AMERICAN UNIVERSITY OF BEIRUT

EVALUATION FRAMEWORK FOR ORGANIZATION-BASED RIDESHARING: SERVICE DESIGN CONSIDERATIONS AND POTENTIAL FOR AUB

by
HANI ABDUL RAHMAN AL NAGHI

A dissertation
submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
to the Department of Civil and Environmental Engineering
of the Faculty of Engineering and Architecture
at the American University of Beirut

Beirut, Lebanon
September 2014

AMERICAN UNIVERSITY OF BEIRUT

EVALUATION FRAMEWORK FOR ORGANIZATION-BASED RIDESHARING: SERVICE DESIGN CONSIDERATIONS AND POTENTIAL FOR AUB

by
HANI AL NAGHI

Approved by:

Dr. Mounir Mabsout, Professor — Chair of Committee
Civil and Environmental Engineering

Dr. Isam A. Kaysi, Professor — Co-Advisor
Civil and Environmental Engineering

Dr. Maya Abou Zeid, Assistant Professor — Co-Advisor
Civil and Environmental Engineering

Dr. Cynthia Myntti, Professor — Member of Committee
Public Health Practice and Project Leader,
Neighborhood Initiative Office of the President

Dr. Hani Mahmassani, Professor — Member of Committee
W.A. Patterson Distinguished Chair in
Transportation and Director, Transportation
Center at Northwestern University

Dr. Abdul-Nasser Kassar, Associate Professor — Member of Committee
Department of General Business
Lebanese American University

Date of dissertation defense: September 9, 2014

AMERICAN UNIVERSITY OF BEIRUT

THESIS, DISSERTATION, PROJECT RELEASE FORM

Student Name: ___________ AL NAGHI____HANI___ABDUL RAHMAN______
Last First Middle

○ Master's Thesis ○ Master's Project ● Doctoral Dissertation

☐ I authorize the American University of Beirut to: (a) reproduce hard or electronic copies of my thesis, dissertation, or project; (b) include such copies in the archives and digital repositories of the University; and (c) make freely available such copies to third parties for research or educational purposes.

X I authorize the American University of Beirut, **three years after the date of submitting my thesis, dissertation, or project,** to: (a) reproduce hard or electronic copies of it; (b) include such copies in the archives and digital repositories of the University; and (c) make freely available such copies to third parties for research or educational purposes.

____

Signature Date

ACKNOWLEDGMENTS

Thank God I finally made it! This work was accomplished with the encouragement of my beloved family, and the support of my professors and I am grateful for their great support and help.

Special thanks go to Prof. Isam Kaysi and Prof. Maya Abou Zeid for their guidance and assistance throughout the years of my doctoral studies.

I would like to thank Prof. Mounir Mabsout, the Chair, for his continuous support during all my years of studies at AUB. I would also want to express my thankfulness to my committee members Prof. Cynthia Myntti, Prof. Hani Mahmassani, and Prof. Abdul-Nasser Kassar. They were always available and supportive at all times.

I am also very grateful for the great inputs and help from Prof. Ibrahim Osman, Prof. Larry Snyder, and Prof. Jean-François Cordeau.

This research was partially funded by the Dean's office of the Faculty of Engineering and Architecture, the Department of Civil and Environmental Engineering at the American University of Beirut, and the Centre of Research Excellence in Hajj and Omrah at Umm Al-Qura University.

AN ABSTRACT OF THE DISSERTATION OF

Hani Abdul Rahman Al Naghi for Doctor of Philosophy
Major: Civil Engineering

Title: Evaluation Framework for Organization-Based Ridesharing: Service Design Considerations and Potential for AUB

Ridesharing services, including Carpooling and Demand Responsive Transit, have been gaining increased interest recently by individuals, employers and institutions alike. From the individual traveler's perspective, car ownership and increasing fuel costs represent the main drivers to seek ridesharing services, especially in areas lacking reliable and attractive public transport services. On the other hand, the objective of employers and institutions (such as universities, hospitals, etc.) is to reduce car parking demand by their personnel (employees, students, etc.), as well as to reduce traffic congestion in their surroundings, while at the same time maintaining feasible travel alternatives for affiliated individuals.

This dissertation presents a framework for the evaluation of ridesharing services in an organization-based context encompassing impacts and evaluation criteria and can be used as a decision support tool by any organization. This framework consists of three main modules: the demand estimation module, the service design module, and the evaluation module. Each of the three modules was analyzed taking into account the essential components, methods, and the needed data.

An important aspect of this framework lies in the development of a many-to-one ride matching approach based on the Capacitated Vehicle Routing Problem with Time Windows. The problem is context-related to the ridesharing specifics, including unit demand, asymmetric network, narrow time windows at departure, and common arrival time at destination. New heuristic algorithms are proposed based on different traversals of hierarchical spanning trees derived from the all-pairs shortest path matrix (distance or travel time matrix). A tree type is selected depending on the solution strategy, where the Proximity Clustering Tree (PCT) is used to prioritize matching passengers within proximity clusters while the Minimum Deviation Tree (MDT) is used to match passengers along route with minimum deviations. Results are compared with exact solutions and other known methods, and in most cases have shown near optimal solutions with substantially reduced computational efforts.

A case study is presented to illustrate the implementation of the developed framework using actual data from the American University of Beirut; such data was also documented for future research.

CONTENTS

ILLUSTRATIONS

TABLES

Table Page

LIST OF ABBREVIATIONS

APSP	All Pairs Shortest Path
AUB	American University of Beirut
CP	Carpool
GIS	Geographic Information Systems
GPS	Global Positioning Systems
IVTT	In-Vehicle Travel Time
MDT	Minimum Deviation Tree
MPV	Multi-Purpose Vehicle
OVTT	Out-of-Vehicle Travel Time
PCT	Proximity Clustering Tree
SEC	Sub-tour Elimination Constraint
ST	Shared-Taxi
TDM	Transportation Demand Management
TT	Travel Time
VOT	Value of Time
VRP	Vehicle Routing Problem

CHAPTER 1

INTRODUCTION

Ridesharing services have been gaining increased interest as a contributing factor towards sustainable transport systems by reducing travel cost, congestion, and parking demand. The continuous technological advancement in computational power and the ability to represent more accurate space and time data have allowed for further research into solutions for the complex problem of ridesharing service design.

This research develops and tests a feasibility framework for the evaluation of ridesharing services in an organization-based context. The significance of this research lies in the development of a framework encompassing all impacts and evaluation criteria for organization-based ridesharing and can be used as a decision support tool. Additionally, this work introduces the formulation and development of new ride matching algorithms that achieve higher ride matching opportunities with fast processing compared to known methods in the literature. This chapter provides a historical background of ridesharing, defines the available schemes, and identifies the opportunities for a ridesharing service for the American University of Beirut (AUB).

1.1 Historical Background of Ridesharing

Early forms of organized mass campaigns encouraging people and coworkers to rideshare started as early as World War II. At that time, public posters were used in North America to promote car sharing to reserve national resources for the war. Later, during the 1973 oil crisis, and the 1979 energy crisis, ridesharing was also publicly promoted in campaigns, and its modal share increased considerably reaching 19.7% by the year 1980. This share dropped to 13.4% in the year 1990 due to the drop of gasoline prices and other socio-economic factors (Ferguson 1997), then continued decreasing to become 10.1% in the year 2004, and slightly started to increase to 10.7% in the year 2005 (US Census Bureau, 2004, 2005).

A review of the historical price change of gas over the last century to date shows consistency between the interest in ridesharing and the increase of gas price in the US (Figure 1.1). Over the last few years the gas price (~3.57$/gal) exceeded its maximum historical value during the oil and energy crisis in the mid-seventies (considering the inflated dollar value: 3.44$/gal in 1979). The increased gas price coupled with additional factors (congestion, parking deficit, environmental concerns …), is a major drive for the recent increased interest in ridesharing. In addition, the technological advancement of computing and telecommunication is in a position to provide better implementation solutions.

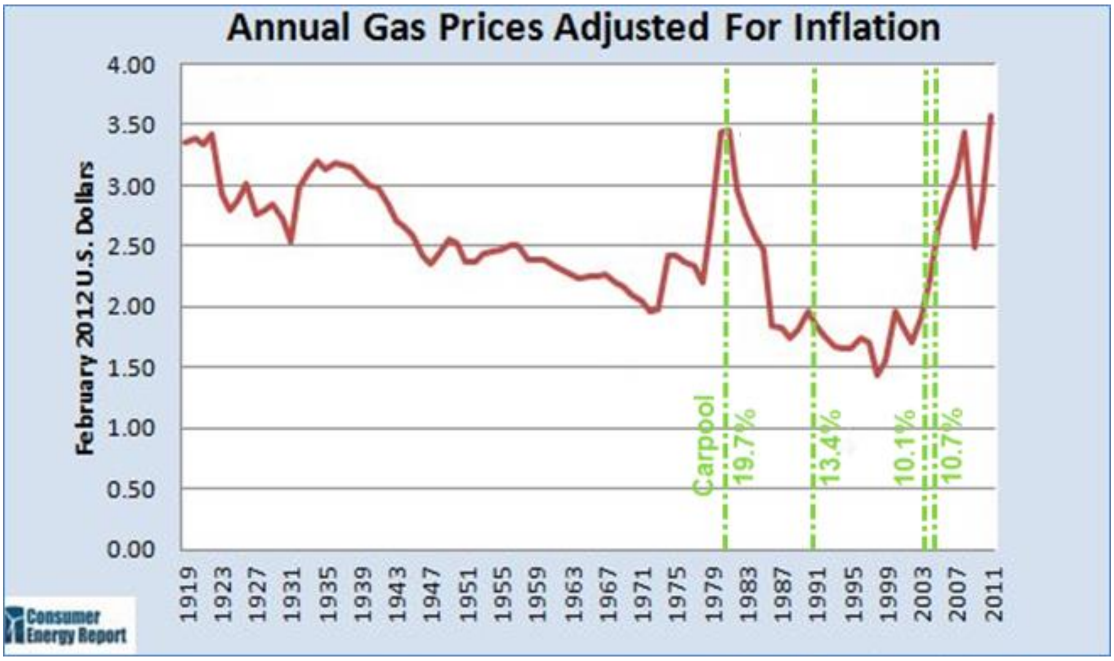

Figure 1.1: Annual Gas Prices Adjusted for Inflation 1919-2011 (cost/gallon in Feb. 2012 U.S. $) (Source: ConsumerEnergyReport.com based on the U.S. EIA data)

In a recent study, Chan and Shaheen (2011) categorized the ridesharing evolution into five phases (Figure 1.2): (1) WWII car-sharing clubs (1942-1945); (2) Major responses to energy crisis (1970s); (3) Early organized ridesharing schemes

(1980-1997); (4) Reliable ridesharing systems (1999-2004); and (5) Strategy-based, technology-enabled ride matching (2004 to present).

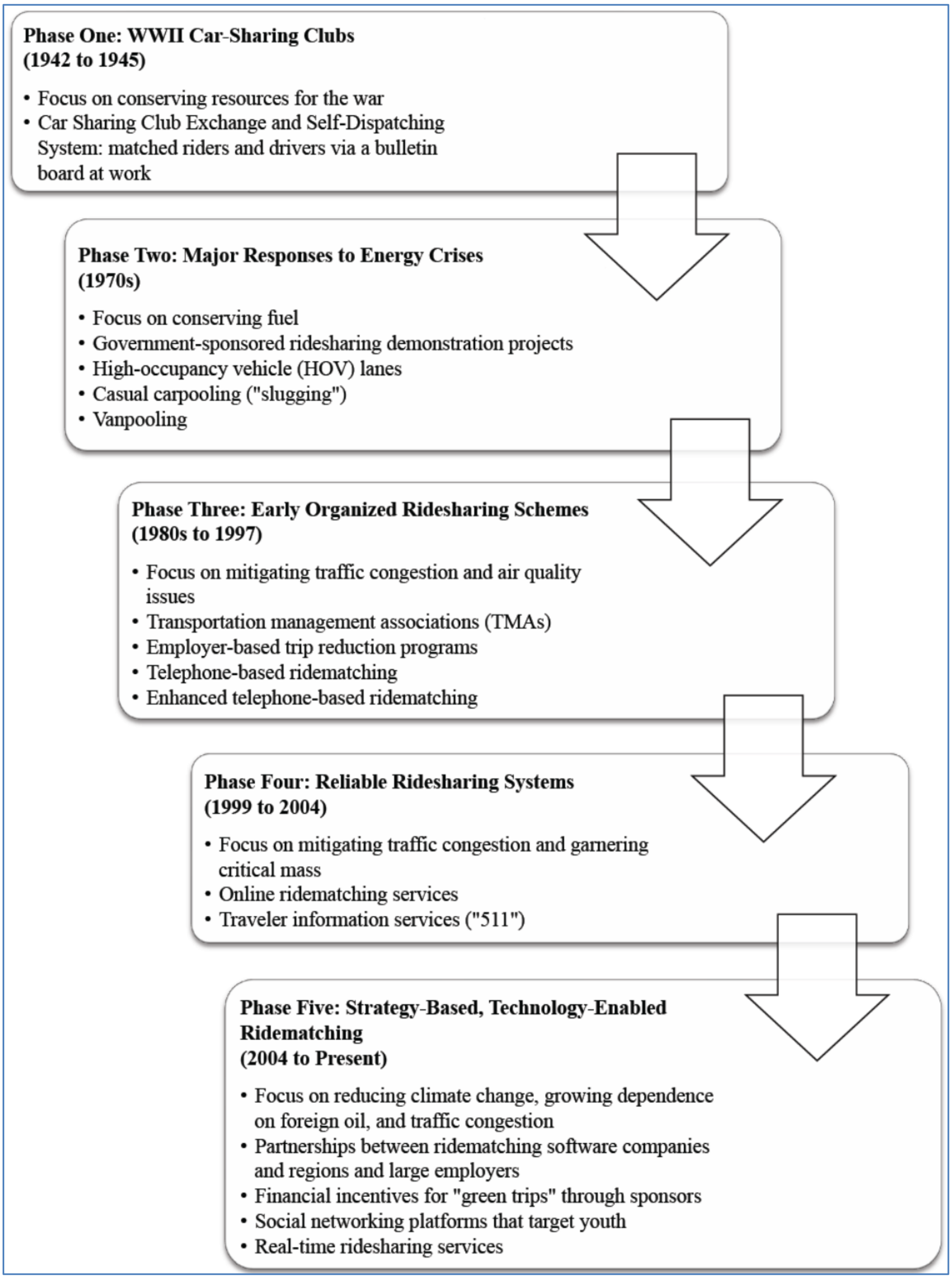

Figure 1.2: Five Phases of North American Ridesharing (Chan and Shaheen 2011)

1.2 Ridesharing Schemes

Ridesharing exists in different schemes. Chan and Shaheen (2012) presented a classification of today's ridesharing schemes and the relationships among its participants (Figure 1.3). Three main categories of ridesharing are identified as follows: "Acquaintance-based" carpool by families, friends, and coworkers; "Organization-based" typically through memberships; and "Ad-hoc" that is more of casual ridesharing. This research is focused on the "Organization-based" ridesharing of coworkers or students using cars or vans that are operated by the owner or by a third-party (e.g. shared-taxi).

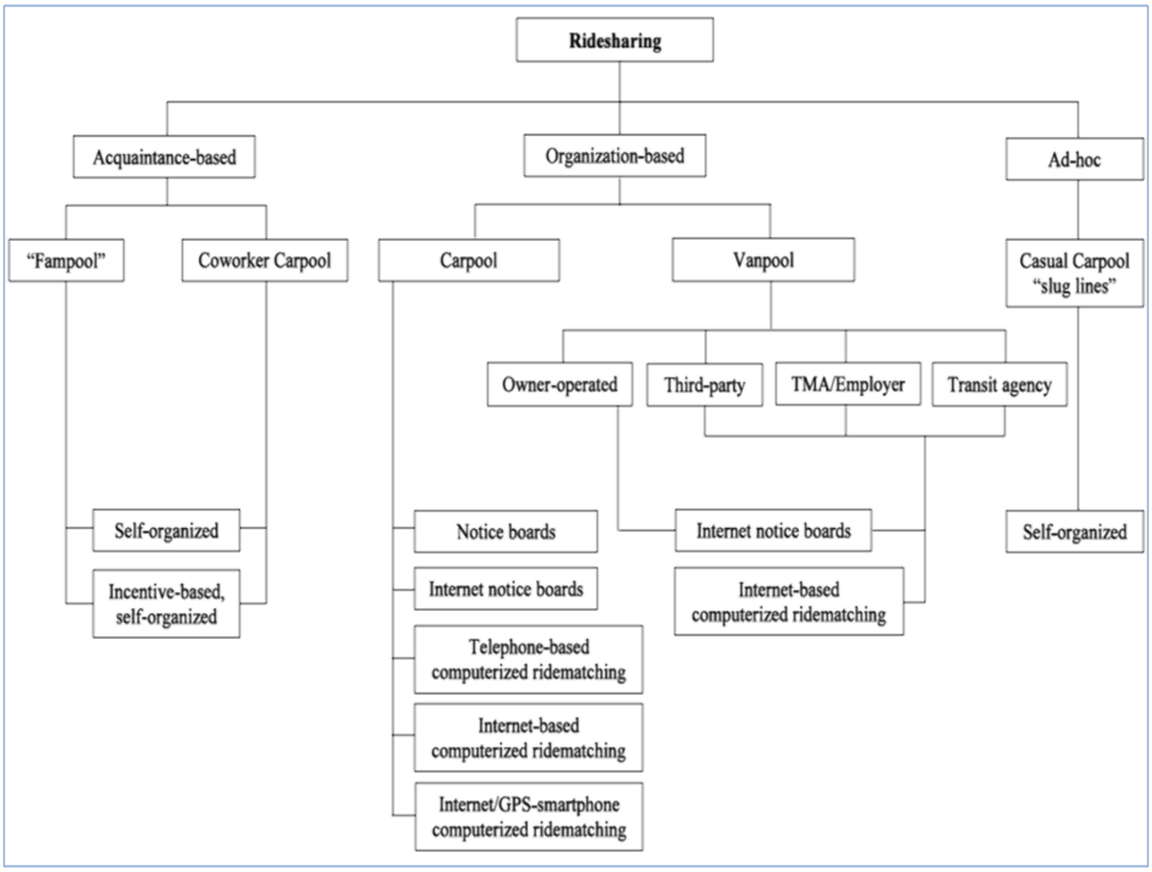

Figure 1.3: Ridesharing Classification Scheme (Chan and Shaheen 2011)

The study by Chan and Shaheen (2011) estimated that there are more than six hundred ride matching services currently operating in the U.S. and Canada. They expected the North American ridesharing to include over the next decade “greater interoperability among services, technology integration, and policy support”. They recommended further research on the understanding of the role of behavioral economics, interoperability, multimodal integration, and public policy in increasing ridesharing potential, as well as the resulting impact of ridesharing on infrastructure, congestion, and emissions.

In Beirut, a common ridesharing service is available in the form of shared taxi (jitneys) and is known locally as “service”. The shared taxi is considered the backbone of mass transportation services in Greater Beirut Area where it serves 14% of the transportation demand (Team International 1999). Jitneys in Beirut“... operate independently and are characterized by their frequency of service and flexibility in routing and scheduling; they respond to hail calls by passengers anywhere along the route and stop at any point for drop-off” (Kaysi et al. 2007).

1.3 Problem Statement

The problem is to evaluate the opportunities of an organization-based ridesharing service as a sustainable solution for the increased parking demand and congestion. An evaluation framework for the feasibility of the ridesharing service is needed. This framework encompasses the different elements that mainly include: the demand estimation for ridesharing, the service design to meet this demand, and the feasibility of this service in terms of service impact, cost, and revenue.

The service design problem is the most challenging component of the evaluation framework. The objective is to design the best ridesharing scheme for transporting a number of passengers from different origins (their homes) to a single destination (organization), and then back (two way, but not necessarily with the same passengers), using a shared-taxi service. The ride matching process is the main component of the service design, and it can be defined as a special case of the general VRP (Vehicle Routing Problem) or an mTSP (multiple Traveling Salesman Problem) for finding the solution for a “many-to-one and one-to-many” problem. The service must satisfy each user’s time window (for departure and arrival), and may operate at different times of the day. The solution is to group passengers into vehicles, and define the tour/route for each vehicle, with the objective of minimizing the total traveled distance by these vehicles, while satisfying the passengers’ time windows and the vehicle capacity constraints.

