights, for the reason that the API document announced that traffic light information in places search API were incomplete.

The third part is the driver locations. Following the rules of the dispatch system, the passenger will be allocated a nearest driver in general dial-a-ride service. In the case of a shared ride with multiple passengers, the driver was set to be within 5min drive from one of the 6 predetermined passengers in this work.

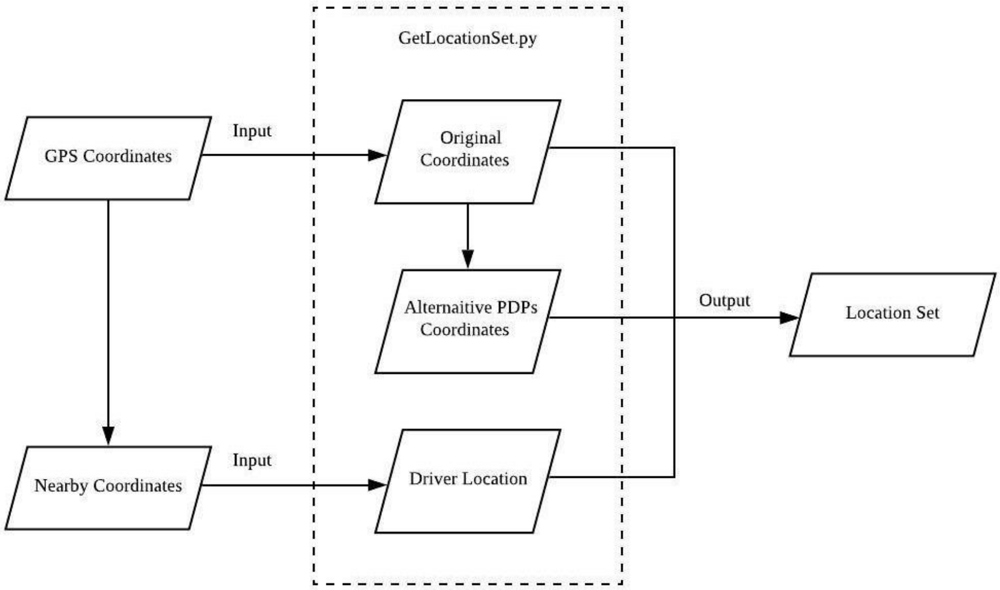


Figure 4-5 The Process of Building Location Set

All the coordinates in the location set were visualized in Amap for manual check, in order to avoid errors such as coordinates differences or PDPs getting too close.

4.3.2. Calculating Optimal Route

This step was conducted in "OptRoutCalculation.py" including 3 parts. Firstly, the file read the location set as a dictionary, then 6 were randomly chosen. The original points of these items were as the departure points and destinations of 3 passengers. For example, the first original point was regarded as the departure point of passenger A, and second original point was the destination of passenger A, and so on. The driver location was randomly chosen among the first, third and fifth items, as known as the departure points in the process. Setting the driver location as starting point and six original points as waypoints and ending point of a ride, multiple routes was calculated by changing the order of six original points in order to reach a sequence optimization based on minimum time cost, which was stored as the original route. Next each original point was iterated by the according PDPs to calculate all the possible alternative routes and during the iterations the time cost of the routes were compared and the one with minimum time was stored as the optimal route.

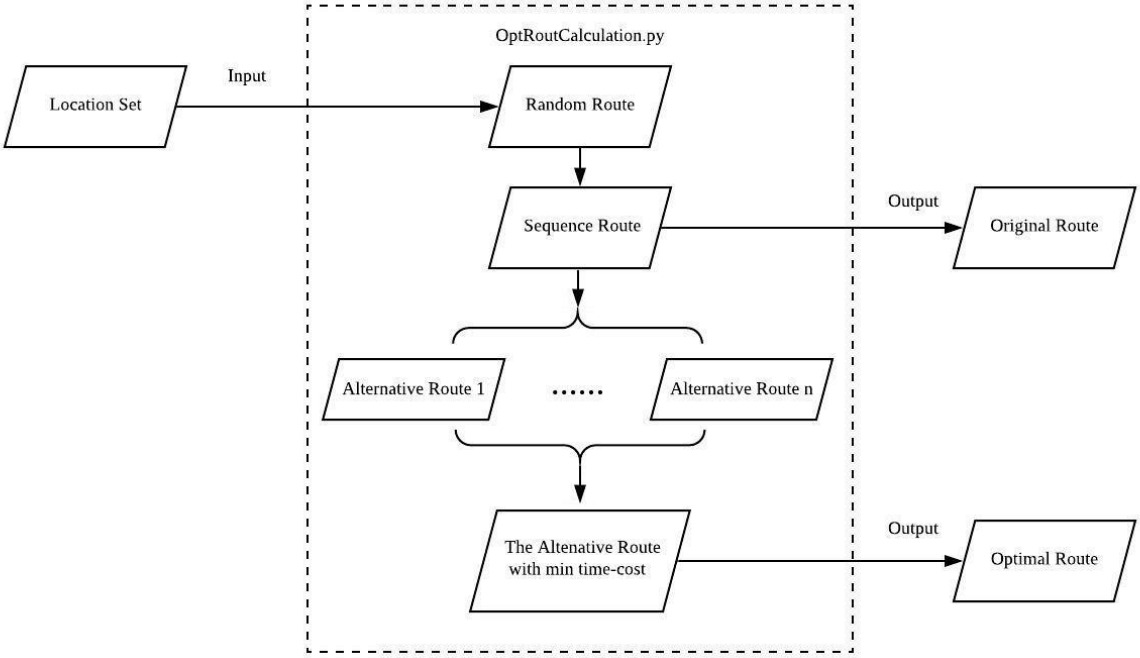


Figure 4-6 The Process of Optimal Route Calculation

4.3.3. Extracting Information

The information extracted from original rout and optimal alternative rout were written as an excel sheet, which was regarded as the output dataset. Attributes of the output dataset are displayed in table 4-4.

Attribute	Description
Time	Total time cost of the shared ride
Distance	Total distance of the shared ride
TrafficLights	Total number of traffic lights in the shared ride
Turns	Total number of turns in the the shared ride
Section	Total road sections in the shared ride
Clear	Total number of clear sections in the shared ride
Clearness	The rate of clear sections
RideTimePas	The riding time of passenger
RideDistPas	The riding distance of passenger
RideFeePas	The riding fee of passenger
WalkTimePPas	The walking time from departure to pickup point of passenger
WalkDistPPas	The walking distance from departure to pickup point of passenger
WalkTimeDPas	The walking time from drop-off point to destination of passenger
WalkDistDPas	The walking distance from drop-off point to destination of passenger
Coordinates	Involved coordinates in the shared ride including the automobile location and 6 PDPs for 3 passengers

Table 4-2 Attributes of Output Dataset

4.3.4. Testing Error

Since the real time traffic is keep changing with time, the result of a route will vary even though other input parameters remain the same. The time lag problem can be formulated as the average error. In this case the process time is about 20 - 25 minutes, hence the time difference among 5, 10, 15, 20 and 25 minutes of total 30 samples were calculated to estimate the error.