1.4 Opportunities for AUB

The American University of Beirut (AUB), an urban campus in the center of Beirut, Lebanon, has a population of around 8,000 students and 4,400 employees including the nearby medical center (academic year 2012/2013). In a recent study on parking demand measures for AUB, Aoun et al. (2013) identified the AUB faculty, staff, and students need for nearly 3,000 external parking spaces in addition to the 1,105 parking spaces on campus. A commute survey was conducted in 2010 and showed that carpooling comprises 12% and 16%, and shared-taxi (service or jitney) comprises 14% and 8%, of the current commuting modes of students and employees, respectively (Khattab et al. 2012). Aoun et al. (2013) indicated that the existing ridesharing schemes were student and employee initiatives (acquaintance-based). They concluded that in seeking solutions to parking and congestion problems in its neighborhood, AUB should look into schemes for encouraging and expanding such activities through an institution-based ridesharing initiative. As such, various forms of service delivery schemes may be considered for analysis including: Carpooling (CP) and Shared-Taxi (ST). The ST scheme may be viewed as a Demand Responsive Transit (DRT: a public transport service characterized by flexible routing and scheduling) and as an innovative transportation demand management (TDM) practice that could be a good fit for AUB whereby users could benefit from an exclusive dynamic taxi-sharing service that combines the benefits of a private taxi (professionalism, reliability, vehicle comfort, etc.) with the cost and occupancy of a shared-taxi. The ST scenario, requiring no parking, is practically the approach that could potentially contribute the most to solving the parking demand problem around AUB campus.

1.5 Scope of Research

The scope of this research consists of three main parts. The first part is a development of an evaluation framework encompassing the elements related to the feasibility of ridesharing systems. This evaluation framework consists of three main modules: the demand estimation module, the service design module, and the feasibility module. An important aspect of this framework is the incorporation of the demand side in the service design process; this has not been addressed previously in the literature. This framework is designed as an interactive user friendly tool that is developed using Excel and ArcGIS programming capabilities. The second part highlights the strengths and weaknesses of previous ride matching methods of the service design module, and introduces and tests a new proposed heuristic algorithm using hierarchical spanning trees. Finally, part three illustrates the implementation of the developed framework in a case study for AUB. The most feasible ridesharing alternative is determined using a simple deterministic demand module and a full implementation of the proposed ride matching algorithm taking into consideration service delivery scenarios and varying the involved parameters. The analysis includes system feasibility assessment in terms of cost and revenue as well as service impact on parking demand and congestion (expressed in terms of the number of students switching from driving their own cars to the ridesharing service).

1.6. Research Contribution

This research develops a comprehensive framework encompassing all factors and criteria for evaluating the feasibility of different potential alternative services for an organization-based ridesharing context. This framework accommodates for an iterative process between the demand estimation and the service design. The research introduces a new proposed ride matching algorithm that is context-related to the organization-based ridesharing problem. This framework is implemented on a complete case study for the American University of Beirut and the used database is documented for future research benchmarking. The original demand, based on which the service design step is undertaken, is based on broad service design parameters.

1.7 Dissertation Structure

The remainder of this dissertation is organized as follows. Chapter 2 presents a literature review identifying the gaps in previous research related to ridesharing services. Chapter 3 investigates the various elements of a ridesharing system and establishes an evaluation framework for the feasibility of ridesharing systems. Chapter 4 proposes a new heuristic algorithm for the service design of ridesharing systems based on hierarchical spanning trees. Chapter 5 presents a case study for a shared taxi system for the American University of Beirut. Chapter 6 concludes the dissertation, identifies the contribution of this research, describes the research limitations, and proposes potential future research.

CHAPTER 2

LITERATURE REVIEW

This chapter provides an overview of the literature related to the different elements of ridesharing studies, and is divided into six sections. Section 2.1 discusses research related to various ridesharing demand estimation models. Section 2.2 investigates the different ride matching methods and algorithms in the ridesharing service design, and orients the ride matching problem within the literature on the Vehicle Routing Problem. Section 2.3 presents the technological enablers for ridesharing that are described in the literature. Section 2.4 provides a brief overview of the literature related to the feasibility and impact of ridesharing services. Section 2.5 is a review of the literature on success and failures of ridesharing systems. Finally, a summary is presented in section 2.6.

2.1 Ridesharing Demand

The estimation of the ridesharing demand is the first and most important step in determining the viability of a ridesharing service. Its objective is to quantify the real market for ridesharing.

In an early study, Gensch (1980) developed a segmentation strategy to increase ridesharing by identifying people willing to switch from the drive alone mode to rideshare. The author proposed a methodology of identifying "switchable" individuals by looking at existing mode choice datasets used in calibrating a logit model for Santa Monica, California. The study showed that individuals who do not perceive significant differences in the satisfaction level of various transport modes are more likely to switch to ridesharing.

Amey (2010) discussed a gap in the literature related to the estimation of realistic demand for ridesharing in general, by attributing this estimation problem to the substantial amount of traveler information needed (detailed information from a large number of people on their daily travel habits) and the challenges associated with access to this private data. He indicated that prospects for demand analysis at the scale of an organization are much better in terms of the data requirements, availability (organization-specific travel surveys), and privacy concerns. He proposed a data driven methodology (using detailed commute survey data) for estimating the potential of ridesharing at an organizational scale. The study presented results for the Massachusetts Institute of Technology (MIT), which have indicated a significant difference between the estimated "potential" rideshare and the "observed" behavior. He made inferences from this comparison about the relative importance of trip characteristics versus the importance of human attitudes in rideshare arrangements. Another study by Deakin et al. (2010) investigated ridesharing opportunities among students at the University of California at Berkeley; they determined the number of users willing to switch to ridesharing services through stated preference surveys. The study concluded on some factors encouraging participation in ridesharing including incentives, cost or time savings, safety and security (ridesharing operator screening other participants and the driver through background checks), and the availability of computer and cell phone messaging. On the other hand, the factors that were identified to discourage shifting from driving alone to ridesharing included the need to make stops en route, flexibility, privacy, and ability to satisfy one's own audio and climate preferences.

Ciari and Axhausen (2012) investigated the impact of selected socio-economic variables (income), travel time, and other indicators that could provide a useful background for policy evaluation and planning of ridesharing initiatives. They used stated preference surveys to develop multinomial logit mode choice models. Respondents were asked to choose among drive alone, public transport, carpooling as driver and carpooling as passenger. The most important variable affecting the switching was found to be the VTTS (value of travel time savings), and the study outcome demonstrated a satisfactory fit of the model, with a higher preference to the carpool "as passenger" compared to the "as driver" option.

2.2. Service Design and Ride Matching Algorithms

This section presents a review of the related service design problems in the literature, discusses the similarities and differences, and indicates the potential contributions of this research in the different aspects of the problem at hand.

2.2.1. The Vehicle Routing Problem

The Vehicle Routing Problem (VRP) was first introduced by Dantzig and Ramser in 1959, and has been under extensive study in the fields of transportation, distribution, and logistics. VRP is often time dependent, and includes partitioning and sequencing sub-problems that are not independent of each other. VRP exists in different variants; we introduce the main types in the following subsections.

The Capacitated VRP (CVRP) problem (Christofides et al. 1981) is the basic example, where the objective is to minimize the total cost of all vehicles while satisfying a single constraint, being each vehicle's capacity. The VRP problem is typically considered for the transportation of goods, and thus the demand at each node is usually different in quantity. Our problem considers the transportation of people; thus we have a unit demand at every node, and the objective is to minimize the cost of supply. This research presents fast heuristics for solving the CVRP with unit demand, while enabling the generation of solutions for different vehicle capacities with the least computational efforts. This is beneficial when investigating the best vehicle size (car or van) for each case study.

The VRP with Time Windows (VRPTW) problem (Solomon 1987, Gehring and Homberger 2005) imposes an additional constraint specifying a time margin at pick-up and/or delivery points. Different schemes of time window distributions exist depending on the problem type. In general, the transportation of goods has longer time window spans than commuter passengers. Our problem considers a group of coworkers or students who share a common fixed arrival time (work/class time), so the time window is considered at the departure point (home). A late departure time (TL) is the desired time for pick-up that is based on a direct route from the origin to the destination without any route deviation. However, due to the need to pick up additional passengers along the way, each passenger is willing to accept an additional in-vehicle travel time (ΔT). This extra travel time deviation is accommodated by an early departure time (TE) where (TE = TL – ΔT). The objective may be based on either maximizing the user utility (by minimizing ΔT), or maximizing the operator profit (by minimizing the total cost while satisfying a defined maximum acceptable ΔT). In this research, we associate the time window constraint with a 'maximum allowable route deviation' being the ratio of ΔT to the direct travel time of each passenger. In any car arrangement of a ridesharing problem, the first picked up passenger always experiences the highest 'deviation', and the last passenger has zero deviation towards the final destination.

The VRP with Pick-ups and Deliveries (VRPPD) problem is a generalized form of the VRP where each node may be visited for pick-up or delivery of goods or passengers. In this problem the vehicle is serving deliveries and pick-ups concurrently, with a “many-origins to many-destinations” scheme. Although our problem involves pick-ups and deliveries, they are not expected to occur concurrently due to the deviation constraint of each passenger. In this case, each vehicle is expected to be either picking up passengers from home to work (many-to-one) or delivering passengers from work back to their homes (one-to-many). For example, if a car is dropping off passengers in an outbound trip from the depot, the sequence of drop-off stops will be from the nearest to the farthest. Any pick-up passenger along its way would rather be picked up after the last passenger is dropped off (at a further distance from the depot), instead of an earlier pick-up with longer deviation.

2.2.2. VRP Solution Approaches

The VRP is known to be NP-Hard, and thus exact algorithms cannot solve large problems in real time. Investigating all possible solutions using naïve or brute force methods is not computationally feasible, even for problems with small numbers of passengers. Therefore, researchers have developed numerous heuristic algorithms to find the best possible solutions. Some known heuristic methods include: Branch-and-Bound (Branch-and-Cut) algorithm, Clarke and Wright's Savings algorithm, Nearest Neighbour (Greedy) algorithm, Column Generation algorithm, Genetic algorithm, and the Ant Colony algorithm.

Following the Laporte and Nobert (1987) survey, VRP algorithms can be classified into three broad categories: Direct Tree Search Methods, Dynamic Programming, and Integer Linear Programming (ILP). The three index vehicle flow formulation, developed by Fisher and Jaikumar (1978), is commonly used in ILP approaches.

Christofides et al. (1981) were the first to investigate algorithms to solve the VRP based on spanning trees and shortest path relaxations. They have used branch-and-bound tree search and demonstrated exact solutions for constraints-free small VRP problems of up to 25 customers.

Araque et al. (1990) focused on a graph-based approach and studied the associated polyhedral structure of the (identical customer) VRP, where the objective is to find a minimum cost set of routes, all originating and terminating from a given depot, with the properties that no two routes intersect at any vertex other than the depot, and no route contains more than K customers. They also noted that if the last link of each route is eliminated, then any feasible set of routes becomes a feasible solution to the subtree cardinality-constrained minimal spanning tree problem. They introduced a number of new valid inequalities and specified conditions for ensuring when these inequalities are facets for the associated integer polyhedra.

2.2.3. Organization-Based Ridesharing

Despite the vast variety of VRP research efforts, little is available on the solutions for the special case of the organization-based ridesharing problem. Most of the relevant literature is focused on the demand, success, and failure of adopted ridesharing systems, while little is found on the routing aspect of the problem.

The typical ride matching processes in a Dial-a-Ride problem (door to door ridesharing service) involve complex algorithms to match multiple origins with multiple destinations (many-to-many). However, researchers have simplified this process in the many-to-one scenario where one common origin/destination is defined for all users (institutional context: universities, hospitals, etc.).

The problem is context-related to the ridesharing specifics, including unit demand, asymmetric networks, narrow time windows at departure, and common arrival time at the destination.

An oversimplified example was the assumption of a uniform spatial distribution of the users across the study area by Tsao and Lin (1999). Other researchers (Sarraino et al. 2008, Deakin et al. 2010, and Buliung et al. 2010) have improved the simple assumption of uniform spatial distribution of users for matching trip ends by identifying users within clusters of a set radius using GIS tools.

The proposed solution approach by Deakin et al. (2010) was mainly matching students based on their spatial and temporal attributes. Students were first matched according to their schedules, and then were matched spatially in proximity clusters. The objective was to maximize matched rides satisfying a geographical cluster size. Nevertheless, the authors did not indicate explicitly the steps or methods in establishing the proximity clusters, and how the students in each cluster were grouped in cars. Despite the effectiveness of this fast approach in the cases where students' home locations may represent a clustered distribution, it is not expected to be as effective in other cases of random or continuous distributions.

On the other hand, Amey (2010) argued that spatial clustering to match students within close proximity may underestimate the trip matching by overlooking opportunities of matching students within a minimum deviation along the route. The author proposed a heuristic method of pairing students in groups of two, and the objective was to maximize matched pairs while considering the highest possible VMT (Vehicle-Miles-Traveled) savings, and satisfying acceptable driver delay constraints. Two approaches were briefly discussed with no indication of the related formulation or procedures. The first involved a fast approach using a simple spreadsheet, while the second used the CPLEX software. The advantage of the pairing approach is the consideration of potential ride matches along the route; however, it is limited to matching only two passengers per car. The proposed process is divided into three main steps:

1- Compute travel time between each user and MIT campus, and between all user pairs.
2- Apply a set of criteria for filtering pairs with potentially feasible pairing (driver with access to a car, willing to accept a maximum of 5-minute additional delay on travel time, and has a maximum 30-minute arrival/departure time difference with the passenger).
3- Use spreadsheet/CPLEX solvers to identify the most feasible pairings.

The strength of this methodology is in exploring all possible pairings compared to geographical clustering techniques that overlook the mid-trip matches. In addition, a major advantage of this process lies in its structure where step 1 (requiring traffic modeling software to calculate origin-destination travel times) is done only once. The remaining steps 2 and 3 can be easily done in simple spreadsheets, thus allowing real time processing of the various parameters/variables involved. Real time (or dynamic) ridesharing increases the pre-booking opportunities through short notice arrangements.

However, there are some limitations in Amey's (2010) proposed approach that can be summarized as follows:

1- Delays at Intersections: The road network model needs to have sufficient level of detail. The author clearly states the issue of not including delays at intersections in the travel time calculation which is expected to render some of the travel time calculation unrealistic.
2- Spatial Aggregation: Aggregating users to the nearest intersection

(automatically) might not be the best option; for example, a passenger might walk a slightly longer distance to a different intersection on the opposite direction to the one selected. This overlooks the road directionality issues as residences on each side of the road may be directed to different intersections (in the presence of a median).

3- Pairing: The approach is designed for “pairing” of trips, and the author assumes very limited opportunity to match three or more feasible rides. This limits the use of the tool to two-person carpools (driver + passenger), and excludes the possibility of using it for multiple passenger rides (car or van). For example, if three users are living in the same (or adjacent) building, the developed tool will match two of them and leave the third one out.

4- Filtering: The author applied filtering to exclude ‘passengers’ living within one mile from the MIT campus; however, this filter was applied at a later stage in the process (after the aggregation and expansion of the calculated travel times). A lot of calculation could be saved by applying this filter at the beginning of the process.

5- Potential Rerouting: The tool does not offer to show the “potential rerouting plan” of the ‘driver’ (how much it changed from his regular commute route due to the deviation to pick up the paired passenger).

Another study of taxi sharing among coworkers in Taiwan was presented earlier by Tao and Chen (2007). They proposed two heuristic algorithms based on the greedy algorithm and the time-space network. Their solution procedure is to search for the nearest passengers while expanding the proximity search radius. The objective was to minimize the VMT and passenger delays, while satisfying passenger preferences (passengers’ gender, desired car occupancy, etc.) and the vehicle capacity constraint.

They performed an actual field trial at Taipei Nei-Hu Science and Technology Park in Taiwan, and concluded with plausible numerical testing results. They used 10 taxi cabs and 798 participants over a period of 17 days and claimed a successful matching rate of 60% with an average occupancy of 2.4 passengers/vehicle. This approach enables matching closest proximity rides, as well as the potential matches along the route. The main disadvantage of this method lies in the computational efforts needed for the time-space network calculations for large problems. It is to be noted that despite the relatively large size of the sample under consideration, introducing user preferences would result in breaking up the problem into much smaller sub-problems instead of complicating the solution.

Yan et al. (2012) have further developed a modified method based on the method proposed by Tao and Chen (2007) of using time-space network flow techniques in studying methods for the taxi pooling (similar to ST) problem. They used three heuristic NBS (Network Based Solution) models and a Lagrangian relaxation-based algorithm. The first model was for fleet and passenger routing and scheduling, and the second and third models were established for passenger matching in a single taxi.

Two main solution strategies can be concluded from the above literature; the first is clustering of customers within a proximity range, while the second is matching customers with minimum deviations along routes. This research proposes a heuristic approach that incorporates both strategies, and presents the results for different problem sizes and customer spatial distributions. The main advantage of this robust heuristic approach is in its ability to solve large problems quickly with the possibility of selecting various car capacities compared to the pairing of two passengers approach presented by Amey (2010). In addition, it presents a practical methodology for proximity clustering that can be used for problems with clustered as well as random and continuous distributions of customers.

2.2.4. Multi-Objective VRP

The design of a typical ridesharing system involves the objective of reducing the operator's total cost while maintaining a predetermined passenger burden constraint. However, this may not be the case in reality. Other objectives may also include minimization of the total number of cars needed, determination of the optimal car size/capacity, and/or maximization of passenger utility by minimizing their travel burden (equity). Jozefowiez et al. (2008) related these objectives to different aspects of vehicle routing problems: tour (cost, profit, makespan, balance...), nodes/arcs (time windows, customer satisfaction...), and resources (management of the fleet, specificities of the product to deliver ...).

In a study by Chevrier et al. (2012) on the solution of the DRT dial-a-ride problem, the authors proposed an evolutionary approach (using hybrid algorithms denoted as: NSGA-II_H, SPEA2_H, IBEA$_H$) that optimizes three objectives concurrently:

- Economic: minimizing the operational costs (number of vehicles used);
- Environmental: minimizing the duration of the vehicles' journeys to limit the emission of pollutants (reducing the carbon tax);
- Quality of service: minimizing the likely delays which may occur.

They applied three state-of-the-art algorithms on synthetic data and realistic problems. The optimization processing time was in the range of one to two minutes. Ultimately, minimizing the processing time is essential in reducing the overhead time delay in matching real time requests for ridesharing.

Perugia et al. (2011) were the first to introduce the multi-objective Home-to-Work Transportation Problem (HWTP) and the associated equilibrium between conflicting criteria such as efficiency, effectiveness, and equity. Although their work was based on the service design of bus routes and stops, their problem is similar to the institutional ridesharing problem at hand. Similarities include the multi-objective consideration of the time window distributions, equity among passengers, and the efficiency of the operational cost.

2.3. Technological Enablers

Technological advancement has enabled accurate location positioning of customers, wireless communication, and the development of online complex ride matching tools with real time processing. Deakin et al. (2010) proposed the use of Global Positioning System (GPS) technology to assist drivers and passengers in finding each other during pick-ups.

In a more recent study, Amey et al. (2011) studied innovative real time ridesharing services that rely heavily on advanced mobile phones. Such a dynamic ridesharing service allows “short-notice” ride matching opportunities. They highlighted the potential opportunities and obstacles, and provided recommendations for this real time innovation, including: targeting large employers, integration of travel information from multiple modes, and comprehensive participant engagement.

Other research by Agatz et al. (2011) on the impact of smart phones technology use in real time ridesharing presented a simulation study based on actual travel demand data of metropolitan Atlanta. The authors compared sophisticated ride matching optimization methods (that account for smart phone advantages) with the Strawman greedy algorithm (requiring no sophisticated software to solve) and the results demonstrated a substantial improvement in ridesharing matches. They implemented their approach in a simulation environment in C++ and CPLEX 11.1 (a linear binary integer programming solver).

Raubal et al. (2007) introduced spatial and temporal concepts that can be employed during the planning process. The aim of their proposed methodology was to significantly reduce the overhead time of the peer-to-peer communication and the computational time of the real-time ride matching. They defined the shared-ride systems as a match of the clients (having travel demand, e.g. pedestrians) and the hosts (vehicles being the supply), and have used “host decision” and “client choice” algorithms in a simulation environment.

2.4. Feasibility and Service Impact

This section presents literature on the feasibility of ridesharing services and the service impact in terms of reducing congestion and emissions.

2.4.1. System Feasibility

Little is found in the literature in relation to costing of ridesharing services as compared to the demand estimation models and the ride matching optimization problem. Deakin et al. (2010) indicated that the cost for a dynamic ridesharing program would include start-up and ongoing staffing, marketing and advertising, incentives to participants, ride matching software and related hardware, and program evaluation. Conducting a cost-benefit analysis was beyond their research scope.

Lee et al. (2005) presented a feasibility study for a taxipooling dispatching system with actual cost parameter values obtained from Taiwan. They presented a sensitivity analysis for the total system cost for a proposed two-step dispatching algorithm under different demand and service design scenarios.

iTrans (2007) conducted a feasibility study of a vanpool program for Greater Toronto Area and Hamilton. The study included a market analysis investigation, a business case for a third-party vanpool operation model, a financial implementation plan, and the expected environmental benefits

2.4.2. Service Impact

Bonsall's (1981) research for ridesharing opportunities in the UK concluded with two main results: ridesharing is an abstraction of patronage from public transport; and the population who would potentially use ridesharing would rarely exceed 2% (much less than the U.S. due to socio-cultural differences and higher public transport availability in the U.K.); thus the impact on energy consumption, road congestion or pollution is extremely limited.

Kocur and Hendrickson (1982) were among the early researchers to develop models to assess cost and fuel savings from ride-sharing. They used probabilistic methods to account for day-to-day variability in demand as well as trip origins and destinations associated with ridesharing. Their model also considered the varying fuel economy with trip length and passenger load.

Evans and Pratt (2005) identified three benefits of implementing vanpool ridesharing programs being "the reductions in work commute travel costs and improved travel comfort", "the reduction of energy consumption and air pollution", and the "reduction of traffic congestion and parking demand at work sites".

Caulfield (2009) studied the reduction of congestion and greenhouse gas emission for the various ride-sharing patterns using 2006 census data and COPERT4 (a traffic emissions software by the European Environment Agency) model in the case of Dublin.

2.5. Successes and Failures of Ridesharing Systems

Numerous case studies of successful ridesharing systems were reported in the literature (Comsis 1993, Evans and Pratt 2005). Buliung et al. (2009) indicated that despite the fact that carpool is one of the most difficult forms of mode choice to achieve, it is possible to identify factors contributing to the success of carpool initiatives including incentives, expansion of carpool facilities (e.g. HOV lanes), employer based programs, and social marketing.

On the other hand, Enoch et al. (2006) investigated the failure reasons in 72 DRT projects from around the world to draw conclusions and lessons learned. The study concluded that “DRT projects are often not realistically costed or designed with a full understanding of the market they are to serve”. They identified the root of the DRT failure to be often found in the working skills and partnership between various stakeholders. The study recommended a phased implementation approach of the DRT with respect to service flexibility and the adaptation of costly technological systems.

2.6. Summary

The literature review presented in this chapter has indicated the different elements that are related to the organization-based ridesharing studies. These elements can be categorized into three main areas: ridesharing demand studies, ridesharing service design, and feasibility of ridesharing services. In general, researchers have addressed each of these elements independently. An evaluation framework integrating these various elements is needed to present the big picture and to provide the interrelationships among these elements.

Moreover, a gap is found in the ride matching methods for the organization-based ridesharing problem. Most of the relevant literature was found to be focused on the demand for ridesharing systems, while little is found on the routing aspect of the problem.

CHAPTER 3

PROPOSED EVALUATION FRAMEWORK

In this chapter, an evaluation framework for the feasibility of institution-based ridesharing services is presented. It integrates the various aspects of the problem that were discussed in the literature review and were addressed independently by other researchers. This chapter is structured into five main sections as follows. Section 3.1 is an overview of the framework, and the following four sections discuss the main components of the framework: the “user and spatial data model”, the “demand estimation module”, the “service design module”, and the “feasibility module” (see Figure 3.1).

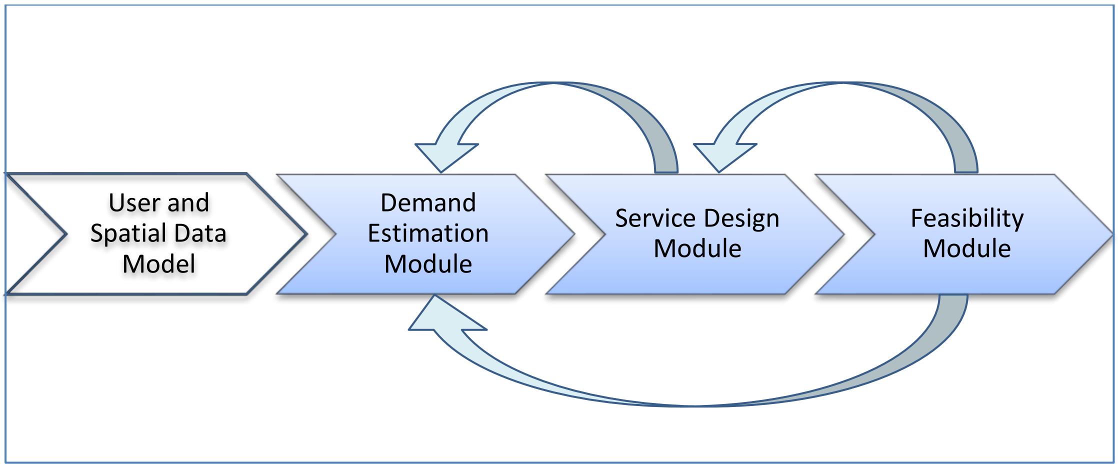

Figure 3.1: Main Components of the Evaluation Framework

3.1. Overview

The proposed analysis framework presented in Figure 3.2 represents the interrelationships among the various elements and processes that comprise the scope of the evaluation of a ridesharing service.

The ultimate objective of the framework is to identify the most feasible ridesharing service design option with a balance between multiple objectives that may be conflicting, such as maximum number of ride matching opportunities, minimum total cost, and minimum user disutility, while considering different service delivery options. The feasibility of each option is determined using cost-benefit analysis at the operator level.

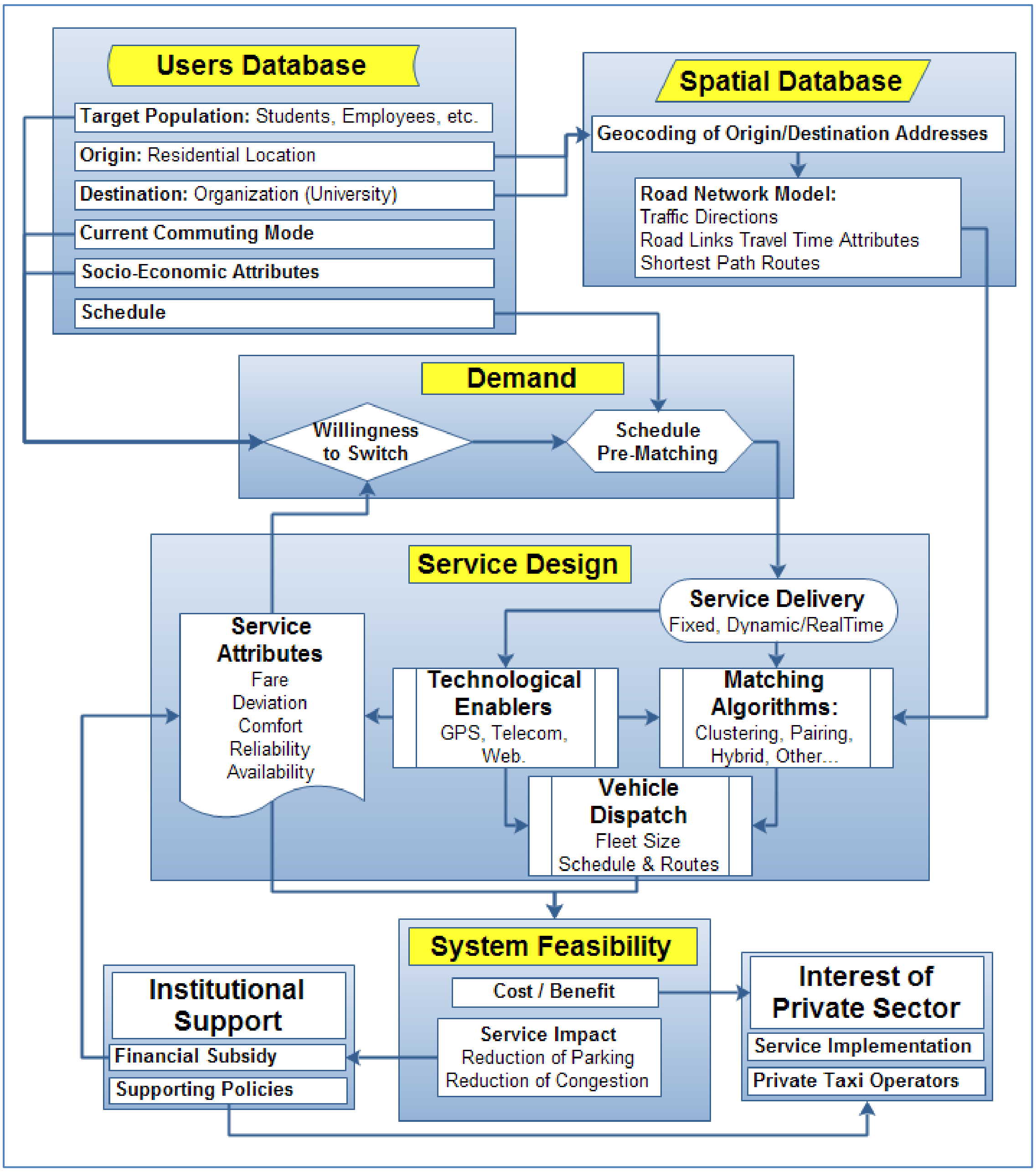

Figure 3.2: Proposed Evaluation Framework

Two sets of inputs are needed for the model: the users database and the spatial database. A three phased iterative process is used to determine the optimal ride matching scheme.

First, the subset of users willing to switch from their current mode of transport to the new ridesharing service is estimated using the demand module. Additional filtering (e.g. passengers' sex, car occupancy, and climate preference) and initial schedule matching is applied to this subset. Second, based on the proposed ridesharing service design specifics (maximum deviation and vehicle capacity), spatial matching algorithms are further applied to the schedule-matched user subset. Service delivery options (pre-booked or real time) and the associated technological enablers are also considered (the main component is the online ride matching tool). Finally, the resulting estimated demand is used for the financial feasibility assessment, and the service impact on the existing parking demand and congestion is evaluated. A feasible system may attract investors from the private sector. A reduction in parking demand may encourage the institution to provide supporting policies and financial subsidies. Reduction of the user cost (by institutional subsidy) can also be tested for an increased willingness to switch scenario. Each service delivery option may lead to different service attributes (cost, deviation, etc.), possibly affecting the "willingness to switch" estimation in phase one. This calls for an iterative process between the three phases allowing the analysis of different "what-if" scenarios (see Figure 3.1). While appearing complex, the iterative approach of this proposed framework makes it useful as a decision aid tool. In the case study presented in Chapter 5, the iterative process is simplified by defining a set of scenarios first and then investigating them in all three phases.

The following subsections discuss the main components of the proposed framework. Each of the main modules of the framework can be further developed using detailed methodologies and advanced tools. However, this research is mainly focused on the service design module, and a new ride matching algorithm is presented in detail in Chapter 4. In addition, a case study with application of all the modules of the framework is elaborated in Chapter 5.

3.2. Users and Spatial Data Model

An input database needs to be developed when investigating the opportunities to introduce a ridesharing service for any organization. This input database consists of the users database and a spatial database.

3.2.1. Users Database

It is a common practice for some organizations to undertake a comprehensive commute survey of its employees/students to better understand their commute patterns and preferences. A typical commute survey includes the spatial, temporal, and other socio-economic characteristics of the target population, and their current commuting patterns. The main interest is typically to reduce the number of “drive alone” users to reduce the parking demand and congestion. The potential users of the ridesharing service among the target population are a subset of employees and/or students (of a given institution) living beyond a walking distance zone.

This data is needed for the spatial database model and for the demand module, and it consists of the following users database:

- User gender, age, position (student, employee, etc.), and other socio-economic data
- Schedule: the daily starting and ending time

- Current commute mode to the organization, and the preference for possible rideshare
- Home address: zone, street, and building

3.2.2. Spatial Database Model

With the availability of advanced GIS (Geographic Information Systems) models, a GIS model may be available or may need to be developed to represent the road network database with travel time attributes (extracted from available traffic models for the study area), as well as other network analysis attributes that are needed for establishing shortest path routes between any given points. The GIS model will also include users' addresses and their organization's address that will be geocoded as point locations (origins/destinations).

This data is needed for the demand and service design modules, and it consists of the following spatial database:

- Point locations of all users and the organization
- Road network for routing
- Travel time between all points (cost matrix)

Given the addresses of all potential users and their destinations, these data are used to determine the grouping of users in cars and the routing plan of each car.

3.3. Demand Estimation Module

After the user and spatial datasets are assembled, they are used in the demand module to estimate the potential user population for the new ridesharing service. The "willingness to switch" is generally a model that estimates the probability of users currently commuting by other modes of transport (drive alone, public transport, private taxi, etc.) to switch to ridesharing given the service attributes. Discrete choice models are typically used to analyze and predict the user's decision of switching to ridesharing. The user cost, travel time, and other service attributes (comfort, reliability, and availability) are the main factors in determining the willingness to switch in addition to users' characteristics, attitudes, and needs. This section presents the user cost and travel time factors, while the other service attributes are discussed in the service design section 3.4.

3.3.1. User Cost

The user cost is determined for the current commuting mode of each user potentially switching to the new ridesharing service. The trip cost for users currently commuting by their own cars is estimated based on their travelled miles (gas and car maintenance) and the parking fees. Users that are currently carpooling may be considered to share the trip cost. The cost for other users that are currently commuting by public transport (bus and/or taxi-service) is estimated based on applicable public transport fares between each user's home location and the organization.

On the other hand, the ridesharing fare is the new user cost after switching to the new ridesharing service. Different scenarios of fare values may be investigated in the demand forecast. Furuhata et al. (2013) identified three industry types of fare pricing rules as follows:

- <u>Catalog price</u>: listing of flat rates, typically based on geographical zones.
- <u>Rule-based pricing</u>: using a cost calculation formula, typically per mile and number of passengers/stop.
- <u>Negotiation-based pricing</u>: price is negotiated between the driver and passenger on a car by car basis.

3.3.2. Travel Time

The travel time for each user is computed for both the current commuting mode and the new ridesharing service. The total door-to-door travel time consists of two components: the IVTT (in-vehicle travel time) and the OVTT (out-of-vehicle travel time). The IVTT is computed from the route length divided by the average speed (different for public transport and private cars), and the OVTT is typically the walking plus waiting time (mainly for public transport).

For the new ridesharing service, the travel time for each user is the direct door-to-door travel time by the taxicab plus an additional delay due to the route deviation to collect additional passengers along the way. For the inbound trips (home-to-work), the first picked up passenger would observe the highest route deviation (not exceeding the maximum allowed), and the last picked up passenger would observe no delay (direct route to the organization). For the outbound trips (work-to-home), the first dropped off passenger would observe no delay, and the last dropped off passenger would observe the maximum delay. The maximum allowable deviation is expressed as a percentage of the direct travel time of each passenger.

In reality the travel time matrix between the different nodes on the network varies throughout the day. For example, a passenger's travel time from his/her home to the destination (the organization) may be 40 minutes during peak hours and 25 minutes during off-peak hours. As such, considering the maximum deviation as a percentage of the travel time may reflect some of this variability of the travel time. However, the actual travel time along different routes may not be proportionally changing at different times of the day. Huang and Gao (2012) addressed the problem of finding optimal paths in networks where all link travel times are stochastic and time-dependent, and correlated over time and space. The authors defined a disutility function of travel time to evaluate the paths using a developed exact label-correcting algorithm, and presented analytical results in small and large networks where the impact on finding the optimal path is closely related to the levels of correlation and risk attitude.

3.3.3. Value of Time

A value of travel time (VOT) factor is considered in conjunction with the user travel time and travel cost when considering shifting to a new travel mode. It is used to assess the amount that a user would be willing to pay in order to save time (e.g. users switching from public transport to the new ridesharing service), or the amount that the user would accept saving as a compensation for the extra travel time (e.g. users switching from private car to the new ridesharing service).

3.4. Service Design Module

The service design module consists of several elements that are identified in the framework as follows: service delivery, service attributes, ride matching tools, technological enablers, and vehicle dispatch. These five components are discussed in the following subsections.

3.4.1. Service Delivery

In general, traditional public transport service design consists of establishing routes, stops, and schedules that are typically predetermined and fixed. In ridesharing service design, these elements are established with flexible arrangements that can vary from pre-booked to real time. Other parameters, related to cost and revenue, are also considered.

For organization-based ridesharing schemes, a defined set of users are typically served on a regular schedule using a dedicated fleet of taxicab vehicles. Since the operation schedule of the organization is typically predetermined, the majority of the trips are expected to be pre-booked. However, the service design should anticipate limited changes in terms of new requests or canceled requests during the operation of any regular day.

3.4.2. Service Attributes

The main service attributes are: the fare for the ride, route deviation (additional delay to the trip travel time), convenience (privacy, perception of security, on-board wifi, and comfort during the trip), system flexibility (real time/dynamic service), service availability (for the different users of the organization), and service reliability (on time departures/arrivals and guaranteed rides in emergencies or unscheduled operations). These attributes contribute directly to the demand module for determining the user's willingness to switch to the ridesharing service. This necessitates iterative processing of the elements of the developed framework when updating the service attributes (potential fare changes due to subsidy, and the impact of the technological enablers on reducing delays, increasing system reliability and service availability) and subsequently establishing a new demand estimate. For the purposes of the case study in Chapter 5, a simple deterministic demand model was implemented taking into consideration the user cost and travel time in association with the value of time.

3.4.3. Ride Matching Tools

The proposed service design in the developed framework is intended to be used for Shared-Taxi (all-passengers ride matching scenario) but is flexible and generic to enable consideration of other ridesharing service options, i.e. carpool (driver-passenger ride matching scenario). As such, temporal matching might be one-way (possibly different passengers in each direction) or two-way (same passengers are coming and leaving together).

Two main ride matching approaches (clustering and pairing) were identified and discussed in the literature review. The advantages and disadvantages of each of the ride matching approaches are summarized in Table 3.1 below.

Table 3.1: Comparison of Existing Ride Matching Methods

Method	Advantages	Disadvantages
Clustering	Best for defining fare structures Matches multiple passengers	Misses out passengers along the way
Pairing	Captures possible matches along the way	Matches only one passenger to each driver Uncertainty about the actual delay resulting from the route deviation (travel time variability/reliability)

This research proposes a new hybrid method using a heuristic algorithm that combines the advantages of both methods. This new proposed method is discussed in detail in Chapter 4 of this thesis.

3.4.4. Technological Enablers

Technological advancement in computational speed (micro-processors), telecommunication (3G, Web, SMS, etc.) and location based systems (GPS, AGPS, and other geo-location capabilities) provides the possibility to upgrade static scheduling and assignment to dynamic (i.e. real time) matching. This may include mobile application for reservations (dynamic ridesharing), driver to passenger communication and notification at pick-up, on-board wifi facility, and vehicle tracking. The selection of the type and specifications of the technological enablers is based mainly on the intended service delivery that will either require fixed pre-booking or real time requests.