Table 4-3 Average ratio of time calculation error among 5, 10,15, 20 and 25 minutes in peak hours and off-peak hours

	5-minute	10-minute	15-minute	20-minute	25-minute	Average
Peak Hour	0.0130	0.0277	0.0424	0.0478	0.0456	0.0353
Off-peak Hour	0.0116	0.0113	0.0117	0.0101	0.0132	0.0116

4.4. Results

4.4.1. Results of the First dataset

The first dataset includes 30 samples, consists of original points and two alternative PDPs. Samples were randomly chosen from the location set, and each sample has original routing result and optimal routing result calculated by the chosen points. When the optimal result returns with same waypoints and destination locations of original points, it was regarded as no locations shifting, which meant that the optimal route is equal to the original route. Also, it can be reflected in the distance of the route. In this situation the optimal route is noneffective. Hence a pre-judgement was done to estimate the dataset by calculating the number of effective optimal routes.

Figure 4-7 showed the difference in distance between original route and optimal route, where only 10 samples have different length, indicating that 33.3% of routes are effective in this dataset. Since this percentage was evidently low, this dataset was considered as the one with poor quality which should be modified and recreated to the second dataset.

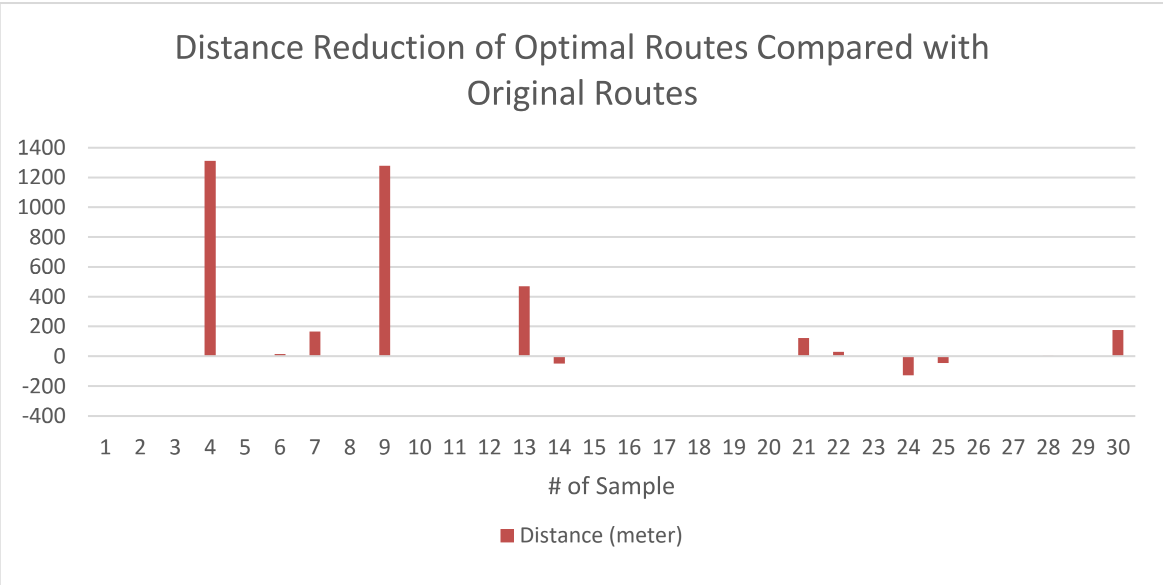


Figure 4-7 Result of Distance Reduction of the First dataset

4.4.2. Results of the Second dataset

The second dataset including 30 samples is the extension of the first dataset, which contains one or two added alternative PDPs that are located in a longer distance to original points. Different from the first dataset, the second dataset was designed that the alternative route only contained alternative PDPs due to the limitation of time complexity. Therefore, in this case the way to determine whether the optimal route is effective (i.e. optimal route is not the same as the original route) is the time reduction. If the time reduction is positive then this optimal route is effective, vice versa.

4.4.2.1. Time

Time reduction is calculated as the time of original route minus time of alternative route. See figure 4-8, the result showed that 24 of 30 samples had a positive time reduction, implying that 80% samples successfully reduce time cost by adopting the proposed approach. Besides, the maximum reduction is 35.5, average is 8.85, and maximum additional time is 9.5.

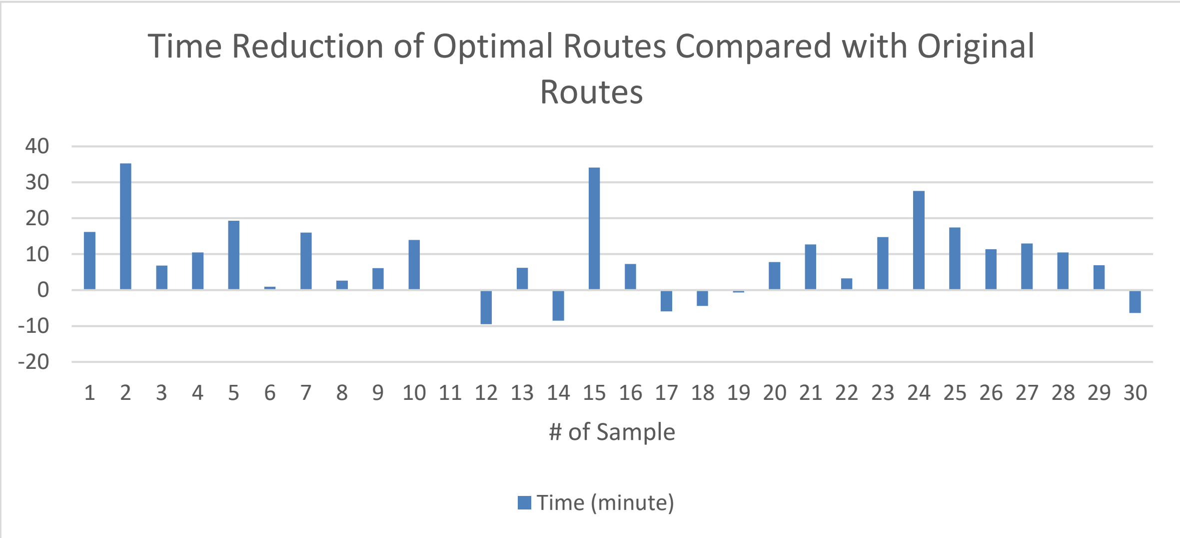


Figure 4-8 Result of Time Reduction of the Second dataset

4.4.2.2. Distance

Distance reduction is calculated as the distance of original route minus distance of alternative route. See figure 4-9, it showed that only half of samples reduce the total distance of the route, which is evidently less

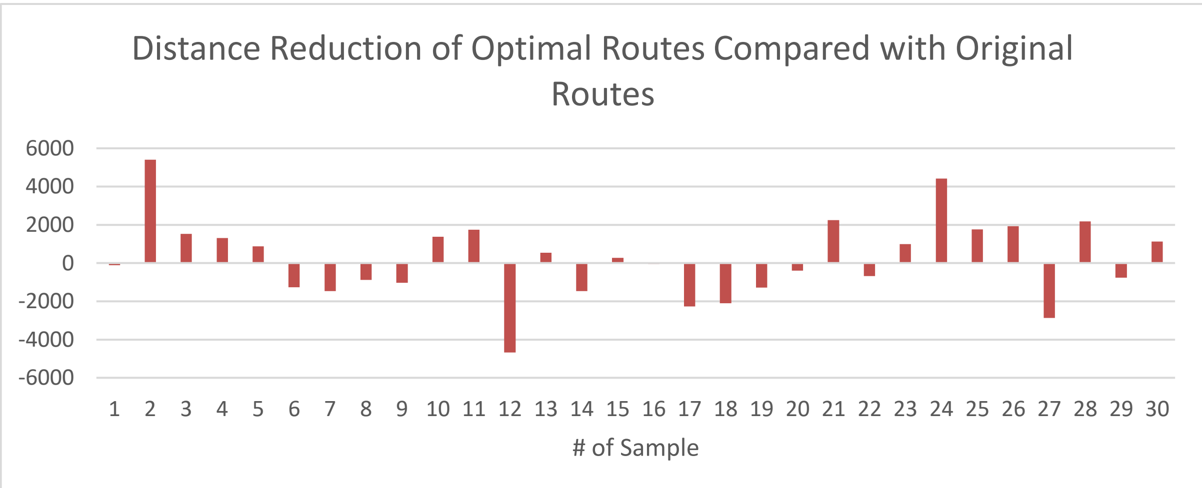


Figure 4-9 Result of Distance Reduction of the Second dataset

than time reduction. The maximum reduced distance is 5410 meters while the maximum additional distance is 4671 meters. The average distance is 211.7m and the median is 110.5m.