3.4.5. Vehicle Dispatch

A vehicle dispatch tool is needed depending on the operation schedule of the organization. In the case of an organization with the same starting time in the morning and ending time in the evening, a vehicle is dispatched to make a single tour per day. On the other hand, a vehicle may be dispatched to make multiple tours per day for other cases of organizations that have different starting and ending times per user groups (i.e. factory shifts, hospitals, or universities). The proposed ride matching algorithm solves the problem for each group of users sharing the same starting and/or ending time separately. The vehicle dispatch provides the link between the trips of the whole day; it also includes routing and scheduling of the vehicles and the drivers. The ride matching tool may be integrated with the vehicle dispatch tool for the optimization of the taxicab fleet size. This integration may be in 2-step processing (ride matching then dispatching) or combined in complex algorithms with multi-objective optimization of the overall system. For the purpose of this research, a simple greedy vehicle dispatch method is adopted as a post processing of the ride matching algorithm (this may not guarantee the optimal number of required cars).

3.5. System Feasibility Module

Evaluating the feasibility of any proposed ridesharing service involves both financial and economic decisions. A cost-benefit analysis, comparing expenditures and revenues, is typically used for the financial decision. The economic decision seeks the impact of the ridesharing service on the different stakeholders (the users, the organization, the operator, and the neighborhood of the organization).

3.5.1. Operator's Cost-Benefit

The resulting estimated demand for the ridesharing service is the key element of the developed framework. The system feasibility is established using the estimated capital and operational costs of the service and the expected revenue from the ridesharing demand.

The main components of the operator's cost include the price for the online ride matching tool, the acquisition cost for the vehicle fleet, and the operational costs for fuel, salaries, office rent, and other expenses. On the other hand, the operator's revenue consists of the fare collection and may also include financial subsidy from the organization served.

3.5.2. Service Impact

The proposed ridesharing service may have different impacts on the various stakeholders. Table 3.2 summarizes the impacts of ridesharing from the perspectives of user, the institution, the neighborhood, and the operator.

Table 3.2: Impacts of Ridesharing on the Different Stakeholders

<table>
<tr><th>User's Perspective</th><th>Institutional Perspective</th><th>Neighborhood Perspective</th><th>Operator's Perspective</th></tr>
<tr><td>Personal economic and time benefits</td><td colspan="2">Reduction in parking demand and congestion (sustainable transport)</td><td>Profit</td></tr>
<tr><td colspan="2">Safety</td><td>Environmental benefit (reduction of emissions and noise)</td><td></td></tr>
<tr><td>Convenience
Reduce reliance on private auto</td><td></td><td></td><td></td></tr>
</table>

3.5.3. Institutional Support

The estimated service impact is a determining factor for motivating the institutional support, through financial subsidy and/or supporting policies, which in turn will increase the opportunities for higher demand. For example, a university or institution might favor partially subsidizing a low-fare ridesharing service instead of building a new parking facility to meet the increased demand.

3.5.4. Interest of the Private Sector

A profit opportunity coupled with institutional support offers an attractive scenario for the private sector in general and the private taxi operators in specific to invest in the implementation of the ridesharing service.

3.5.5. Policy Scenarios

The proposed evaluation framework is used to test policy scenarios. Three important factors are to be investigated when planning different scenarios of a proposed ridesharing service. These factors are the fare level, the maximum allowable deviation, and the vehicle capacity. Figure 3.3 below presents the interrelationships between these factors and the main elements of the framework (scenario parameters in yellow, demand module in pink, service design module in blue, and feasibility module in green).

The demand is mainly affected by the fare and the maximum deviation values. Consequently, the service design is mainly dependent on the demand size, the maximum deviation, and the vehicle capacity. As result of the service design, the observed deviations may be considerably less than the maximum allowable deviation, and thus it may feed back into the demand module and result in an increase in the demand. This was identified as a gap in the literature where the service design process was addressed by researchers independently, assuming a fixed demand.

The service impact is also determined by the demand, and in scenarios where higher demand leads to a considerable reduction in parking demand and congestion the organization may be encouraged to provide financial subsidy to reduce the fare to increase the demand.

The service design determines the fleet size and the vehicle miles which constitute the main elements of the operator's cost. The operator's revenue is calculated using the demand and the fare price. A cost-benefit analysis may lead into lowering or increasing the fare price which in turn feeds back into the demand module affecting the remaining elements of the framework.

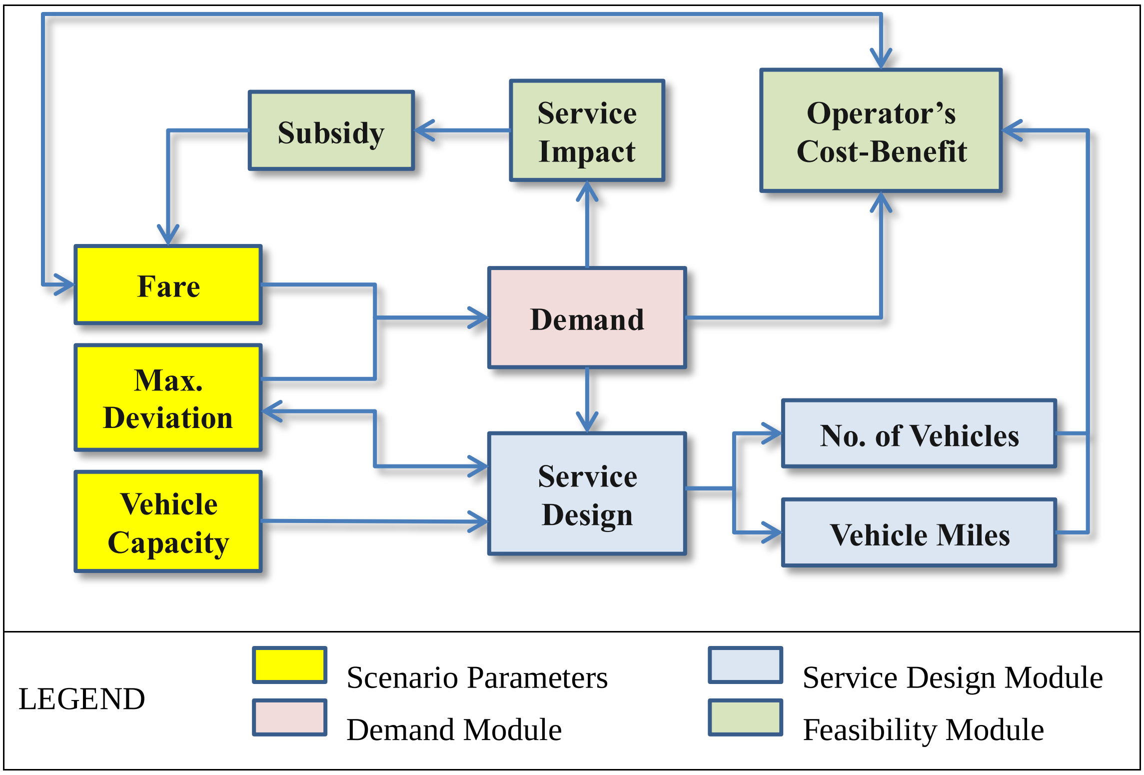

Figure 3.3: Interrelationships among the Main Elements of the Framework

CHAPTER 4

PROPOSED RIDEMATCHING ALGORITHM

This chapter proposes a new many-to-one ride matching algorithm based on the Capacitated Vehicle Routing Problem with Time Windows. The problem is focused on the context of organization-based ridesharing, including unit demand, asymmetric network, narrow time windows at departure, and common arrival time at destination. This chapter is organized into five main sections as follows. Section 4.1 presents two motivating examples explaining the solution strategies identified in the literature. Section 4.2 describes a proposed new heuristic algorithm that combines the advantages of both solution strategies (clustering and pairing) and with capabilities of fast solving large size problems with different vehicle capacities. A step-by-step example of using the proposed algorithm is elaborated in section 4.3. Section 4.4 provides methods for finding optimal solutions by implementing a mathematical formulation in CPLEX. Section 4.5 presents the simulation results of small and large problems using the developed algorithms. Finally, conclusions are drawn in Section 4.6.

4.1. Motivating Examples

4.1.2. Example 1

The ride matching approach proposed in this research utilizes both strategies discussed in the literature: matching of proximity clustered passengers, and matching passengers with minimum deviation along a route. The following is a small example that illustrates the difference between proximity clustering and minimum deviation strategies, and their implications on maximizing the user utility or minimizing the operator's cost.

The problem consists of transporting 4 passengers P1, P2, P3, and P4 to the destination depot D (see Figure 4.1). Two cars (each with a capacity of 2) are available at the depot, and each car will need to collect a maximum of two passengers and then return to the depot. The travel time matrix is presented in the same Figure,

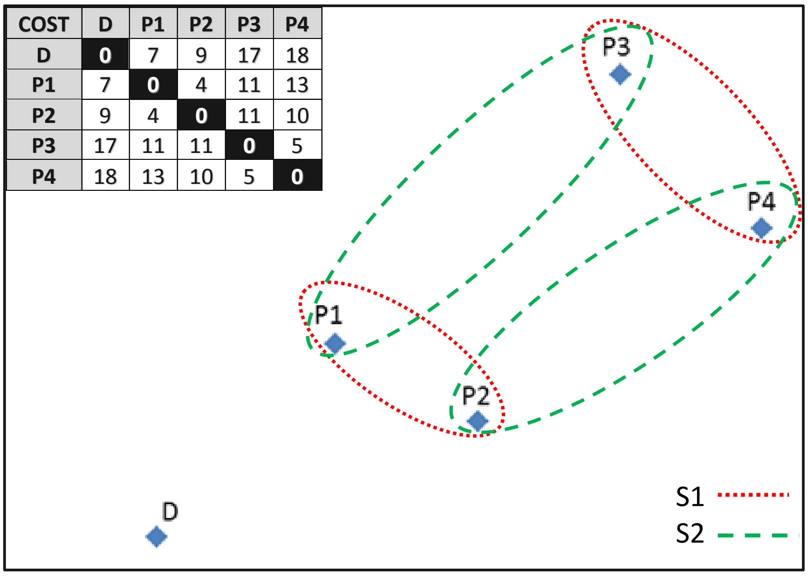

Figure 4.1: Schematic Showing the Four Passengers and the Depot

Considering that the farthest passenger is always picked up first, the possible solutions consist of three combinations: S1 = {P4-P3, P2-P1}, S2 = {P4-P2, P3-P1}, and S3 = {P4-P1, P3-P2}. The summary of the results is presented in Table 4.1 below.

Table 4.1: Results of Example 1

		Passengers		Cost (total travel time)		Deviation (ΔT) on
Solution	**Car**	**1st**	**2nd**	**Per Car**	**Total**	**1st Passenger**
S1	1	P4	P3	40	**60**	4
	2	P2	P1	20		2
S2	1	P4	P2	37	**72**	1
	2	P3	P1	35		1
S3	1	P4	P1	38	**75**	2
	2	P3	P2	37		3

Solution S1 has the least total cost; one car is assigned to the remote passengers 4 and 3, and the other car is assigned to the close passengers 2 and 1. The solution strategy can be described as "clustering neighboring passengers", and then assigning a car to each cluster.

On the other hand, although solution S2 has a 20% higher total cost, it improves the user utility by reducing the extra travel time burden (deviation ΔT) on the first passenger of each car, from 4 and 2 to 1 each. This solution strategy can be described as "matching passengers along the routes" (least deviation).

Solution S3 is inferior to solution S2 on all fronts; it has the highest total cost, and does not offer a better user utility. Compared to S1, only passenger P4 has a lower deviation in S3, while the total cost is substantially higher than in S1.

If the objective is to minimize the total cost, then S1 is the optimal solution. However, if a constraint is imposed by limiting the maximum acceptable passenger burden to be 2, then S1 becomes infeasible, and S2 becomes the optimal solution.

4.1.2. Example 2

The first motivating example illustrated the trade-off between the passenger deviation and the total cost. Another equally significant factor in VRP solutions is the number of cars needed. The number of available cars may be limited (considered as a constraint), or the solution needs to find the least feasible number of cars (considered as objective). The following example is a further illustration of the variability of the two solution strategies (proximity clustering and minimum deviation) on all three factors.

The problem consists of transporting 6 passengers A, A', B, B', C, and C' to the destination depot D (see Figure 4.2). To reduce the number of possible solutions, passengers (A, B, C) and (A', B', C') were located in a symmetrical grid configuration from the depot, with (Y/2) vertical distance from the axis of symmetry, and (X_1, X_2, X_3) horizontal distances, respectively. The cost (travel distance) from any point to the depot is calculated as the Euclidean distance.

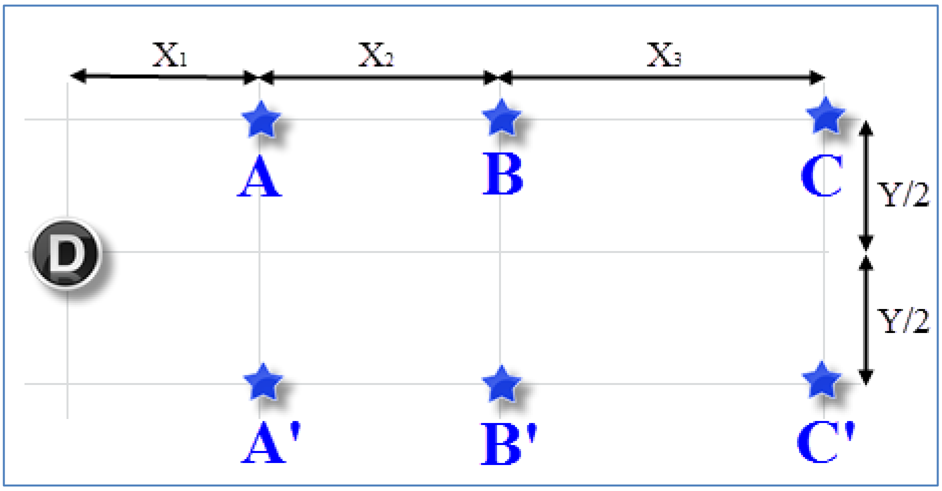

Figure 4.2: Schematic Showing the Six Passengers and the Depot

Assuming cars with three passenger capacities are available at the depot, two scenarios were investigated. The first considers a maximum passenger deviation value equivalent to Y (similar to the cost term, the deviation is in distance units), with no constraint imposed on the number of cars available. The second considers a maximum of two cars available with no constraint imposed on the maximum deviation.

<u>Scenario 1:</u>

If Y is less than X_1, X_2, and X_3, there will be only two feasible solutions. Since the maximum deviation is Y, any car packing of a passenger and its symmetric location (Y distance apart) will reach its maximum allowable deviation and thus cannot deviate to pack any third passenger. As a result, this will entail only two feasible solutions for this problem. The first solution S1, depicting the first strategy of "clustering proximity passengers", entails three cars as follows {(A, A'), (B, B'), and (C, C')}. On the other hand, the second solution S2, presenting the "route deviation" strategy, consists of two cars as follows {(A, B, C) and (A', B', C')}. This explains the efficiency of "route deviation" strategy in achieving higher matches for problems with tight passenger deviation constraints.

Having considered the number of required cars for the two solutions, it is also reasonable to look into their total cost objective. Two numerical applications were considered as follows, {X_1= 10, X_2= 20, X_3= 30, Y= 3} were assigned to Scenario 1a, while Scenario 1b was assigned the same values except for {X_3 = 40}. A summary of the results is presented in Table 4.2 below.

Table 4.2: Results of Scenario 1

Scenario	**X_1**	**X_2**	**X_3**	**Y**	**Solution**		**Num. of cars**	**Total Cost**	**Max. Dev.**
1a	10	20	30	3	S1	(A, A'), (B, B'), and (C, C')	3	129.41	3
					S2	(C, B, A) and (C', B', A')	2	120.30	0.07
1b	10	20	40	3	S1	(A, A'), (B, B'), and (C, C')	3	149.39	3
					S2	(C, B, A) and (C', B', A')	2	160.28	0.08

Numerical results in Table 4.2 demonstrated that even with the same problem configuration, increasing the distance X_3 from 30 to 40 has changed the total cost for solution S2 (route deviation strategy) from being 7% lower than S1 (proximity clustering strategy) to become 7% higher. Therefore, solutions with a smaller number of cars may not necessarily lead to a lower total travel time (or distance) cost. On the other hand, the maximum deviation among all passengers is considerably less for S2 in both scenarios.

Scenario 2:

In this scenario, the maximum deviation constraint is relaxed, and the number of cars is fixed at its maximum of two fully packed cars. For this scenario, solution S1 is infeasible (requiring 3 cars), but Solution S2 is feasible. In addition, there exist three new feasible solutions that can be described as hybrid approaches of clustering two neighboring passengers with a third passenger along the way. A numerical application for Scenarios 2a and 2b is considered using the same distance values of Scenarios 1a and 1b, respectively. A summary of the results is presented in Table 4.3 below. It is to be noted that other solutions exist by interchanging any or all passengers of each car by their symmetry (A with A', B with B', and C with C'); this will either lead to a longer or a symmetric solution relative to the solutions presented in Table 4.3 below.

Table 4.3: Results of Scenario 2

Scenario	**X_1**	**X_2**	**X_3**	**Y**	**Solution**		**Total Cost**	**Max. Dev.**
2a	10	20	30	3	S1	Infeasible		
					S2	(C, B, A) and (C', B', A')	120.30	0.07
					S3	(C, C', B') and (B, A', A)	100.26	3.05
					S4	(C, C', A') and (B', B, A)	100.26	3.07
					S5	(C, B, B') and (C', A', A)	126.24	3.07
2b	10	20	40	3	S1	Infeasible		
					S2	(C, B, A) and (C', B', A')	160.28	0.08
					S3	(C, C', B') and (B, A', A)	120.25	3.05
					S4	(C, C', A') and (B', B, A)	120.25	3.08
					S5	(C, B, B') and (C', A', A)	166.22	3.08

Solutions S3 and S4 are the optimal solution for the lowest cost objective; they both present a hybrid strategy (proximity clustering then route deviation). However, S3 has marginally lower deviation than S4 (since it picks the nearest third passenger). This hybrid solution has substantially lower total cost than both S1 and S2, although S1 becomes infeasible in scenario 2 due to the maximum number of cars constraint.

Solution S5 is also a hybrid solution, but in the opposite order (route deviation then proximity clustering). Solution S5 is the worst in both cost objective and maximum deviation.

In conclusion, a hybrid solution approach needs to be developed. It would combine the advantage of both solution strategies (proximity and deviation). At each passenger location, a binary decision needs to be made for the next passenger, either picking the closest proximity passenger, or the passenger with the least route deviation.

4.2. Proposed Heuristic Approach

Three ride matching solutions for the organization-based ridesharing problem were identified in the literature. Tao and Chen (2007) presented a greedy approach by matching the nearest neighbor while satisfying a time-space network flow. Deakin et al. (2010) presented a simple clustering strategy that matches nearest neighbors satisfying a cluster size. Amey (2010) highlighted the opportunities of matching passengers along the route, but presented a solution that matches two passengers only. This section describes a proposed new heuristic algorithm that combines the advantages of both solution strategies (clustering and pairing) and with capabilities of fast solving large size problems with different vehicle capacities.

The proposed heuristic approach for solving the given ridesharing problem comprises three steps; the first is establishing the cost matrix that forms the basis of any solution approach. Second, a hierarchical spanning tree, rooted at the organization location (considered to be the depot), is derived from the cost matrix to structure the search of feasible ride matches. The final step is an enumerated tree traversal algorithm to pack the feasible nodes in the tree into cars. This approach enables searching for solution improvements by iterating the third step using different values for the maximum deviation and/or car capacities based on different time windows.

4.2.1. The Cost Matrix

Establishing the cost matrix is the first step toward solving any routing problem. It comprises finding the minimum cost for a vehicle to travel between every pair of nodes to be visited. The unit of the cost term depends on whether it is based on the travel distance, the travel time, or the financial cost.

In graph theory the cost matrix is known as the All Pairs Shortest Path (APSP) matrix, in which we have to find a shortest path between every pair of nodes. It contains all the edges that can form any possible solution of the routing problem. There exist various methods and algorithms for solving the APSP including: Dijkstra's, Bellman-Ford, Floyd-Warshall and Johnson’s algorithms.