Also, no sufficient evidence to show that there is obvious correlation between time reduction and distance reduction, the relevance between time and distance varies from different samples. Take sample #15 as example, from figure 4-8 and figure 4-9 it is shown that the time reduction of #15 is 34.1 minutes which ranks the second highest among total examples, but its distance reduction is only 271 meters. As comparison the time reduction of #2 is 35.3 minutes and the distance reduction are 5410 meters, both ranking the highest among all samples. Figure 4-10 showed the scatter chart of time and distance reduction.

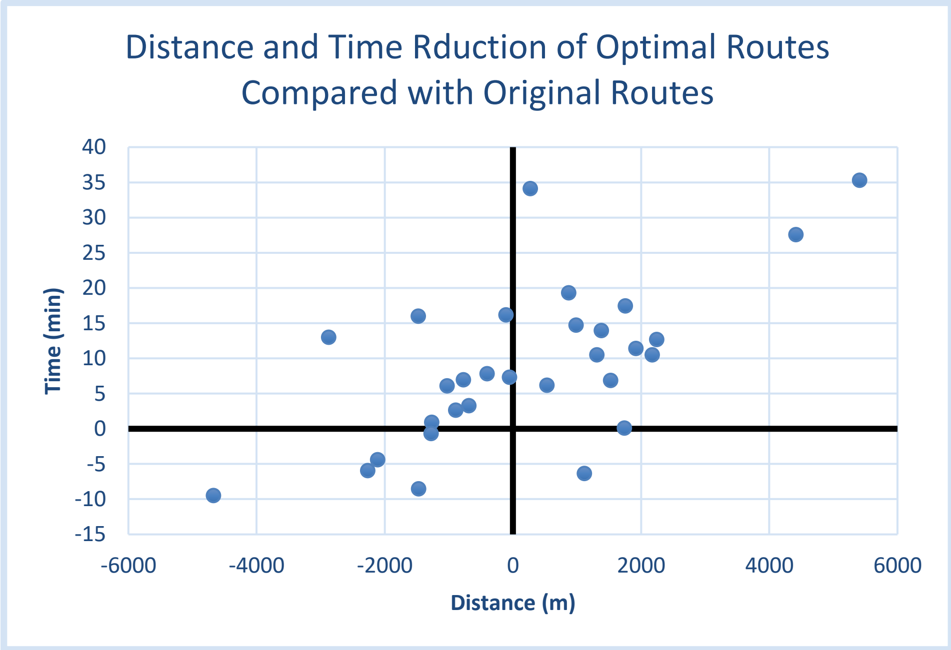


Figure 4-10 Scatter chart of Time and Distance Reduction of the Second dataset

4.4.2.3. Traffic Lights and Turns

The number of turns or traffic lights reduction showed how many turns or traffic lights were avoided in the optimal route compared with the original route. Figure 4-11 showed that 11 of 30 samples have a positive reduction in the number of traffic lights, the maximum traffic lights reduction is 22 and the maximum addition is 16. However, turns reduction is vastly different. In total 29 of 30 samples result in a positive reduction in amount of turns, except the sample #12, had one additional turn in optimal routes. Maximum reduced turns are 34 and average is 19.

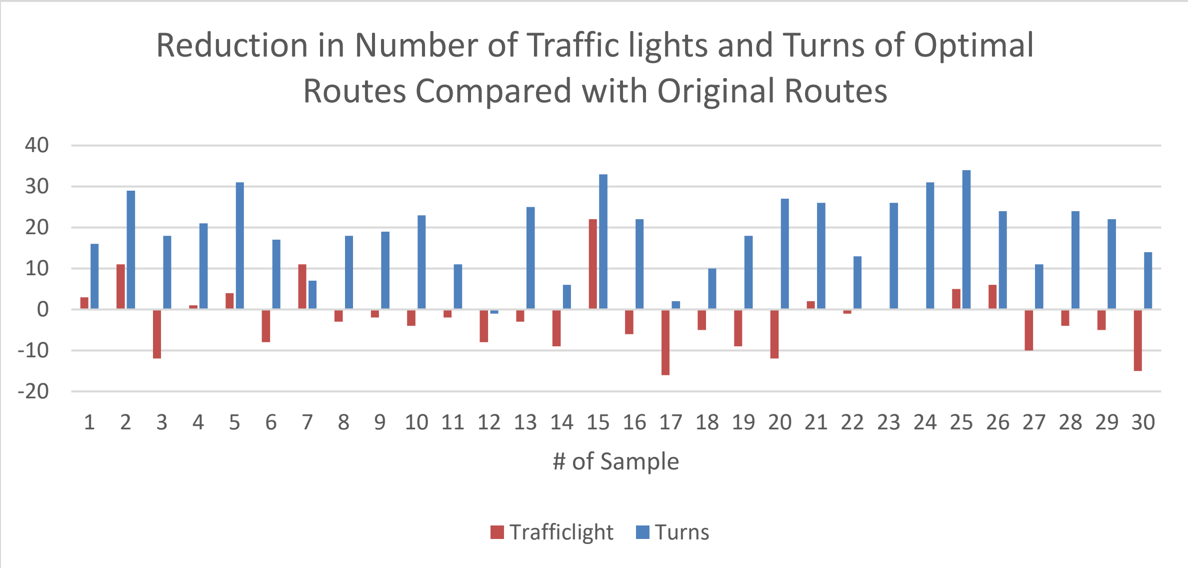


Figure 4-11 Result of Traffic Lights and Turns Reduction of the Second dataset

4.4.2.4. Section and Rate of Clearness

The clearness rate is the percentage of clear sections out of all sections. It should be noted that the number of sections is not proportional to the total distance for the reason that each section may have various lengths. Figure 4-12 showed that 29 samples had reduced the number of sections and clearness. In most of the cases the number of sections and clearness were reduced simultaneously except two samples, #12 and #14, the former one is the number of sections increases while clearness decreases, and the latter is opposite.