In typical VRP problems, and in most known benchmark data (Solomon 1987, Gehring and Homberger 2005), the nodes are defined by their geographical coordinates, and the shortest path can then be computed as the Euclidean, Manhattan, or Great Circle distance. Such simplifications may be practical in urban street networks, but will always result in a symmetrical cost matrix and are not practical when the travel time is in consideration. With the availability of advanced GIS (Geographic Information Systems) models, travel time cost matrices can be generated from the GIS network analysis tools. This method reflects the actual congested speeds on roads in the computation of travel times, and enables the proper representation of the asymmetrical nature of the road network.

4.2.2. The Hierarchical Spanning Tree Structures

Given a full APSP matrix that represents all the edges connecting every pair of nodes, the problem can be defined as a complete graph (or complete digraph in the case of asymmetric networks). Finding the edges forming a hierarchical spanning tree with the depot as the source node is possible by searching the APSP for a single linkage for each node (*i*) to its parent node (*j*). We propose two possible hierarchical tree structures that reflect each of the solution strategies: the proximity clustering and the minimum route deviation approach. If the solution strategy is based on proximity clustering, then the <u>Proximity Clustering Tree (PCT)</u> can be established, where (*j*) is the closest to (*i*) and is closer to the depot than (*i*). On the other hand, when the hierarchy is based on minimum route deviation, then each node (*i*) is linked to the node (*j*) that will incur the least cost increase for travel from (*i*) to the depot (compared to direct travel without deviation) irrespective of the proximity. Therefore, another spanning tree may be defined as the <u>Minimum Deviation Tree (MDT)</u>, where each node (*i*) is linked to its parent node (*j*), where (*j*) has the least route deviation for (*i*), and is closer to the depot than (*i*). The approaches of finding the PCT and the MDT are illustrated in the flowcharts in Figure 4.3 below, where the complexity of each method is determined to be $\Theta(n^2)$ for n nodes.

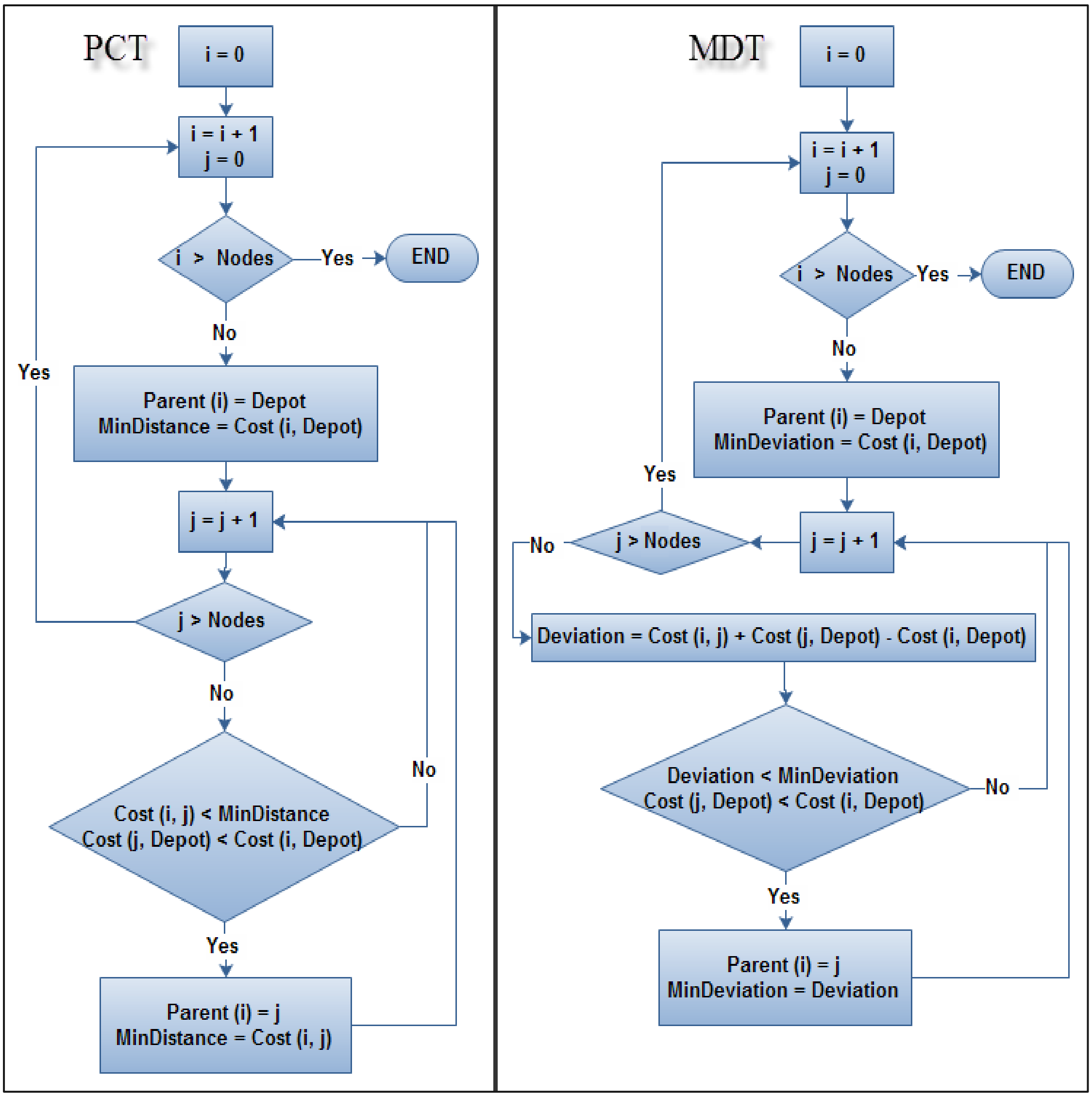

Figure 4.3: Flowcharts of the PCT and MDT Methods

An example illustrating the PCT and MDT of a 24-node problem is presented in Figure 4.4. The child-parent relationship in the PCT is based on the closest proximity distance, i.e. the parent is the closest node to the child while in MDT the parent has the least deviation to the child. In this example, in the PCT tree the parent of node 9 is node 20 and the parent of node 20 is node 10. However, in the MDT tree all nodes 9, 20, and 10 have the same parent node 1. In general the PCT has the greater depth and the MDT has the greater breadth. Each of the two tree structures may lead to different car packing arrangements that will work best depending on the structure of the problem, i.e. whether the nodes are generally in clustered or random distributions.

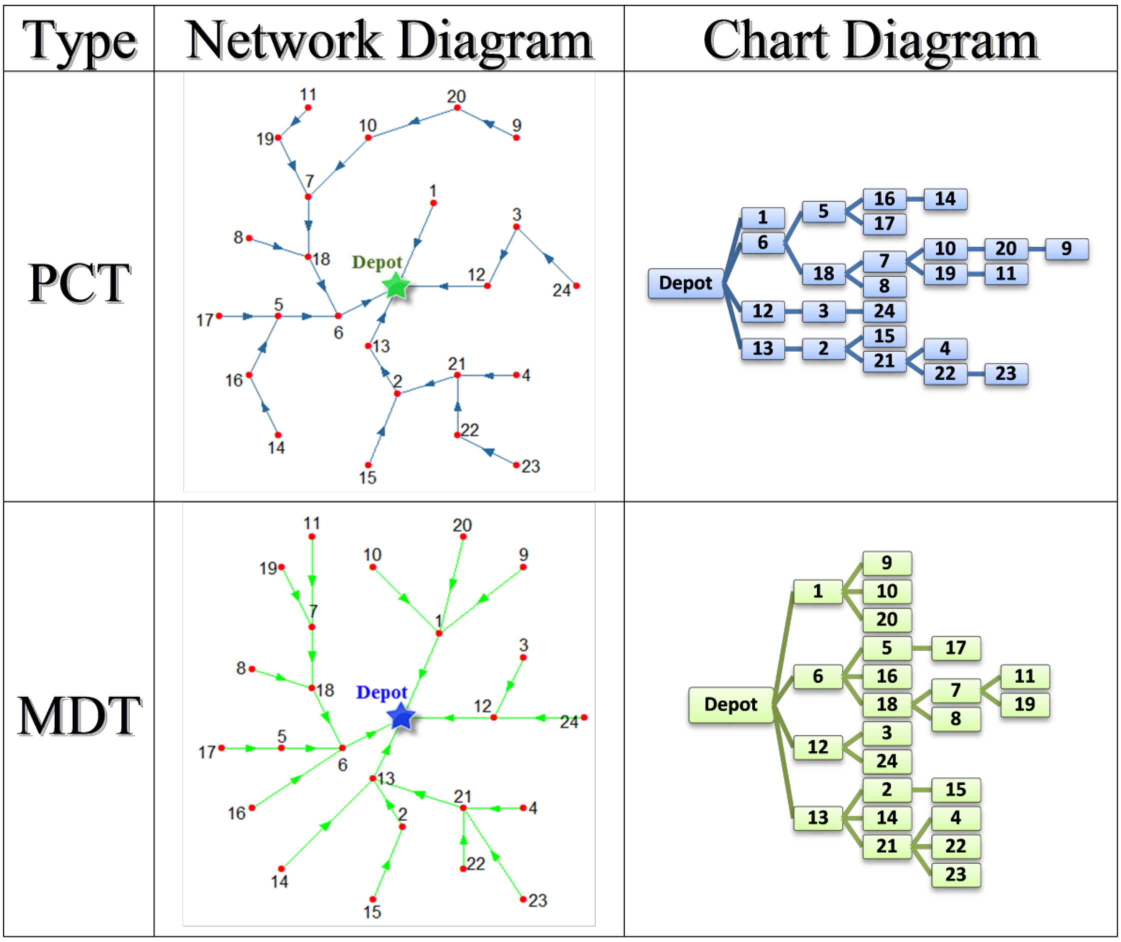

Figure 4.4: Illustration Example of the PCT and MDT Network and Chart Diagrams

4.2.3. Tree Traversal Algorithm

After constructing the PCT and MDT trees, an enumerated tree traversal algorithm is used to pack the passengers into cars. The hierarchical tree structure will enable a fast search by trying to match sibling nodes (nodes having the same parent) then moving up to their parent. The procedure may be described in the following steps: start a new car from a leaf node (*i*) that is the farthest from the depot for PCT (or the farthest node among the nodes with maximum tree level in the case of MDT), then try to pack with its siblings starting from the "closest to (*i*)" to the "farthest from (*i*)" while satisfying the time window constraint of each passenger in the car. If the car capacity is not reached after searching all available siblings, the search location demotes (by moving up to the parent level) and then tries to pack with the parent and then its siblings in the same manner. Once the depot and/or the car capacity are reached, a new car is started by repeating the above steps until all passengers are picked up. Alternatively, if the vehicle fleet size is strictly constrained, then time constraint violations are allowed for any car packing that does not reach capacity; the packing steps of this specific car are repeated (starting from the first passenger again) with an increased "maximum allowable deviation" value until the car is fully packed (in the case of the many-to-one, the implication of the increased maximum allowable deviation should be anticipated in earlier departure time rather than late arrival time). A flowchart of the tree traversal algorithm is presented in Figure 4.5, where the complexity of this method is determined to be $\Theta(n^3)$ for n nodes.

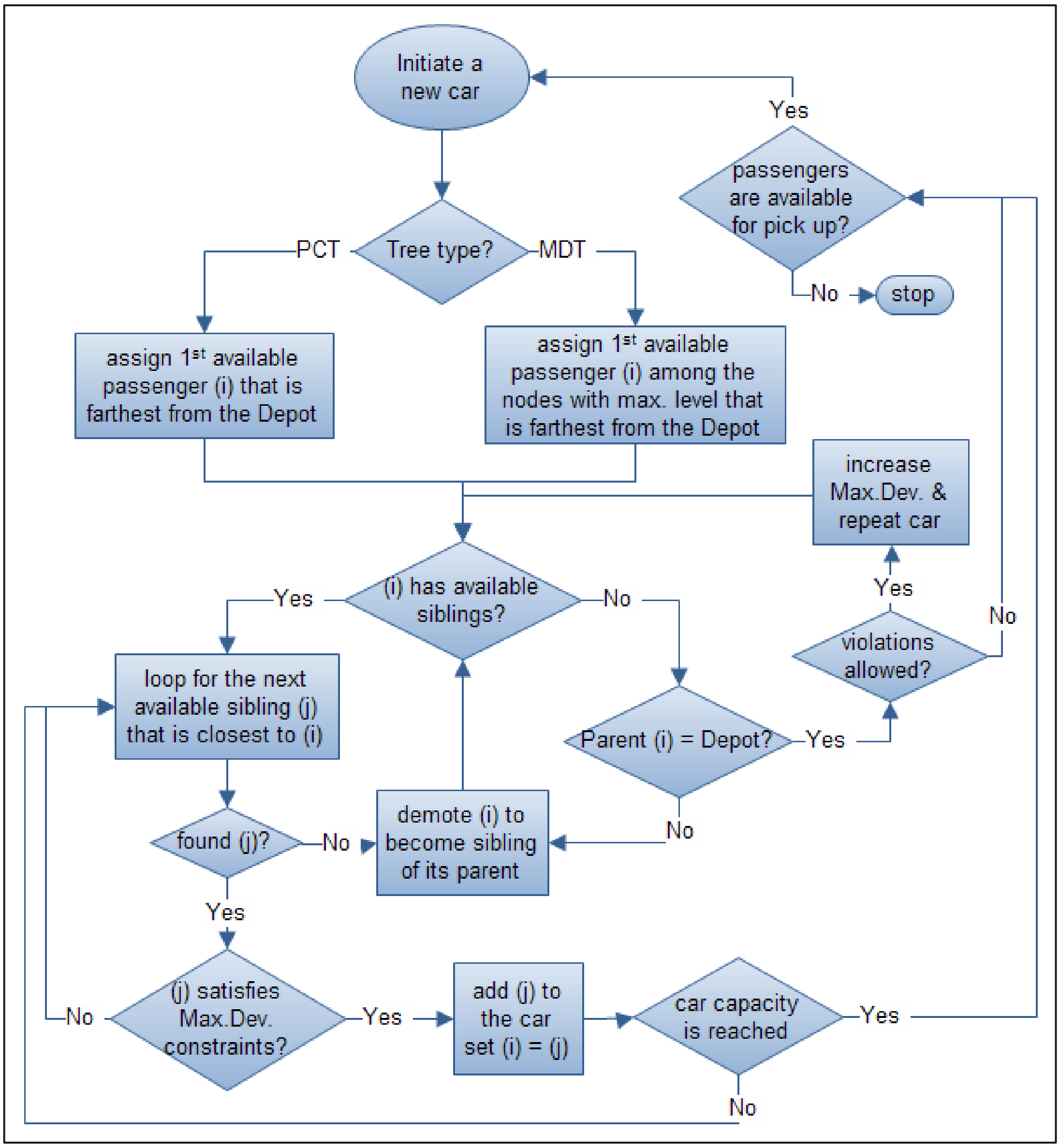

Figure 4.5: Flowchart of the Tree Traversal Algorithm

4.3. Step-by-Step Example 3

This example illustrates the steps of solving a small problem of 10 nodes (9 passengers and the depot) using the proposed heuristic approach. The coordinates of the nodes are presented in Table 4.4 and in Figure 4.6. The problem consists of transporting the 9 passengers to the destination depot D. Cars with three passenger capacities are available at the depot, and the maximum allowable deviation for each passenger is 20% of his/her direct route distance.

Table 4.4: X and Y Coordinate of Nodes (Example 3)

Node	X	Y
Depot	0	0
1	5	5
2	5	10
3	11	14
4	15	10
5	4	18
6	10	20
7	15	19
8	20	20
9	20	15

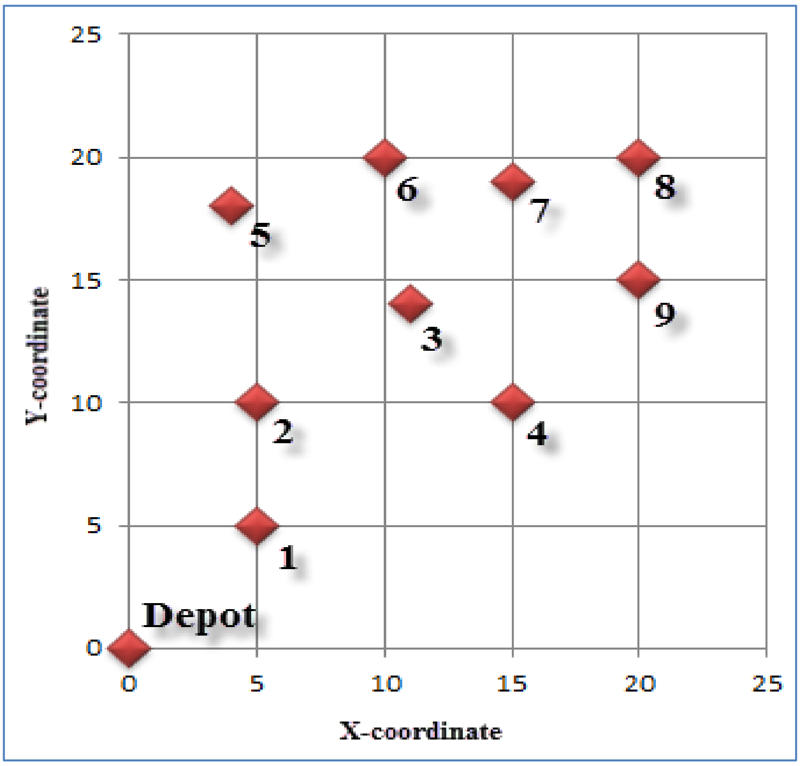

Figure 4.6: Distribution of the Nodes (Example 3)

4.3.1. Step 1: Cost Matrix

The first step is to calculate the cost matrix. The cost may be travel time, distance, or the associated financial cost. In this problem the Euclidean distance is considered as the cost ($C_{i,j}$) between any two nodes (*i* and *j*). The coordinates in Table 4.4 are used to calculate the APSP and the resulting cost matrix is presented in Table

4.5 below. Although the cost matrix in this example is symmetric, the proposed heuristic is applicable for problems with asymmetric cost matrices as well.

Table 4.5: Cost Matrix (Example 3)

O\D	Depot	1	2	3	4	5	6	7	8	9
Depot	**0.0**	7.1	11.2	17.8	18.0	18.4	22.4	24.2	28.3	25.0
1	7.1	**0.0**	5.0	10.8	11.2	13.0	15.8	17.2	21.2	18.0
2	11.2	5.0	**0.0**	7.2	10.0	8.1	11.2	13.5	18.0	15.8
3	17.8	10.8	7.2	**0.0**	5.7	8.1	6.1	6.4	10.8	9.1
4	18.0	11.2	10.0	5.7	**0.0**	13.6	11.2	9.0	11.2	7.1
5	18.4	13.0	8.1	8.1	13.6	**0.0**	6.3	11.0	16.1	16.3
6	22.4	15.8	11.2	6.1	11.2	6.3	**0.0**	5.1	10.0	11.2
7	24.2	17.2	13.5	6.4	9.0	11.0	5.1	**0.0**	5.1	6.4
8	28.3	21.2	18.0	10.8	11.2	16.1	10.0	5.1	**0.0**	5.0
9	25.0	18.0	15.8	9.1	7.1	16.3	11.2	6.4	5.0	**0.0**

4.3.2. Step 2: Hierarchical Trees

Given the cost matrix, the hierarchical trees depicting the spatial structure of the nodes can be determined. This step requires linking each node to its parent node (single linkage clustering, every node has a single parent while a parent may have more than one child). This is done by looping over the 9 nodes and comparing the distances between each node and all other nodes. For PCT the parent is the closest node to the node under consideration, while at the same time being closer to the depot. The distance from node 1 to the depot is 7.1, and the closest node to 1 is node 2, but node 2 is 11.2 away from the depot. Therefore 2 cannot be the parent of 1, and the same applies for all other nodes as node 1 is the closest to the depot. As a result, the parent of 1 is the depot. Next, node 1 is determined to be the parent of node 2, as it is the closest to it (distance from 2 to 1 is 5), and node 1 is closer to the depot. In a similar fashion, the parents of nodes 3, 4, 5, 6, 7, 8, and 9 are the nodes 2, 3, 2, 3, 6, 9, and 7, respectively.