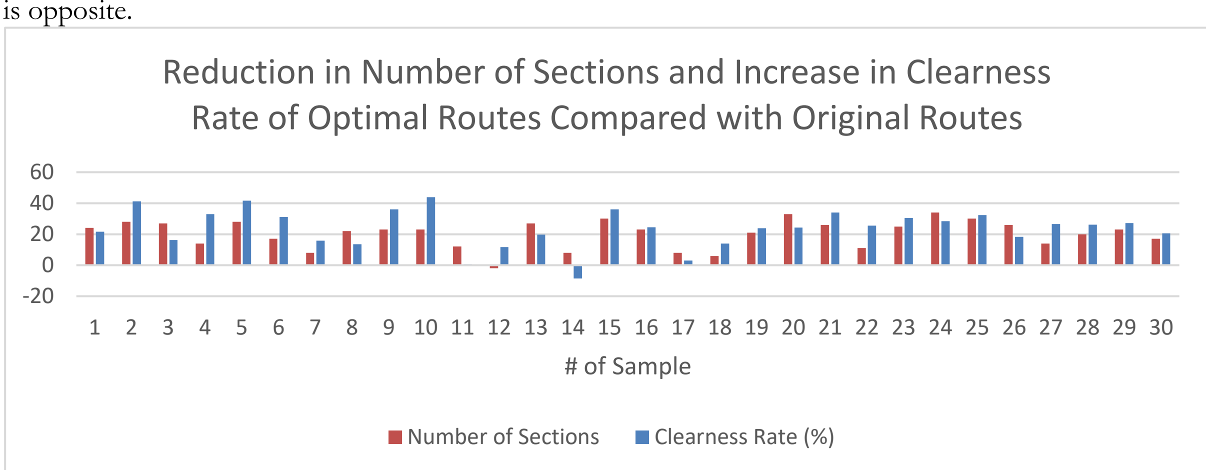


Figure 4-12 Result of Road Sections and Clearness Rate Reduction of the Second dataset

4.4.2.5. Trajectory

The trajectories of sample #2 and #12 were analysed. The sample #2 was considered as the sample having the best result, which ranked the top 1 in time and distance reduction. See figure 4-13 and 4-14, the general trajectories of the original route and optimal route was different, which were specific in the original route was making more turns and a long detour. In general, the automobile traced back to the same road in alternative route while in the original one it detoured to another road in a longer distance.

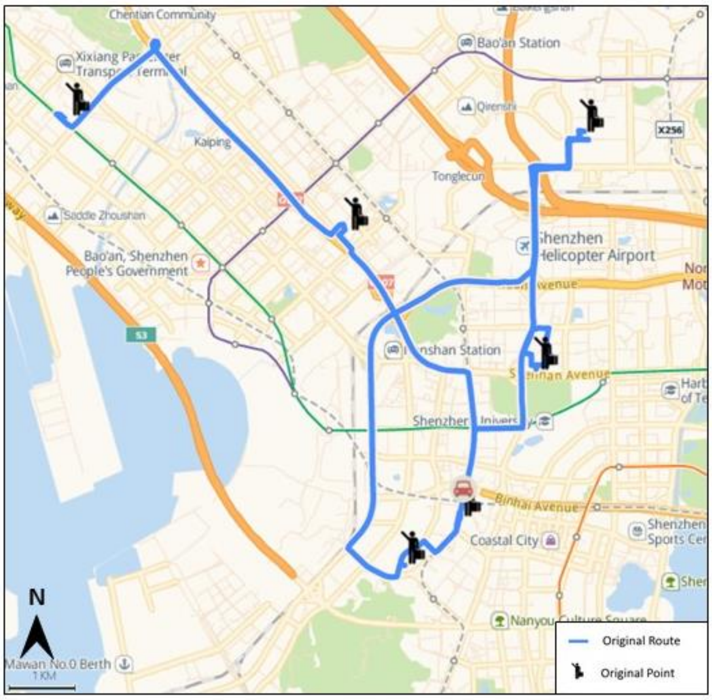


Figure 4-13 Original Route Visualization of Sample #2

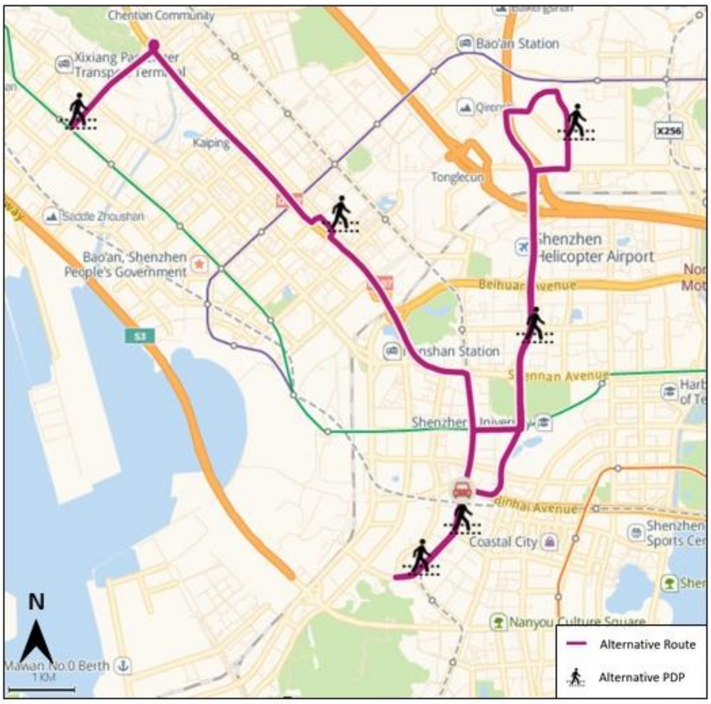
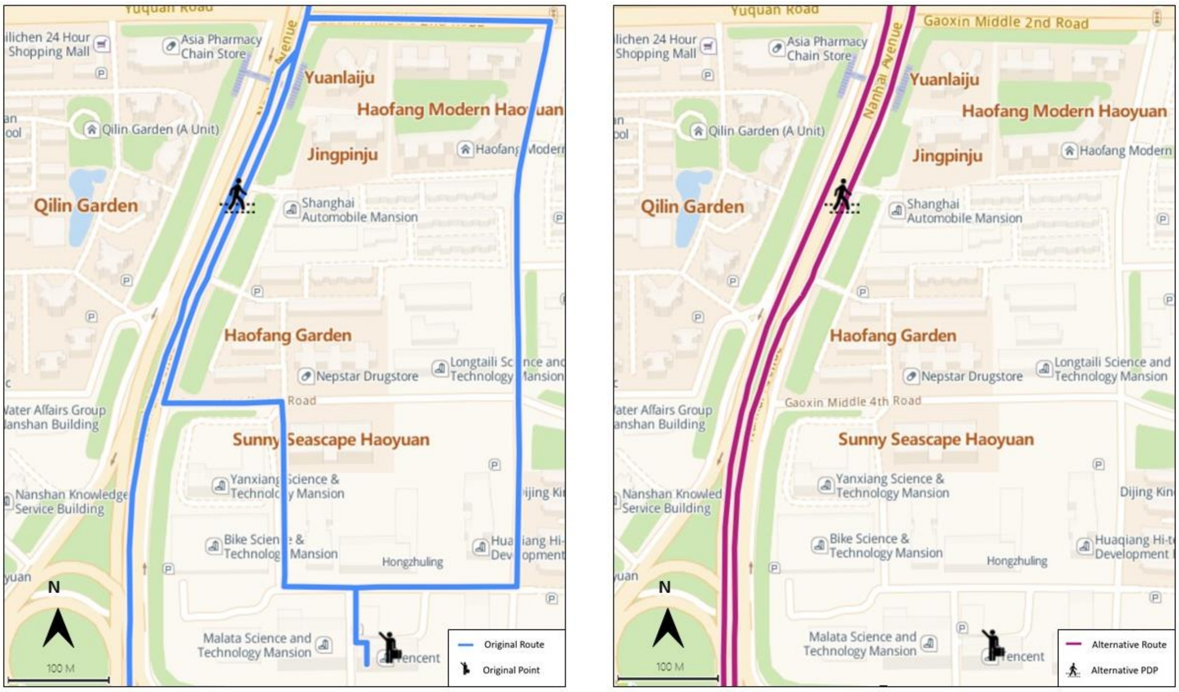


Figure 4-14 Optimal Route Visualization of Sample #2

Focus deep into the detail, see figure 4-15, which showed the different routing result at this part, without taking the alternative pickup point, the automobile was required to take a detour to pick the passenger up while making 6 extra turns.