For MDT the parent is the node that results in the least route deviation to the node under consideration, while at the same time being closer to the depot. The deviation made by node $\boldsymbol{j}$ for node $\boldsymbol{i}$ is calculated as ($C_{i,j} + C_{j,D} - C_{i,D}$). Node 1 is already determined to be the closest to the depot, so the parent of node 1 is the depot. For node 2, the only possible parent is node 1, since it is the only node closer to the depot than 2. Next, node 3 has both nodes 1 and 2 closer to the depot. The deviations for node 3 from nodes 1 and 2 are 0.1 and 0.6, respectively. Therefore, the parent of node 3 is node 1. In a similar fashion, the parents of nodes 4, 5, 6, 7, 8, and 9 are the nodes 1, 2, 2, 3, 1, and 1, respectively. Chart diagrams of the PCT and MDT trees are illustrated in Figure 4.7a.

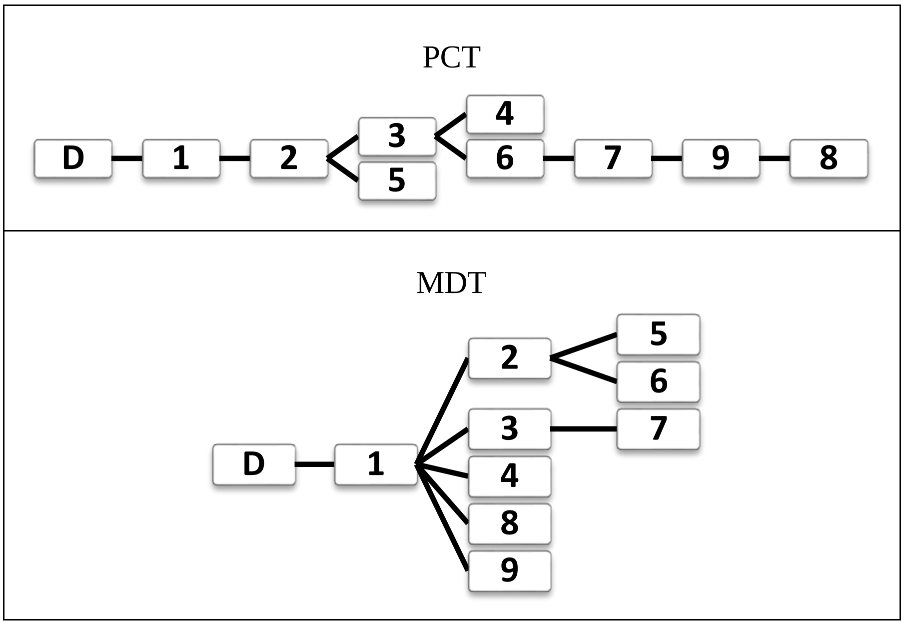

Figure 4.7a: Hierarchical Trees (Example 3)

4.3.3. Step 3: Tree Traversal

The third and final step is to traverse the hierarchical trees given the problem constraints. Any variation in the problem constraints would only require repeating this step without any impact on steps 1 and 2. The tree traversal is the same for both PCT and MDT except for the choice of the first passenger in each new car.

The PCT starts by assigning the farthest available node from the depot to the first car. In this problem node 8 is the farthest. So car 1 in the PCT solution will first pick the passenger at node 8, and since the car capacity is still not reached it searches for additional passengers by investigating any available siblings for 8. Since node 8 has no siblings, the search moves to investigate the parent node. The parent of node 8 is node 9 and it is available, and the deviation constraint is satisfied (the deviation that node 9 imposes on node 8 is 1.7 or 6.1% of its direct cost to the depot). Therefore, the passenger at node 9 is assigned to the car. Every time a passenger is picked up it is labeled as being no longer available for pickup again. Next, since the car capacity is still not reached, the search continues for a third passenger. Node 9 has no siblings so the parent node 7 is available, but the deviation constraint is not satisfied with respect to node 8 (the deviation imposed by node 7 on nodes 8 and 9 is 25.9% and 22.4%, respectively). So the search continues for any siblings for node 7, then its parent node 6 which also leads to violating the deviation constraint for both nodes 8 and 9 (deviations of 36.3% and 34.2%, respectively). And the search continues to node 4, the sibling of node 6, and it satisfies the deviation constraint for both nodes 8 and 9 (6.4% and 0.4%, respectively). After assigning node 4 as the third passenger in the car, the car capacity is reached and a new car is started by assigning the farthest available node from the depot (being node 7 now). In a similar fashion the remaining passengers are identified and packed into cars. Table 4.6a presents a summary of results of the PCT solution.

Table 4.6a: PCT Solution (Example 3)

Cars	Passengers			Cost	Deviations (1st and 2nd)			
Car 1	**8**	**9**	**4**	**58.4**	**1.8**	**0.1**	6.4%	0.4%
Car 2	**7**	**6**	**3**	**53.2**	**4.8**	**1.5**	19.7%	6.8%
Car 3	**5**	**2**	**1**	**38.6**	**1.7**	**0.9**	9.2%	8.0%
		Total		**150.1**	**10.8**			

On the other hand, the MDT starts assigning the farthest node to the depot, among the available nodes with highest level in the tree. In this problem, nodes 5, 6, 7 have the highest level in the tree (level 4); and among all three nodes, node 7 is the farthest from the depot. So car 1 in the MDT solution will first pick the passenger at node 7, and continue searching for additional passengers in the same manner as in PCT. Table 4.6b presents a summary of results of the MDT solution.

Table 4.6b: MDT Solution (Example 3)

Cars	Passengers			Cost	Deviations (1st and 2nd)			
Car 1	**7**	**3**	**2**	**49.0**	**0.6**	**0.6**	2.4%	3.3%
Car 2	**8**	**9**	**4**	**58.4**	**1.8**	**0.1**	6.4%	0.4%
Car 3	**6**	**5**	**1**	**48.8**	**4.1**	**1.7**	18.2%	9.1%
		TOTAL		**156.2**	**8.8**			

As shown in Tables 4.6a and 4.6b, the PCT resulted in lower total cost but higher total deviations than the MDT. Both solutions achieved full packing of three cars; however, if the maximum deviation constraint is reduced to 19%, the MDT solution would still be feasible but the PCT solution would require a fourth car for the passenger at node 3.

A color coding for each of the three cars in the PCT and MDT solutions was used for illustration of the steps. Cars 1, 2, and 3 were colored in blue, red, and green, respectively. The colors are highlighted in Tables 4.6a and 4.6b and in Figure 4.7b.

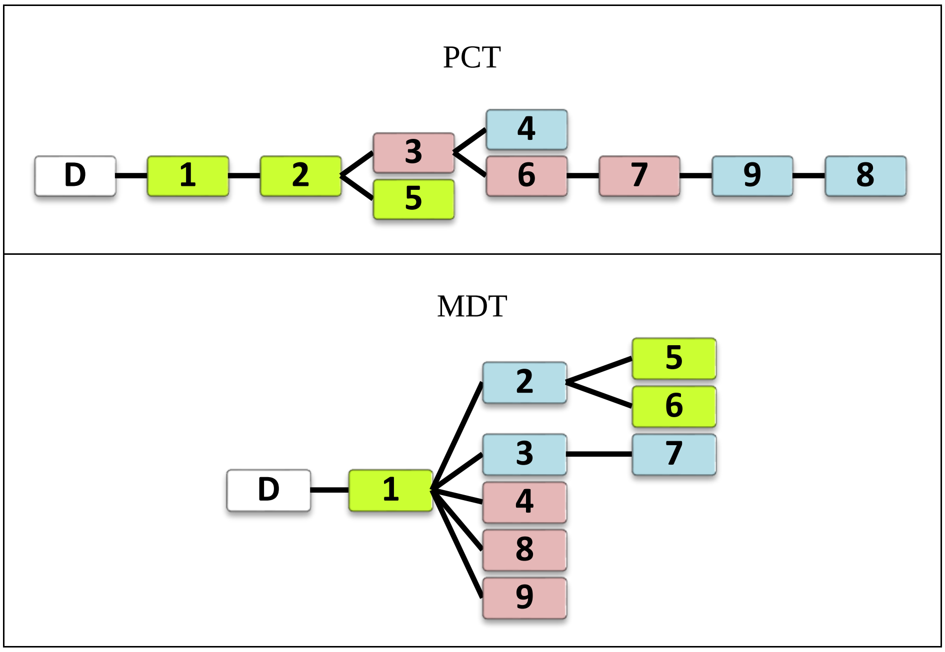

Figure 4.7b: Color Coding of the Hierarchical Trees (Example 3)

Nodes 8, 9, and 7 present a proximity cluster (maximum distance between the nodes is 6.4), but car 1 in the PCT solution excluded node 7 due to the deviation constraint, and searched for potential passengers along the way and resulted in a car identical to Car 2 of the MDT solution. Furthermore, nodes 7, 6, and 3 presented another proximity cluster (maximum distance between the nodes is 6.4) that was successfully served by car 2 in the PCT solution. Similar to the PCT the MDT searches the closest proximity siblings of the node before moving to the parent (that has the least deviation), as in the case of nodes 8, 9 and 4 in car 2 of the MDT solution. This demonstrates the advantage of the hybrid strategy of both methods (PCT prioritizes matching passengers within proximity clusters and MDT prioritizes matching passengers along the same route).

4.4. Optimal Solutions

In order to assess the results of the proposed heuristic approach, optimal solutions need to be established for benchmarking. The VRPTW is known to be a strongly NP-hard optimization problem, thus requiring efficient algorithms and computer software implementation for estimating optimal solutions. The most commonly used solution approach is the three index vehicle flow formulation. This approach is an Integer Linear Programming (ILP) formulation that was first introduced by Fisher and Jaikumar (1978). This research implemented this approach using the IBM ILOG CPLEX Optimization Studio for the exercise of establishing benchmark optimal solutions. Different objectives may be considered in the optimization of a VRP problem, including minimizing the "total cost", minimizing the "number of cars", or minimizing the "total passenger deviation". Typically, the main objective of the VRPTW problem is to minimize the total cost, while the number of cars and the time windows are defined as constraints.

4.4.1. Mathematical Formulation

The following is the three index vehicle flow formulation for the VRPTW problem as presented by Desrosiers et al. (1995).

<u>Notation:</u>

- Let N = {1 . . . . , n} be the set of customers.
- K, indexed by k, is the set of available vehicles to be routed & scheduled.
- Consider the graphs $G^k = (V^k, A^k)$, for all $k \in K$, each of them consisting of a set V^k of nodes and a set A^k of arcs.
- The set V^k consists of $N \cup \{o(k), d(k)\}$, where o(k) and d(k) represent respectively the origin-depot and the destination-depot of vehicle k, $k \in K$.
- The set A^k contains all feasible arcs, which is a subset of $V^k \times V^k$.
- $[a_i , b_i]$ is the time window within which customer $i \in N$ is visited.
- For each arc $(i, j) \in A^k$, $k \in K$, there is a cost c^k_{ij} and a travel time t^k_{ij}.
- Assume that the service time at node i is included in the travel time t^k_{ij}, for all i.
- All the customers must be assigned to at most v vehicles, $v \leq |K|$, such that the capacity Q^k of each vehicle is not exceeded.

Decision Variables:

- Flow variables $X^k_{i,j}$ (i, j) ∊ A^k , k ∊ K, a binary variable which is equal to 1 if arc (i,j) is used by vehicle k, and 0 otherwise;
- Time variables T^k_i , i ∊ V^k , k ∊ K, specifying the start of service at node i.

Formulation:

The problem of finding the minimal cost set of routes satisfying the VRPTW constraints can then be formulated as follows:

$$\text{Minimize} \sum_{k\in K} \sum_{(i,j)\in A^k} c^k_{ij} X^k_{ij} \tag{4.1}$$

Subject to:

$$\sum_{k\in K} \sum_{j\in N\cup\{d(k)\}} X^k_{ij} = 1, \quad \forall i \in N \tag{4.2}$$

$$\sum_{k\in K} \sum_{j\in N} X^k_{o(k),j} \leq v, \tag{4.3}$$

$$\sum_{j\in N\cup\{d(k)\}} X^k_{o(k),j} = 1, \quad \forall k \in K \tag{4.4}$$

$$\sum_{i\in N\cup\{o(k)\}} X^k_{i,d(k)} = 1, \quad \forall k \in K \tag{4.5}$$

$$\sum_{i\in N\cup\{o(k)\}} X^k_{ij} - \sum_{i\in N\cup\{d(k)\}} X^k_{ji} = 0, \quad \forall k \in K,\ \forall j \in V^k \setminus \{o(k), d(k)\} \tag{4.6}$$

$$X^k_{ij}(T^k_i + t^k_{ij} - T^k_j) \leq 0, \quad \forall k \in K,\ \forall (i,j) \in A^k \tag{4.7}$$

$$a_i \leq T^k_i \leq b_i, \quad \forall k \in K,\ \forall i \in V^k \tag{4.8}$$

$$\sum_{i\in N} \sum_{j\in N\cup\{d(k)\}} X^k_{ij} \leq Q^k, \quad \forall k \in K \tag{4.9}$$

The objective function (4.1) represents the total cost. Equality (4.2) is used to ensure that each customer is assigned once to a vehicle. Constraint (4.3) is used to ensure that the maximum number of vehicles is not exceeded, and might be changed to equality to fix the number of vehicles used at exactly v. Equality (4.4) is used to ensure that the origin depot, for any vehicle k, has a departure to exactly one node. Equality (4.5) is used to ensure that the destination depot, for any vehicle k, is arrived at from exactly one node. Flow conservation at each node for each vehicle is ensured using equation (4.6). Constraints (4.7) and (4.8) ensure the time window feasibility, while constraint (4.9) guarantees the feasibility of car capacities.

The heuristic approach for the ridesharing problem in this research may additionally be compared with optimal solutions minimizing the "total passenger deviation" as an objective instead of the time window constraints. Therefore, the objective function (4.1) may be modified to account for the deviation of the first passenger (being the passenger to observe the total deviation of the car). This can be done by subtracting the direct cost of the first passenger from the total cost of each vehicle as shown in the new function (4.10) below.

$$\text{Minimize} \sum_{k \in K} \sum_{(i,j) \in A^k} (c_{ij}^k X_{ij}^k - (c_{o(k),i}^k + c_{i,d(k)}^k)\, X_{o(k),i}^k) \qquad (4.10)$$

4.4.2. Implementation in CPLEX

The advantage of the three index vehicle flow formulation lies in the matrix representation of the decision variables and constraints. For example, the decision variables $X^k_{i,j}$ are implemented in K matrices of size $n \times n$. This enables the implementation of the problem in the Excel add-in of CPLEX.

Special cases of time window relaxation and limited car capacities are proposed for the benchmarking problems in this research. As a result of the time window relaxation the constraints (4.7) and (4.8) are taken out, and should be replaced by "Sub-tour Elimination Constraints" SEC (Solomon 1983, Desrosiers et al. 1995). The SEC equation by Miller-Tucker-Zemlin (MTZ 1960) requires the use of mathematical programming languages (to include multiplications) and cannot be implemented in the available Excel module of CPLEX. Therefore, the simulation example was used for problems with car capacities equal to 3 passengers. Then if any link $X_{i,j}$ between two passengers *i* and *j* is part of the solution ($X_{i,j} = 1$), either *i* or *j* must be connected to the depot ($\mathbf{X^{k}_{o,i}} = 1$ or $\mathbf{X^{k}_{j,d}} = 1$). In other words, since the passengers are 3 then if ($X_{i,j} = 1$) then either *i* must be the first passenger ($X_{d,i} = 1$) or *j* must be the third passenger ($X_{j,d} = 1$). As such an SEC may be implemented using the following equation 4.11.

$$\mathbf{X^{k}_{ij} = X^{k}_{di} + X^{k}_{jd}} \tag{4.11}$$

In the case of two passengers in the car, Equation 4.11 may be written as:

$$\mathbf{X^{k}_{ij} = X^{k}_{di} = X^{k}_{jd}} \tag{4.12}$$

4.5. Simulation Results

To the authors' knowledge, there is no documentation of available benchmark datasets that are relevant to the problem of organization-based ridesharing. As such two types of simulations were carried out: the first using small problems of 24 nodes that were tested against optimal solutions, and the second using large problems of 600 nodes of actual data.

4.5.1. Simulation of Small Problems

For practical purposes, we created a variation of Solomon's (1987) VRPTW benchmark data that includes clustered and random problems with 100 customer instances each. We divided each of the two problem types into 4 subsets (A, B, C, and D) of 24 customers each, and excluded the remaining customers (see Figures 4.8a and 4.8b). To increase the possibilities of having passengers along the route, the depot was considered to be at one corner (with coordinates X = 0, Y = 0). The varying demand at each node was converted to unity. The coordinates of the eight benchmark problems are presented in Table 4.7.

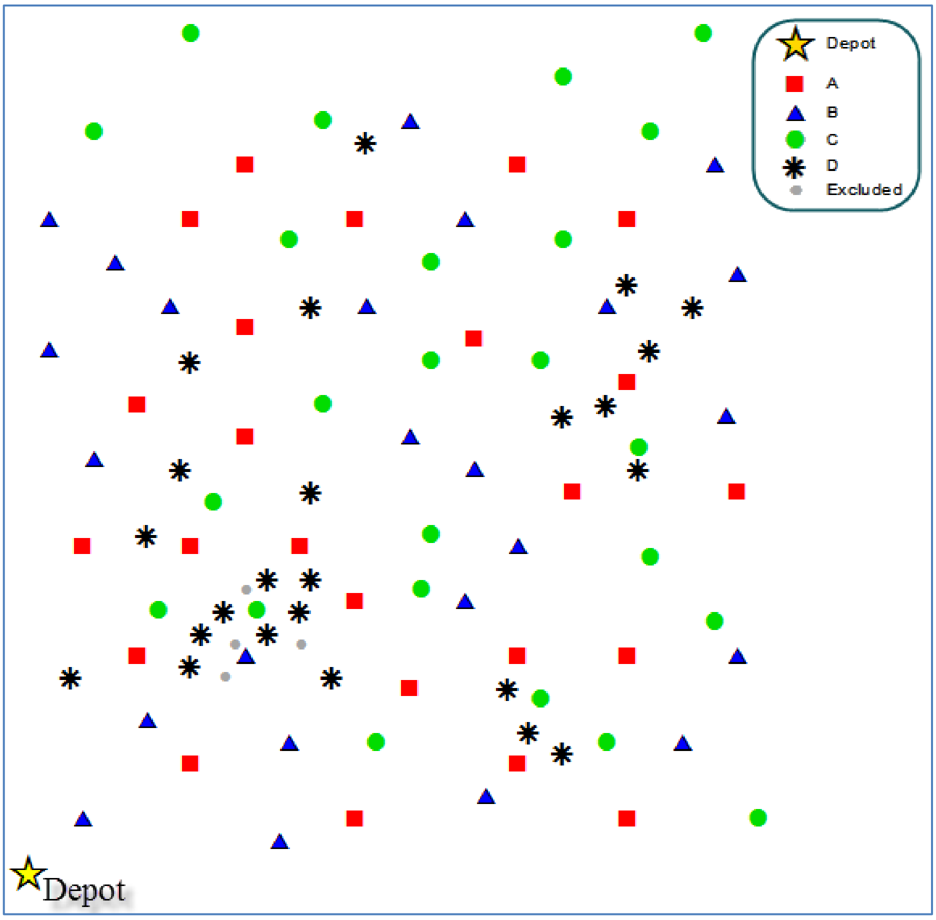

Figure 4.8a: Partitioning Solomon's Random Benchmark Data (R101)

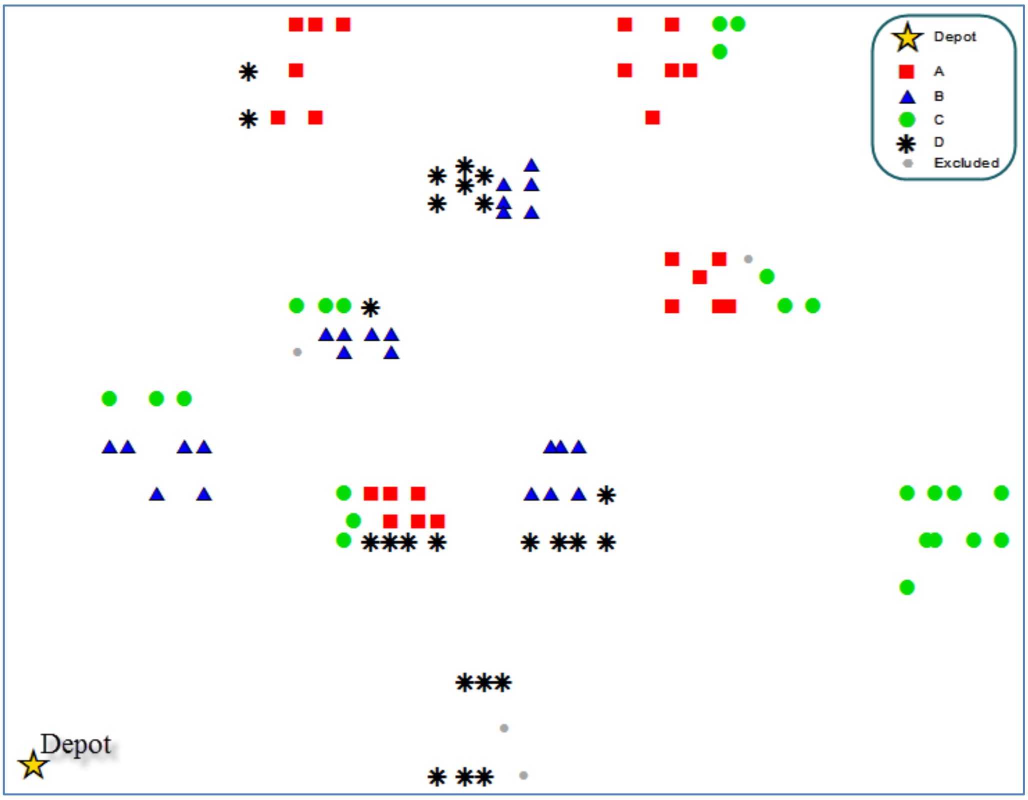

Figure 4.8b: Partitioning Solomon's Clustered Benchmark Data (C101)

Table 4.7: Coordinates of the Eight Benchmark Problems

Node	R101A		R101B		R101C		R101D		C101A		C101B		C101C		C101D	
	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y
Depot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	41	49	65	20	6	68	44	17	25	85	45	68	25	55	40	69
2	35	17	45	30	47	47	46	13	22	75	45	70	23	55	38	68
3	55	45	35	40	49	58	49	11	22	85	42	66	20	55	38	70
4	55	20	41	37	27	43	49	42	20	80	42	68	8	45	35	66
5	15	30	64	42	37	31	53	43	20	85	42	65	5	45	35	69
6	25	30	40	60	57	29	61	52	18	75	30	50	0	45	15	75
7	20	50	31	52	63	23	57	48	35	32	30	52	26	32	15	80
8	10	43	35	69	53	12	56	37	33	32	28	52	25	30	28	55
9	55	60	53	52	32	12	55	54	33	35	25	50	25	35	20	50
10	30	60	65	55	36	26	15	47	30	32	25	52	95	30	35	30
11	20	65	63	65	21	24	14	37	30	35	23	52	95	35	32	30
12	50	35	2	60	17	34	11	31	28	35	10	35	92	30	30	30
13	30	25	20	20	12	24	16	22	66	55	10	40	90	35	28	30
14	15	10	5	5	24	58	4	18	65	55	8	40	88	30	42	15
15	30	5	60	12	27	69	28	18	65	60	5	35	88	35	40	5
16	10	20	40	25	15	77	26	52	63	58	2	40	87	30	40	15
17	5	30	42	7	62	77	26	35	60	55	0	40	85	25	38	5
18	20	40	24	12	49	73	31	67	60	60	50	35	85	35	38	15
19	15	60	23	3	67	5	15	19	62	80	50	40	75	55	35	5
20	45	65	11	14	56	39	22	22	60	80	48	40	72	55	50	30
21	45	20	6	38	37	47	18	24	60	85	47	35	70	58	48	30
22	45	10	2	48	37	56	26	27	58	75	47	40	67	85	45	30
23	55	5	8	56	57	68	25	24	55	80	45	35	65	85	53	30
24	65	35	13	52	47	16	22	27	55	85	45	65	65	82	53	35

The objective is to find low cost solutions while considering equity among passengers (in terms of reducing the maximum deviation). First, we tried to solve each of the eight problems using the proposed heuristic approach considering a car capacity of three passengers and a fixed number of eight cars to be fully packed. The desired "maximum allowable deviation" is set to 10%, and violations of this "maximum deviation" were allowed in cases where a full car packing was not possible. Table 4.8a presents a summary of the results of the eight benchmark problems using both PCT and MDT of the heuristic approach. Three values are presented for each solution: the "total cost" (of all cars), the "total deviation" (of all passengers), and the "maximum deviation" (the highest observed passenger deviation expressed in percent of his/her direct cost). In general, the PCT has resulted in lower values for the "total cost", while the MDT results are lower in terms of "total deviations" and "maximum deviations", especially in problems of random customer locations.

Second, to benchmark the results of the proposed heuristic approach with optimal solutions, we implemented two CPLEX models in Excel using the three index vehicle flow formulation as presented by Desrosiers et al. (1995). The number of cars was fixed at eight vehicles, each with a capacity of three passengers. The first model assumes a time window relaxation with the objective of minimizing the total cost (to obtain lower bound minimum cost solutions). The second model is a modification of the objective function of the first model (see Eq. 4.10), where the new objective is set to minimize the total of "all first passenger deviations" (being the total vehicle cost minus the direct cost of the first passenger). This objective approximates the goal of minimizing total deviation since the first passenger deviation is typically the largest. Table 4.8b summarizes the results of the optimal solutions that were established in

CPLEX (or when the “Mixed Integer Programming” stops for a relative gap tolerance of 0.0001). These lower bound ‘total cost’ and ‘total first deviation’ solutions are then compared with the generated results using the proposed heuristic approach.

The chart in Figure 4.9a presents the ‘total cost’ values of all eight problems (normalized by the lower bound value of the first CPLEX model), while the chart in Figure 4.9b presents the ‘total deviation’ values of all eight problems (normalized by the lower bound value of the second CPLEX model). The results of both PCT and MDT of the heuristic approach lie in general between the lower bound obtained from CPLEX 1 model and the value obtained from the second CPLEX model (except for R101 that is slightly higher for MDT). It can be noted that the PCT would generally result in lower total cost (the closest towards the lower bound ‘minimum cost’ solutions of CPLEX 1, and with lower deviations), while the MDT would generally result in lower ‘deviation’ (the closest towards the lower bound ‘total deviation’ solutions of CPLEX 2, and with lower total cost). The computational time for each problem ranged from 20 minutes to 1 hour in CPLEX, compared to a maximum of 5 seconds in the proposed heuristic approaches (for both steps: tree building and tree traversal). All computations were performed on a 64-bit Intel Core i7 Central Processing Unit (CPU) with 1.6 Gigahertz (GHz) processor speed and 6 Gigabyte (GB) random access memory (RAM) computer.

Table 4.8a: Simulation Results Using Heuristic Approaches

Sample		PCT			MDT		
		Total Cost	Total Dev.	Max. Dev.	Total Cost	Total Dev.	Max. Dev.
Random Customer Locations	R101A	1,125.7	70.9	37%	1,121.3	26.9	12%
	R101B	1,060.9	69.2	61%	1,163.8	64.7	22%
	R101C	1,243.1	76.3	14%	1,287.0	40.2	9%
	R101D	928.6	55.7	25%	1,007.5	28.5	12%
Clustered Customer Locations	C101A	1,323.5	53.3	10%	1,394.1	30.9	7%
	C101B	991.6	28.5	11%	992.2	34.7	11%
	C101C	1,308.5	39.1	16%	1,316.2	34.3	16%
	C101D	987.3	18.8	4%	998.2	18.9	4%

Table 4.8b: Simulation Results Using CPLEX

Sample		CPLEX 1 (Min. Cost)			CPLEX 2 (Min. First Dev.)		
		Total Cost	Total Dev.	Max. Dev.	Total Cost	Total Dev.	Max. Dev.
Random Customer Locations	R101A	995.9	52.6	43%	1,126.5	14.3	4.7%
	R101B	1,042.1	64.4	28%	1,194.5	16.1	9%
	R101C	1,171.0	102.4	29%	1,281.4	28.0	11%
	R101D	876.7	170.6	170%	1,040.4	14.4	10%
Clustered Customer Locations	C101A	1,311.7	30.5	5%	1,489.5	8.0	3%
	C101B	984.9	18.6	8%	1,072.1	16.8	8%
	C101C	1,306.0	37.2	16%	1,440.0	27.8	16%
	C101D	987.3	18.8	4%	996.8	15.2	4%

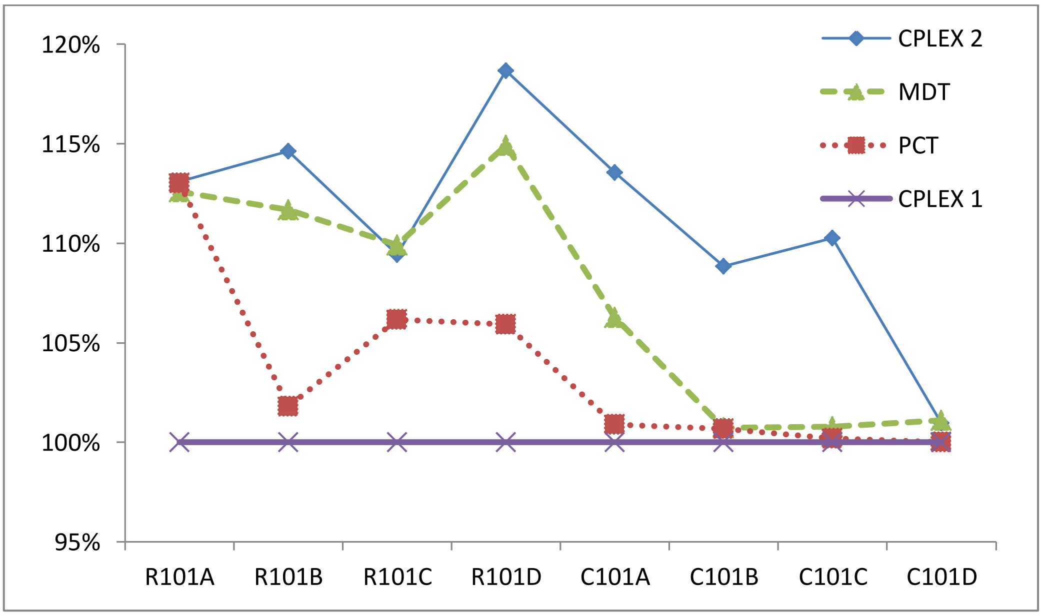

Figure 4.9a: Comparison of the 'Total Cost' Results (normalized by min. total cost)

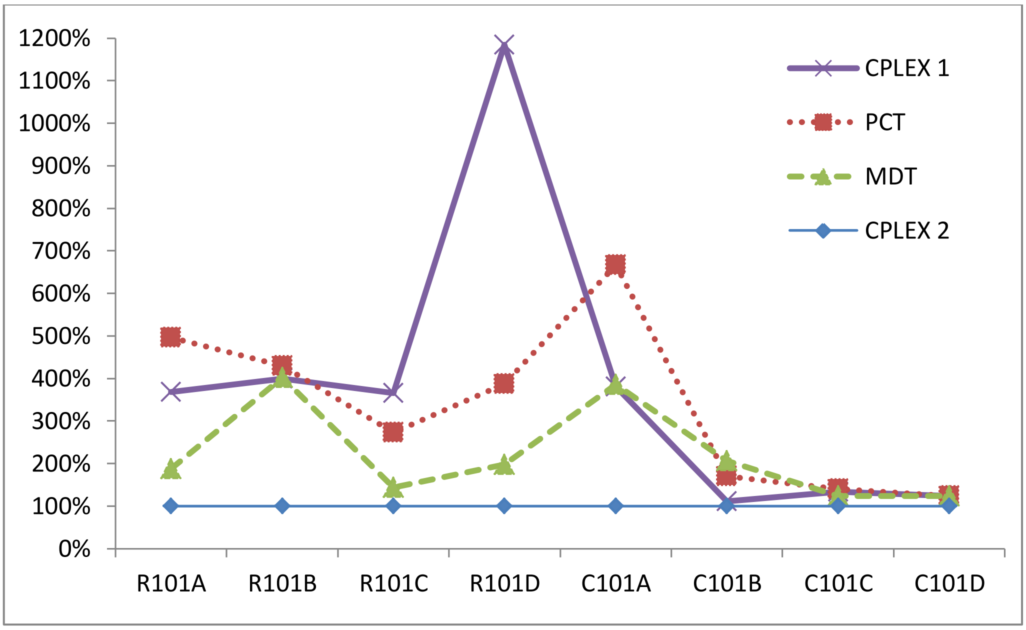

Figure 4.9b: Comparison of the 'Total Deviation' Results (normalized by CPLEX2)

4.5.2. Simulation of Large Problems

The simulation of large problems was undertaken using actual data from the American University of Beirut (AUB). This database is discussed in details as a case study in chapter 5, and is documented for benchmarking in future research. A subset of 600 students was considered for the purpose of this problem. A combined clustered and random spatial distribution of the students was observed in this problem (see Figure 4.10).

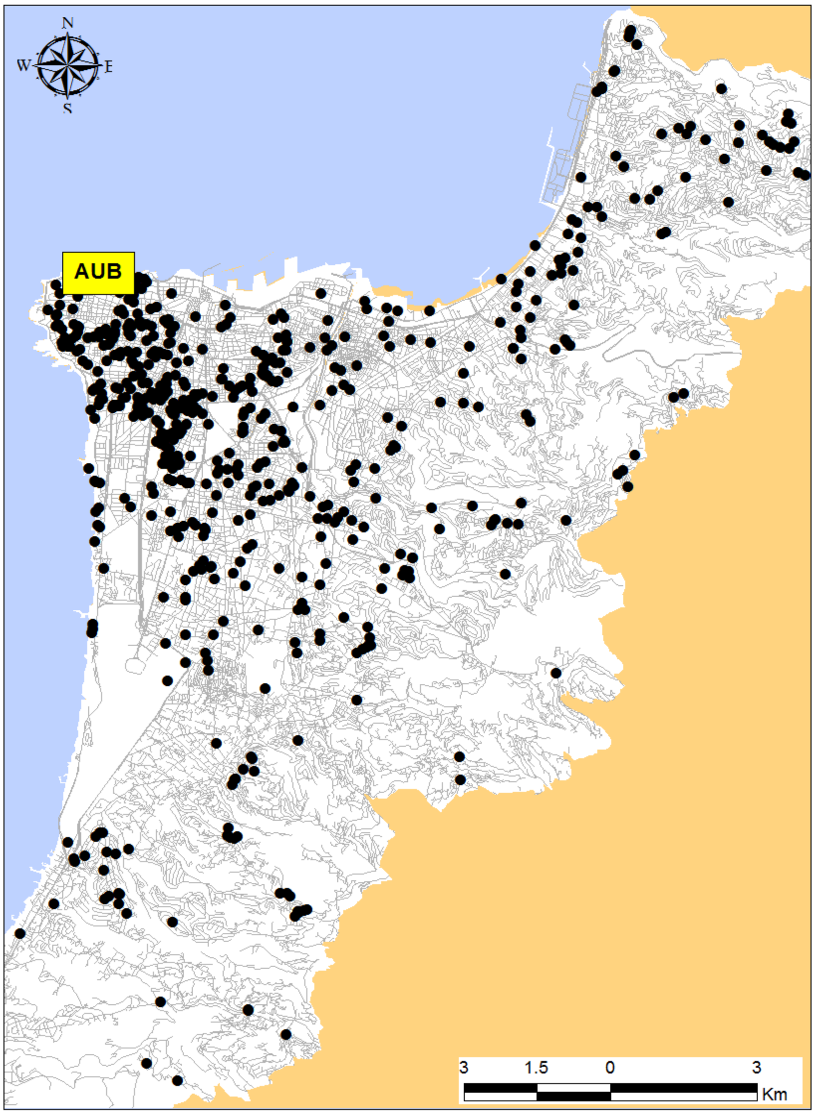

Figure 4.10: Spatial Distribution of the 600-student Case Study

The simulation was conducted using both the PCT and the MDT hierarchical trees, and for different car capacities (3, 4, 5, and 6), and values for the ‘maximum allowable deviation’ (extra travel time burden per passenger) ranging from 10% to 40% (with a 5% increment). The observed computational time for the construction of each of the two hierarchical trees did not exceed 50 seconds, and the run time of the ‘tree traversal algorithm’ for each scenario (different car capacities and maximum burden) did not exceed 30 seconds.

In this problem the number of cars is not constrained, and the results will be compared with respect to the resulting total cost, the number of cars that are fully occupied, and the total number of cars needed to serve all 600 students given the different burden ranges. A summary of the results is presented in Table 4.9 below.

Table 4.9: Simulation Results of Large Problems

Max. Deviation Allowed	PCT			MDT			% Diff. in Total Cost
	Number of Cars	Cars Fully Occupied	Total Cost (Seconds)	Number of Cars	Cars Fully Occupied	Total Cost (Seconds)	
Car Capacity = 3							
10%	242	156	2,472,192	242	160	2,495,034	0.9%
15%	228	170	2,361,663	224	178	2,353,806	-0.3%
20%	216	179	2,292,543	212	186	2,280,510	-0.5%
25%	209	188	2,240,451	208	191	2,272,671	1.4%
30%	207	192	2,229,507	206	193	2,258,343	1.3%
35%	205	195	2,225,574	205	195	2,253,069	1.2%
40%	206	193	2,228,634	203	196	2,243,259	0.7%
Car Capacity = 4							
10%	219	82	2,235,879	217	90	2,219,625	-0.7%
15%	198	101	2,043,324	190	107	1,996,083	-2.3%
20%	179	116	1,916,289	180	114	1,926,297	0.5%
25%	170	122	1,846,908	170	126	1,862,973	0.9%
30%	165	131	1,820,061	164	136	1,831,923	0.7%
35%	161	137	1,799,289	160	139	1,819,521	1.1%
40%	160	138	1,780,560	158	141	1,808,064	1.5%
Car Capacity = 5							
10%	213	37	2,138,931	209	54	2,097,180	-2.0%
15%	186	52	1,903,698	180	62	1,841,841	-3.2%
20%	163	73	1,714,275	163	74	1,736,433	1.3%
25%	150	85	1,630,773	148	88	1,647,126	1.0%
30%	144	90	1,600,011	142	94	1,609,290	0.6%
35%	139	94	1,567,764	136	104	1,568,835	0.1%
40%	137	101	1,537,938	132	106	1,535,418	-0.2%
Car Capacity = 6							
10%	211	21	2,113,740	208	22	2,079,853	-1.6%
15%	179	32	1,804,491	173	38	1,754,892	-2.7%
20%	156	44	1,649,583	154	45	1,654,002	0.3%
25%	141	50	1,537,740	138	60	1,532,673	-0.3%
30%	132	62	1,468,107	131	67	1,471,833	0.3%
35%	126	68	1,427,076	124	69	1,456,983	2.1%
40%	121	72	1,400,850	118	79	1,397,241	-0.3%

This case study presents a general real life example where the customers are spatially distributed in both random and clustered structures. It is shown that in general the MDT results in a smaller number of required cars, and a higher number of fully occupied cars, and in many cases a lower total cost than the PCT (the relative difference of the total cost is within ±3%).

A considerable advantage of the proposed heuristic approach lies in the possibility of fast generation of different solutions while varying the values of the time window constraints (in terms of maximum deviation) and the vehicle capacity. A sensitivity analysis can then be easily implemented by observing the variation in results for the given 600-student case study (see Figure 4.11). In this case, we can conclude that the rate of change (decrease) in the total number of cars required becomes less when the maximum deviation exceeds 25% (for all car capacities), and when the car capacity exceeds 5 passengers (for any level of maximum deviation).