(a) Part of Original Route *(b) Part of Optimal Route*

Figure 4-15 Example of Original Points and PDP Visualization of Sample #2

As for sample #12, the alternative route with minimum time cost still required much more time and distance than the original route, which indicated that the optimal route among all the routes was the original one the approach failed to obtain the effective PDPs for passengers. See figure 4-16 and 4-17, it

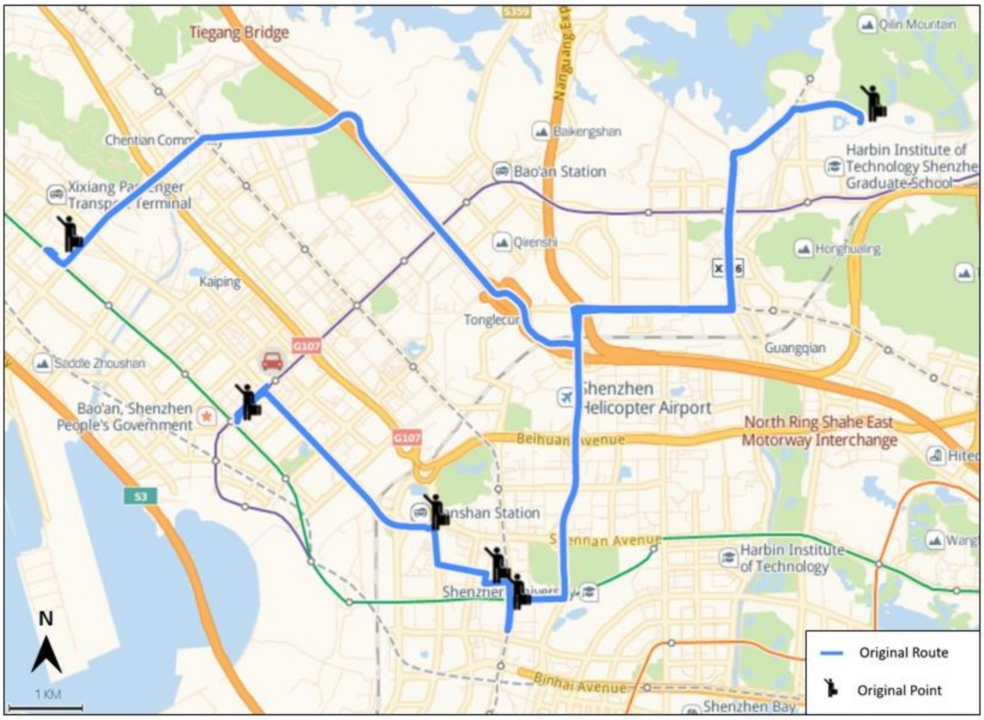


Figure 4-16 Original Route Visualization of Sample #12

can be told that the trajectories of original route and alternative were similar, only some small parts made differences.

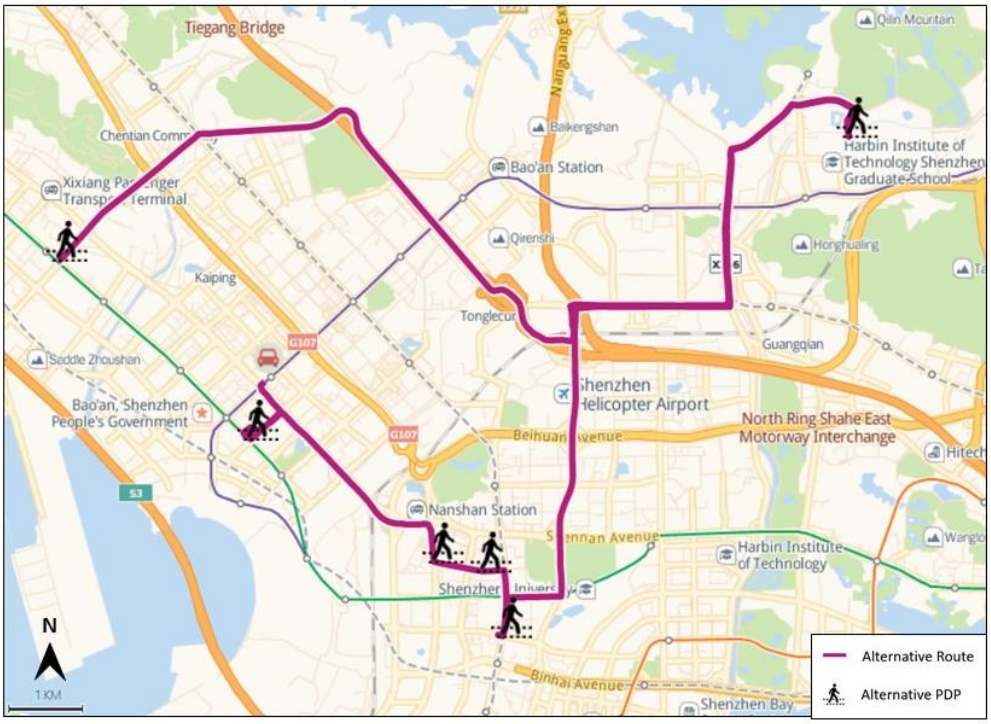
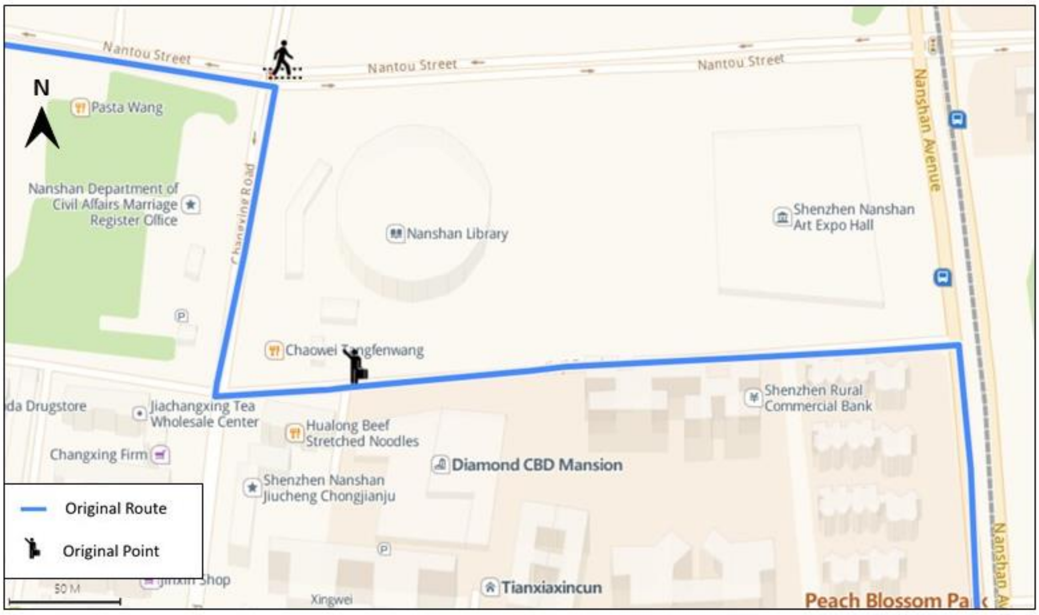
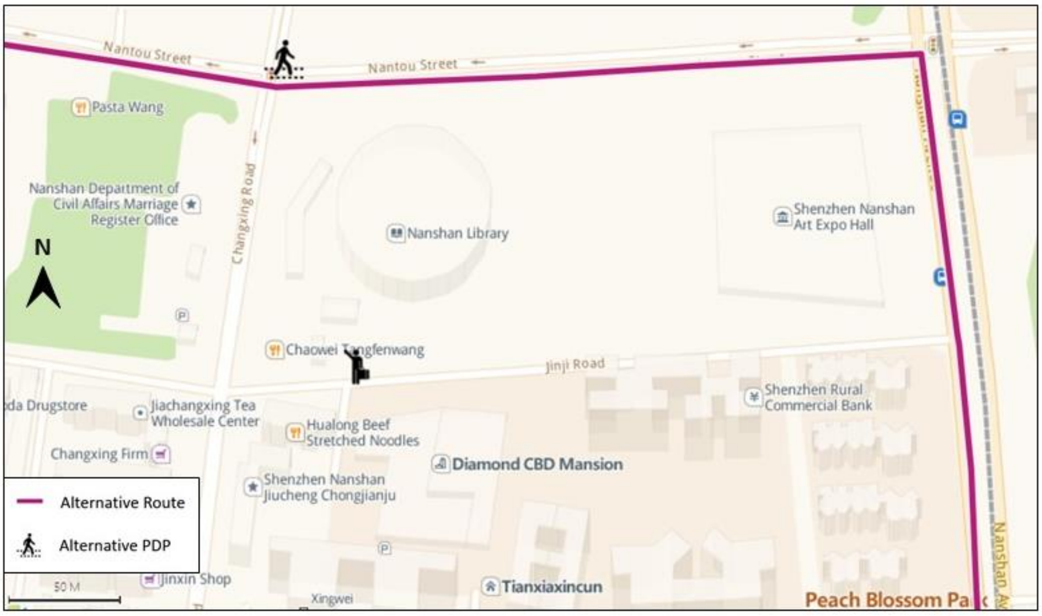


Figure 4-17 Alternative Route with Minimum Time-cost Visualization of Sample #12

For one of the detailed part, see figure 4-18 (a) and (b), the traces varied, it seemed that the alternative route was superior since it only needed one turn while the original route not only took two turns but also had a longer distance. However, if the time spending on walking to the pickup point of the alternative route was taken into account, then the cost of both routes was balanced.



(a) *Part of Original Route*



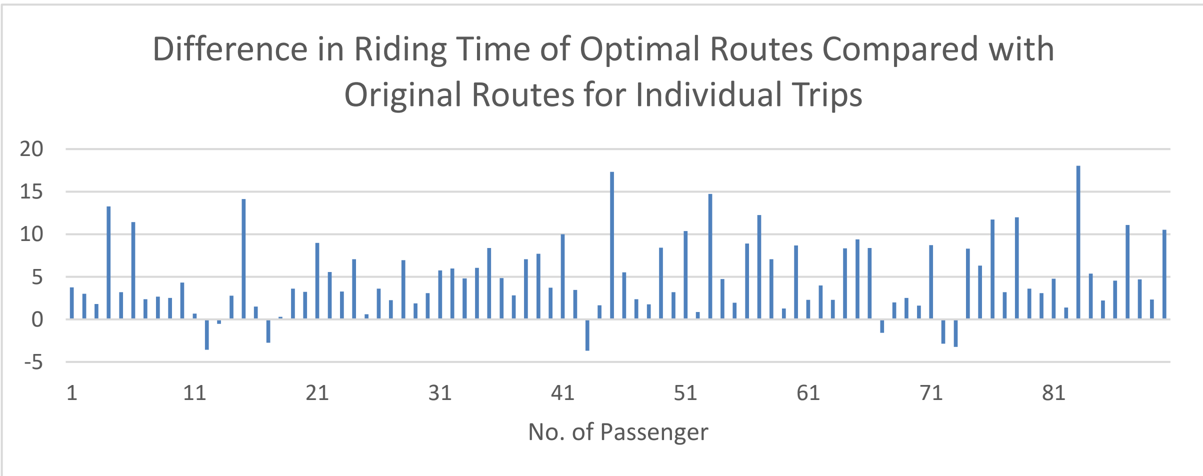
(b) Part of Alternative Routes

Figure 4-18 Example of Original Points and PDP Visualization of Sample #2

4.4.2.6. Individual Trip

There are 30 samples and each sample have three different passengers, hence the total number of individual samples is 90. The results of the individual trip were divided into the riding part and the walking part. The riding part includes riding time and riding distance, and the walking part includes the walking time of pickup and drop-off.

In total 83 individual trips had reduced the riding time when the passenger had chosen the optimal routes, implying 92.2% of them achieved reduction. The average riding time reduction is 4.94 minutes, the maximum reduction is 18.05 minutes and the maximum addition is 3.7 minutes. For the distance, 66 individual trips had reduced the riding distance with a maximum of 4936 meters and average of 686 meters, while the maximum additional distance reached 5430 meters.



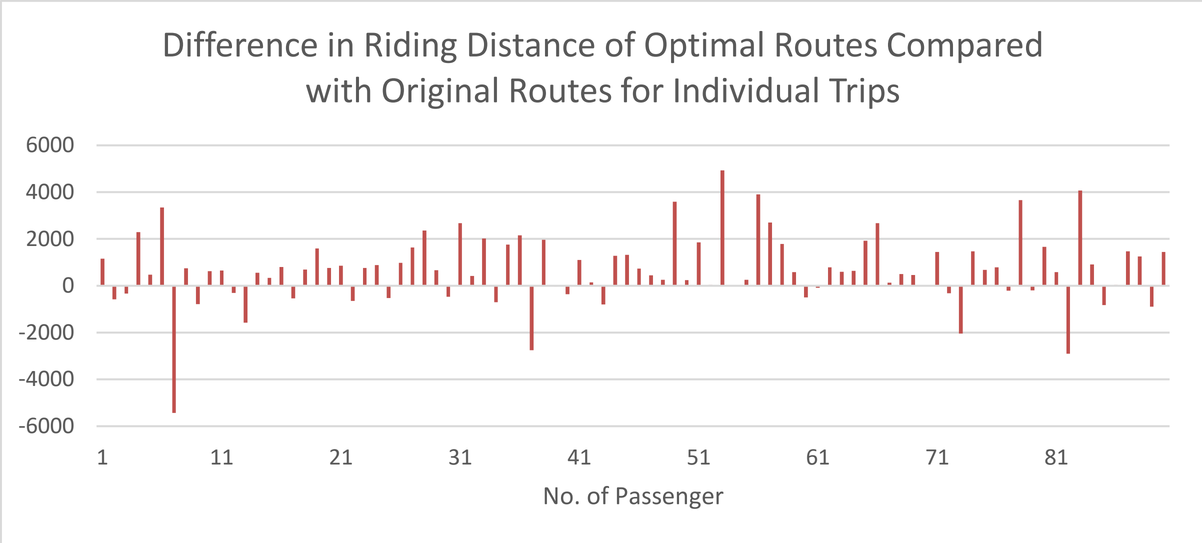


Figure 4-19 Example of Original Points and PDP Visualization of Sample #2

The walking time showed how much time passengers had spent on walking between the original points and alternative PDPs. Among all the walking trip of passengers, 88 passengers were required to walk within 15 minutes to and off the PDPs, the average required time is 9.7 minutes, maximum is 20.43 minutes and minimum is 4.17 minutes.

Each passenger had two parts of walking sub-trip, one is from original point to pick up point, and the other is from drop-off point to original point. Among 180 sub-trips, walking time of 108 sub-trips are less or equal to 5 minutes, 69 sub-trips are between 5 and 10 minutes, and 3 sub-trips are greater than 10 minute, which indicated that over 98% walking sub-trips are under the limitation of 10-minute walk.

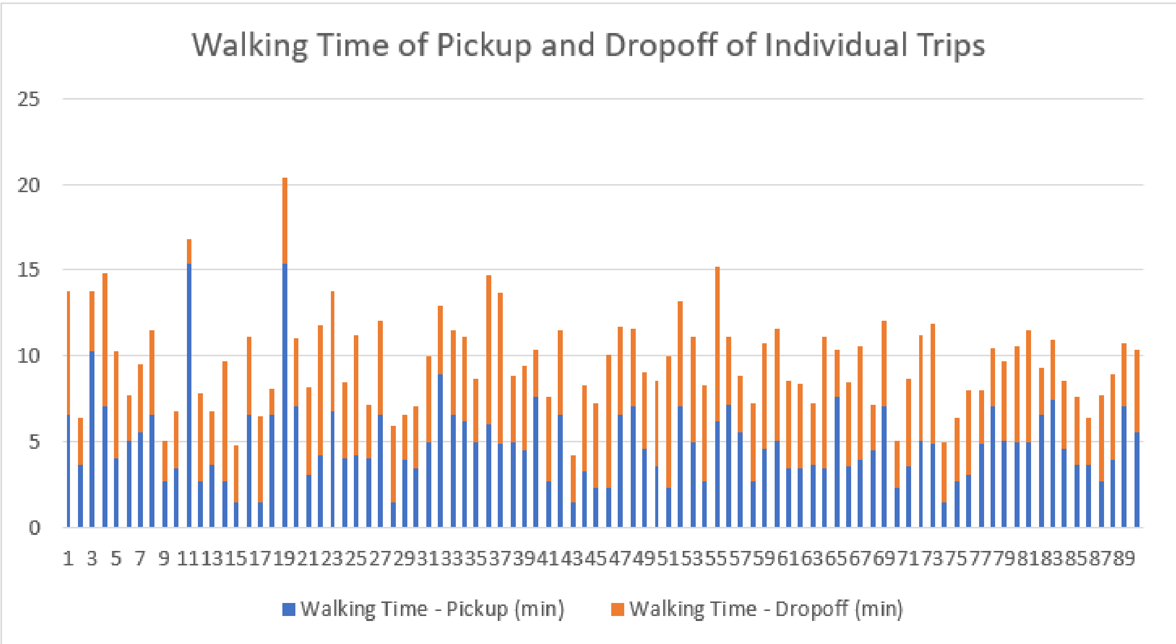


Figure 4-20 Result of Walking Time of Pickup and Dropoff for Individual Trips in the Second dataset

4.5. Discussion on Results

As shown in above, the proposed approach using the second dataset had a better result compared to the first dataset. In the first dataset, the alternative PDPs were selected within a short distance to the original points which made it have less opportunities to choose a point that may alter the route. For example, see figure 4-21, the two alternative is two closest intersections to the original point, however in most cases these PDP would not work on altering the route to a better one for the reasons that all three points are alongside the major road, and the PDP 1 and 2 are the junctions of a major road and small lower-level roads, which are less expected to pass through in the route planning. According to these situations, the second dataset allowed the further points to be selected, which made it possible to choose a junction of major roads, or not simply in a same line along the road. And as a result, it successfully decreased the number of situations where the optimal route is the same as the original route.

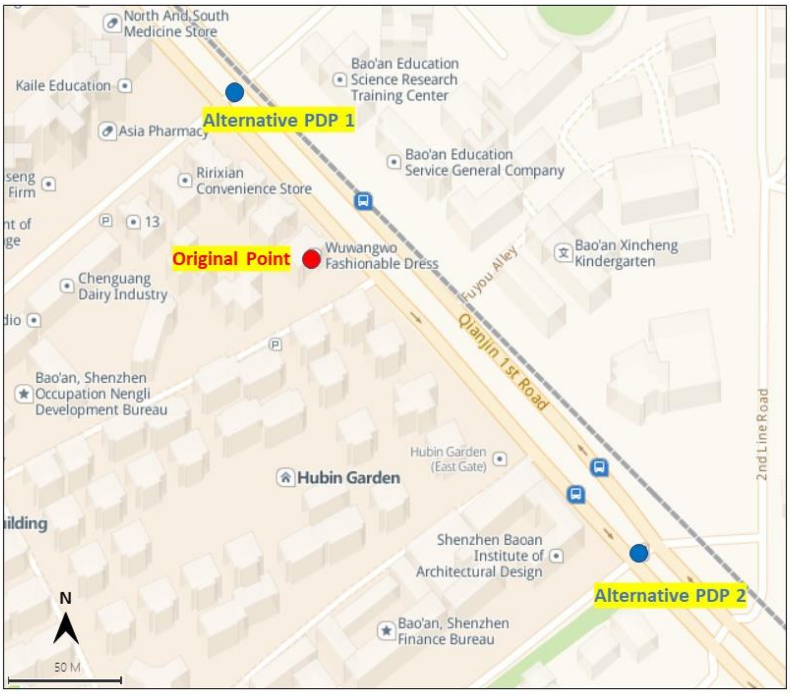


Figure 4-21 Example of Original Points and PDPs in the First dataset

About the time cost. Time cost is the most important evaluating criteria in this work since the aim of this approach is to exploit the flexible PDPs to find a time-sufficient route for ridesharing. It is also through the whole calculation: The routing strategy is based on the shortest time, and the judgement condition for determining the optimal route is the minimum duration. The second dataset showed 80% samples have a time reduction while using the alternative PDPs, which indicated that the proposed approach is effective in reducing time cost. However, it should be noted that only 50% samples reduced the distance, and the time is not significantly correlated with the distance. Explanations can be related to reduction in section clearness and number of traffic lights, turns and sections, which means that time-cost of longer distance can be counteracted by making less turns, less waiting time for the traffic lights, and passing through the clear sections with higher speed.

About the traffic light and turns. Results showed that only 36% samples had reduced the number of traffic lights, which is less than expected. One possible reason can be the alternative routes are more likely to pass the major roads since some detours that turn into small roads for picking up or dropping off passengers were avoided, while the traffic lights are commonly positioned in the major roads. Contrary to traffic lights, the number of turns had been significantly reduced in most samples. Only one sample in the second dataset had an additional turn in the optimal routes while others obviously reduced the number the turns. This also can be explained with the same reason as traffic lights that the small detours were avoided, example see figure 4-15.

About the number of sections and clearness. Results showed that for most samples the optimal routes reduced the number of sections and increased the clearness. Also, for the same reason as traffic lights and turns, the avoidance of detours contributed to the section reduction. The increasing clearness of the route can be explained as the consequence of minimum time cost conditions.

About individual trip. For each individual passenger, most of them had a trip with less time cost when the alternative PDPs were chosen. The average riding time reduction of each passenger is 4.94 minutes, however if taking the walking time into account the average time-cost was increased. Using the reduced riding time to counteract the walking, there are still 4.77 minutes increased for each passenger to spend in an individual trip. Therefore, it can be considered that choosing the PDPs is beneficial in reducing time-cost and detours for the whole shared ride, but not time-efficient for individual passengers.

5. CONCLUSION

This chapter summarized the conclusions of the work by answering the research questions and discussing the limitations and future work.

5.1. Overview

The objective of this work is to utilize the flexible nature of ridesharing for improving the ridesharing experience in practice. This objective is achieved by designing an approach to determine the optimal alternative pickup or drop-off points and analysing the changes of the shared rides between using and not using this approach. The way to implement this approach is to develop a webserver and the tool is Amap-API.

The existing works related to the alternative pickup and drop-off locations are more prone to theoretical level such as proposing models or algorithms. Compared with other works, the proposed approach in this work was discussed in terms of practice, which focused on the practical application by building a webserver using Amap-API and adopting real time information, which implied that this approach is based on the dataset and platform that are closer to reality.

5.2. Answers to Research Questions

There are one main question and five sub-questions in total, the sub questions would be answered first.

- RQ1. Which kinds of indicators will affect pickup and drop-off points in ridesharing? And RQ2. How do these indicators affect the identification of possible pickup and drop-of points?

The possible indicators which were extracted by literature review are walking distance, intersection and walking distance. The walking distance is how far passengers are willing to walk, which can be measured by walking time and walking length. It restricted the available area where alternative PDPs were located. Intersections are the junctions of two or more roadways, which could help reduce detours and turns in the route planning. Real time information in this work is specified as traffic speed and traffic events, which would influence the routing results in practice especially in heavy traffic time.

- RQ3. What is the application scope of the proposed approach?

The application scope was defined under a scenario following several presuppositions including: (1) the reservation of passengers and the driver (automobile) in a shared ride were predetermined, which implied that the dynamic matching system and time windows were not parts of the approach. (2) each shared ride had three passengers (3) the driver was initially located nearby one of the passenger's departure point. (4) The starting point of the shared ride was the driver's location and the ending point was the destination of the final passenger. And finally (5) temporarily cancellations of reservations were not considered.

- RQ4. Which tools are used in the alternative pickup and drop-off point determination and why?

The tool adopted in alternative PDPs determination is Amap-API, which provides various services such as positioning, location search, route planning, public transport inquiry and road condition display. Also, it enables other operations like store, search, manage and display different kinds of data. Almost 90% of domestic travel applications such as DiDi, which is the most popular ride sharing platform in China, use the map, navigation, route planning and automobile matching services provided by Amap.

- RQ5. How to determine all possible alternative pickup and drop-off points of passengers?

Alternative PDPs determination is based on the indicators. Candidate locations are limited by walking distance, intersection and real time traffic. In this work walking distance was not set up as an actual maximum value but determined by running different choices, such as around 5 minutes, 10 minutes and 15 minutes' walk. Also, all the PDPs were located at the intersection. Two kinds of real time traffic information were taken into account, one is traffic speed which is achieved by adopting the driving strategy of congestion avoidance, the other is traffic events which can be achieved by setting the area or sections where traffic events happen as the avoid-area or avoid-road for the routing parameters. Due to the incomplete traffic information provided by Amap, the traffic events were not implemented in the work.

- RQ6. How to determine the optimal pickup and drop-off points among all the possible alternative points?

Optimal PDPs determination was achieved by calculating the optimal route on the foundation of minimum time cost, the locations that involved in this route would be regarded as the optimal PDPs. The method to determine the optimal route is calculating all the possible candidate routes and comparing their total time, among which the route with minimum predicted time cost would be selected as the optimal one. Candidate routes include one original route, which consists of original points of each passenger, and hundreds of alternative routes, each of which consists of PDPs of passengers. The number of alternative routes depended on how many passengers were in a shared ride and how many alternative PDPs each original location had.

- RQ7. What are the metrics to define whether the driving rout is effectively improved?

The metrics to measure the changes of a shared ride adopting the proposed approach are divided into two parts: one is for the whole shared ride and the other is for individual passengers. The metrics of the whole shared ride consist of time, distance, number of traffic lights, number of turns that the automobile had made, the number of total sections of the route, and the percentage of clear sections. For the individual trip, the metrics were riding distance, riding time, riding fee, walking time and walking distance from original point (departure) to pick up point, walking time and walking distance from drop-off point to original point (destination). Besides, the trajectory of the route was considered.

- RQ8. How does this approach perform in practice?

The performance was evaluated based on a case study in Shenzhen by comparing the results, which consist of the metrics mentioned in RQ4, of original route and optimal route. In the case study, 30 samples were calculated, each of which consisted of the results of an original route and an optimal route. The optimal route can be the original route if the time cost of alternative routes were all greater than the original one. In this work, the approach was considered as effective only when over half of the optimal routes are alternative routes which consist of PDPs.

5.3. Limitations

Challenges on the effectiveness/timeliness of real time information. Duration of the whole process to calculate the optimal route was about 20 - 25 minutes, during this time literation of all possible alternative routes took place, which implied that the result of the first alternative route might not have the same real time condition as the final one. For example, if the calculation started at 8 a.m, the first alternative route was calculated at 8 a.m and after about 728 times of iteration, the final alternative route was calculated at 8:35 a.m. The traffic status might be different between these two points, which made the first route and final route have different time condition input. This problem was considered to be caused by the lengthy response time (TTLB) and redundancy of the algorithm.

The narrow scope of application. The proposed approach was limited by the current capability of the API so that it was built around several specific premises, such as defining that each shared ride would have three passengers in the plan at the beginning and no other passengers would be picked up before these three passengers were dropped off. This is kind of different from how the urban ridesharing works because in most of the time the drivers do not have a plan of picking their specific passengers and they would like to accept the requests from passengers on the way under the restrictions of time windows and available seats. This would make it a more complicated problem while implementing in practice, but also a more interesting and realistic problem to be solved.

5.4. Future Work

To deal with the challenges of real time information, it might include two directions: to decrease the number of iterations and to increase the response speed. At first each alternative route calculation was operated in one iteration, which indicated that if there are n alternative routes need to be calculated and compared, n iterations and n GET were required. Adopting the batch interfaces, which would use the POST as the parent request, can be one of the methods to reduce the iteration. As for increasing the response speed, cloud computing platforms such as AWS, Google Cloud and Alibaba Cloud.

To extend the scope of application. The Dial-a-ride problem (DARP) can be introduced to enrich the context of urban ridesharing with the consideration of dispatching systems and time windows. Also, it can be tested in other cities to discover the difference of how far passengers are willing to walk and the connection between walking distance and the available number of alternative PDPs.

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