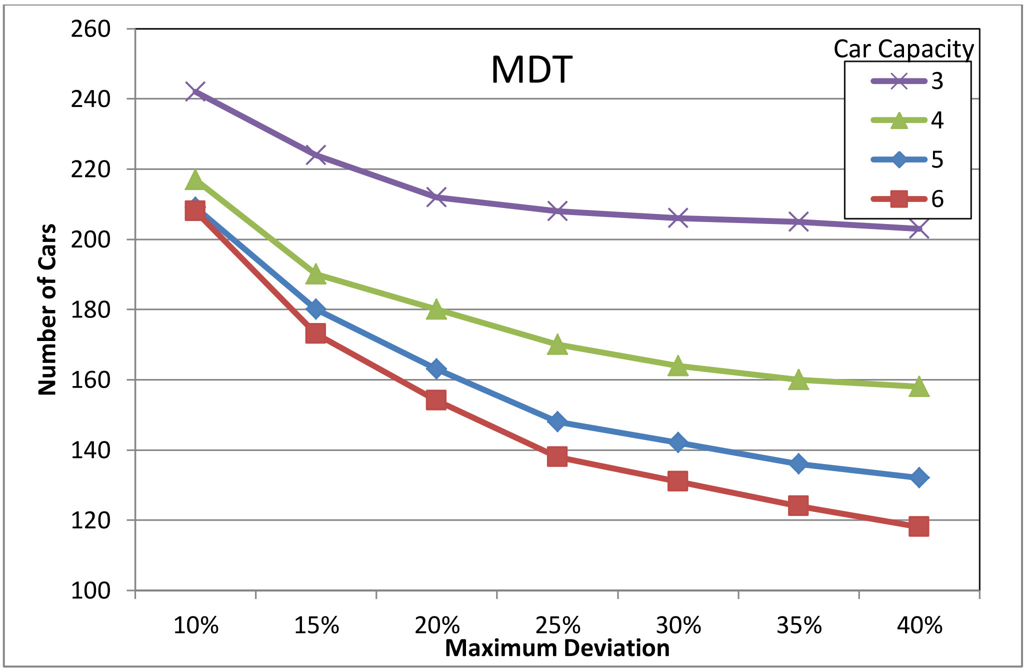

Figure 4.11: Results of the 600-student Simulation Problem

4.6. Summary and Conclusion

This research investigates different solution approaches for the design of organization-based ridesharing services. This type of problem is a special case of the general vehicle routing problem, and can be generalized as CVRPTW problem. Additional problem specifics include unit demand, asymmetric network, narrow time windows at departure, and common arrival time at destination. In this context, little research was found to offer a detailed solution methodology for this specific problem. In general, the solution approaches include matching passengers within a proximity cluster and matching passengers within a minimum route deviation. This research presents a three-step solution approach incorporating two solution strategies in the form of hierarchical spanning trees (PCT and MDT). The structure of the hierarchical trees enables the fast search of feasible solutions through an enumerated tree traversal algorithm. Simulation results for small problems were compared with optimal solutions implemented in CPLEX (with 'least cost' and 'least deviation' objectives), and have shown that the PCT results in lower 'total cost' (closest to the cost lower bound), and the MDT results in lower 'total deviation' and 'maximum deviation' (closest to the deviation lower bound). With the lack of benchmark data for the problem at hand, actual data from the American University of Beirut were used and are documented for future research.

In the case of large problems with a combined random and clustered customers' distribution, the PCT and MDT were tested against each other for different values of the 'maximum allowable deviation' and 'car capacities'. It was shown that in general the MDT results in a smaller number of required cars, a higher number of fully occupied cars, and a total cost within ±3% of the PCT solutions. Table 4.10 below presents a summary that characterizes the general performance of the PCT and MDT along different dimensions.

Table 4.10: General Performance of the PCT and MDT along Different Dimensions

Indicator	PCT	MDT
Strategy	Proximity passengers	Along route passengers
Max. Deviation	Higher	Lower
Travel Cost (travel time/distance)	Lower	Higher
Number of Cars	Higher	Lower
Fare	Same within car	Varying along route
Operator cost	Trade-off between the travel cost and the cost for vehicle fleet	

This research presented a fast heuristic approach for solving the CVRPTW with unit demand that may be used in real-time (less than 50 seconds for problems with 600 instances). Its main advantage lies in the capability to generate solutions for different vehicle capacities and time window constraints with substantially reduced computational efforts. This is beneficial when investigating the sensitivity to "cost", "vehicle capacity", and "maximum acceptable delay" for each case study.

Additional work may investigate the possibility of integrating the hierarchical structure of the PCT and MDT into a single solution. It may also be expanded to solve the general case of CVRPTW with varying demand. Other extensions may also include adding user preferences like matching by gender and/or vehicle occupancy preference. Although our problem anticipates pick-ups and deliveries to occur separately, additional considerations for vehicle dispatch should be made for the case of sequential pick-ups and deliveries (e.g. for university students), where a car may be assigned to start a new pick-up after delivering the last passenger without returning to the depot. Such considerations are addressed in the context of the case study in Chapter 5.

The developed many-to-one ride matching algorithm may be expanded to solve many-to-few problems for consideration of more than a single destination (e.g. multiple organizations within close proximity). The PCT and MDT trees can be established based on a central node between the organizations. The packing of cars in the tree traversal algorithm will prioritize matching passengers of the same organization in the same car. If the car capacity is not reached and there are no more passengers that can be packed while satisfying the time window of the passengers in the car, the algorithm then tries to match additional passengers from another organization. The car will first be routed to the organization of the first passenger(s); the additional passenger(s) will be mainly observing the deviation for the route between the first and the second destinations (organizations). A problem similar to Example 2 in section 4.1.2 consists of transporting two sets of three passengers A, B, C, and A', B', C' to the destination depots D and D' respectively, (see Figure 4.12). If the maximum deviation is Y, only one solution of 2 cars is possible as follows, Car 1 {C, B, A', D, D'} and Car 2 {C', B', A, D', D}.

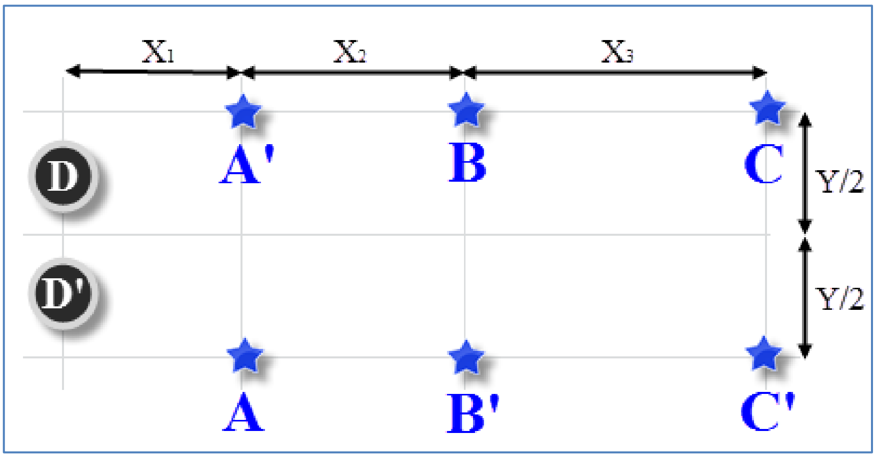

Figure 4.12: Distribution of Nodes in a Many-to-Few Example

CHAPTER 5

CASE STUDY

The proposed evaluation framework in this research is generic and could be used for any organization or institution for which the pertinent data is available. This chapter presents a case study which considers the feasibility of new ridesharing services at the American University of Beirut (AUB), and is organized into six main sections as follows. Section 5.1 provides an overview of AUB. Section 5.2 discusses the developed AUB database for this case study. Section 5.3 presents a deterministic demand estimation model using different scenarios (different fares and maximum deviations) for the AUB case study. Section 5.4 describes the proposed service design and the results of the ride matching simulations using the developed heuristic approach. Section 5.5 presents the feasibility of the different demand, service design, and policy scenarios. And finally, conclusions are drawn in Section 5.6.

5.1. Overview

Despite the lack of any on-campus parking facility for AUB students, nearly one third of the students commute to the university by driving their own car (Khattab et al. 2012). While the number of enrolled students at AUB has increased by 18% over the last 10 years (6,947 in 2003-04 to 8,171 in 2012-13), the parking deficiency in the campus neighborhood is increasing dramatically. Aoun et al. (2013) estimated the AUB demand to be 3,000 external parking spaces in addition to the 1,105 parking spaces on campus (dedicated for full-time faculty and staff). Figure 5.1 illustrates, for a regular working day, the severe packing of parked cars in a typical parking lot in the AUB neighborhood.

Figure 5.1: Packing of Cars in a Typical Parking Lot in the AUB Neighborhood

As part of the AUB Neighborhood Initiative studies, 'student commuting' surveys were conducted during the years 2007 and 2010. All students were asked where they were living during the current term, and which of the following options they use to commute to AUB: walking; public transportation (bus and/or jitney); private taxi; dropped-off; carpool (with other students); drive alone; or other (chauffeur, bicycle, motorcycle, etc.).

Seventy percent of the enrolled students responded to the 2007 survey (4,949 out of 7,047), compared to nearly twenty percent response rate in the 2010 survey (1,468 out of 7,577 students). Results from both surveys indicated that 12% of the students live on campus, and the remaining off-campus residents have exhibited noticeable changes in their commuting patterns as presented in Table 5.1. Despite some differences in the definition/classification of the commuting mode in the two surveys, significant switching may be observed in the students' commute from driving alone (private car) to carpool. This reflects an increased interest in ridesharing among students, and it appears to be related to the increased parking deficiency around the AUB campus, in addition to a 50% increase in gas prices (from 15$/20L in 2007 to 23$/20L in 2010).

Table 5.1: Students' Modal Split Based on the 2007 and 2010 Commute Surveys

2007 Survey	
Mode of commuting	**%**
On campus	12%
Walking	19%
My Car	30%
In other Student's Car	3.5%
Dropped Off	10.5%
Public Transportation	22%
Private Taxi	2%
Other	1%
Grand Total	100%

2010 Survey	
Mode of commuting	**%**
On campus	12%
Walking	18%
Drive Alone	24%
Carpool	12%
Dropped Off	9%
Public Transportation	24%
Private Taxi	1%
Other	0%
Grand Total	100%

5.2. AUB Database

The developed data models for this case study comprise the student commute survey, the spatial databases, and the cost parameters; these are presented in the following three subsections. The database and results of this case study are documented for benchmarking in future research.

5.2.1. Student Commute Survey

The 2007 survey had the higher response rate of 70% (compared to 20% in 2010), and the profile of respondents was found to be matching the student body at large. More importantly, only the 2007 survey data was linked to the actual schedule of each corresponding student due to the availability of student identifier data in that survey but not in the 2010 survey. This rendered the 2007 data practically more usable for the spatial and temporal considerations of this case study.

It is worth noting that the sample considered in this case study comprises the available data of the responding students (70% of student population) and was not expanded to account for the remaining 30%. A subset of this sample was eventually used, representing the potential users data for the proposed ridesharing services. The following criteria were used in defining this subset: (i) students who live within Greater Beirut Area (GBA) and (ii) students who commute to AUB by any of the following modes: private car, private taxi, drop-off, carpool, and public transport (see Table 5.2).

Table 5.2: Data Subset of Potential Users

MODE	Students	%
My Car	**1,177**	**42%**
Public Transportation	**944**	**34%**
Dropped off	**443**	**16%**
With Other Student	**130**	**5%**
Private Taxi	**94**	**3%**
TOTAL	**2,788**	**100%**

In addition to their commuting mode, each of the 2,788 students in Table 5.2 has a known address location during the current term (zone level), as well as a specific term schedule (starting time, ending time, and the days for all registered courses).

5.2.2. Spatial Database

A geographically referenced digital model of the Greater Beirut Area (GBA) was developed for this case study and included the zone boundaries, the road network, and the students' home locations. The following is the detailed description of every data layer:

➢ Zone Boundaries

The GBA is divided into 63 Traffic Analysis Zones (TAZ) that have been conventionally used in almost all transportation studies (Team 1999) over the last two decades (Figure 5.2). With the lack of a structured format for addresses in Beirut, the students were asked to identify where they live by referring to the GBA map and then selecting their zone of residence from a drop-down menu. These zones were used in determining the address of every student in both the 2007 and 2010 commute surveys.

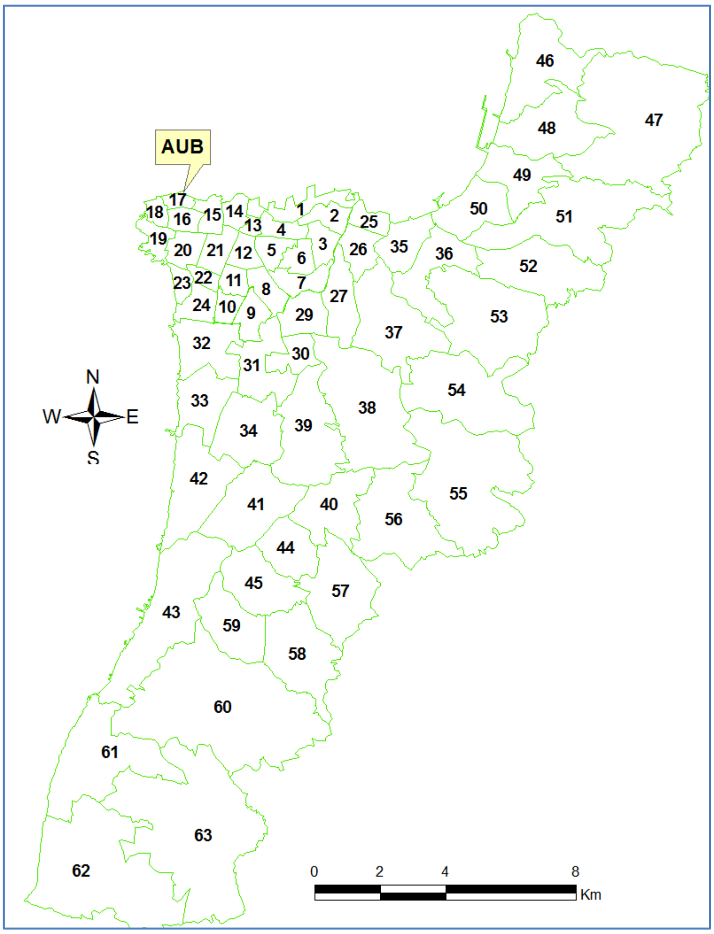

Figure 5.2: GBA Zone Boundaries

➢ Students' Home Locations

The student home locations are represented by a point layer that contains the exact location of each student and is used for scheduling and routing considerations (pick-up/drop-off). It is typically a geocoding process of converting the structured address provided by each student into a point location on the map. However, with the absence of a structured address format for the GBA, this geocoding process was not possible for this case study. As a consequence of the fact that the address of each student was only available by its relevant zone number, the data representing the home location of each student was synthesized. Given a polygon layer of the footprints of existing buildings in the GBA, each student was randomly associated to one of the buildings within his/her zone, and was represented by a point location depicting the centroid of the building's footprint. Figure 5.3 shows the home locations of the data subset of potential users listed in Table 5.2.

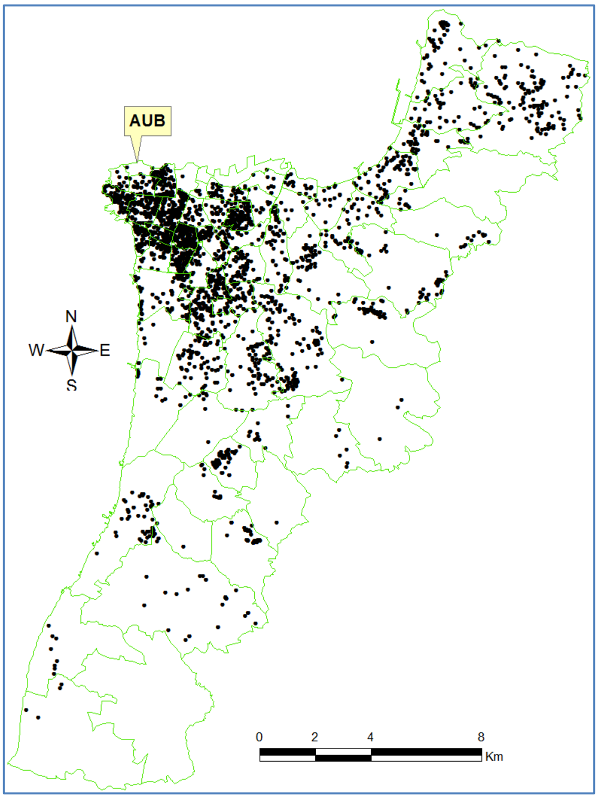

Figure 5.3: Students' Home Locations

➢ <u>Road Network</u>

As part of the integrated GIS database of the AUB neighborhood studies, a detailed road network model for the GBA was made available for this case study. This data layer consists of 3,520 kilometers of roads in GBA, represented by nearly 40,000 road links that are fully attributed with road class, congested average speed, and traffic directions. The GBA road network layer is presented in Figure 5.4 below. Together with the students' home locations layer, this road layer is used to determine the shortest path between any two students, and between each student and AUB (including the direct route and the associated travel distance and travel time during congestion).

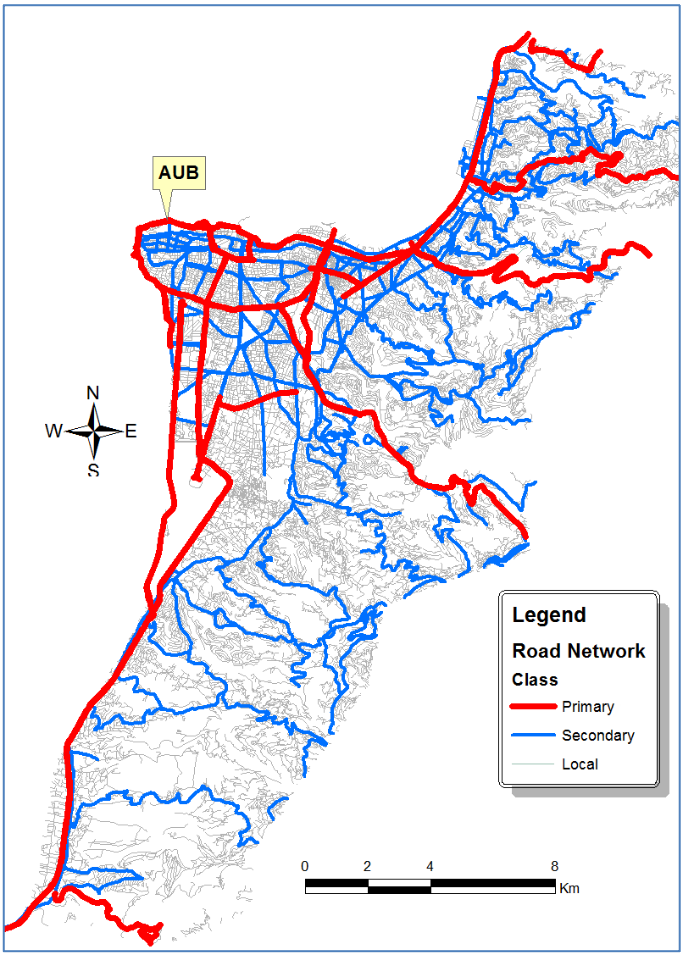

Figure 5.4: GBA Road Network Model

5.2.3. Cost Parameters

Two types of cost parameters are needed for the financial assessment exercise of this case study. The first type is the user cost that includes estimation of the cost of the current commute mode of each student and the fare structure for the proposed shared-taxi. The second type is the taxi sharing operator's costs.

➢ <u>Cost of the current commute modes</u>

The potential users that are under consideration in this case study are the students commuting by one of the following five modes: "My car", "Public Transportation", "Dropped off", "With Other Student", and "Private Taxi". Figure 5.5 below presents the current fare structures of private taxi (source: Allo Taxi leading taxi company in Beirut), and of public transport (average fares of buses and jitneys).

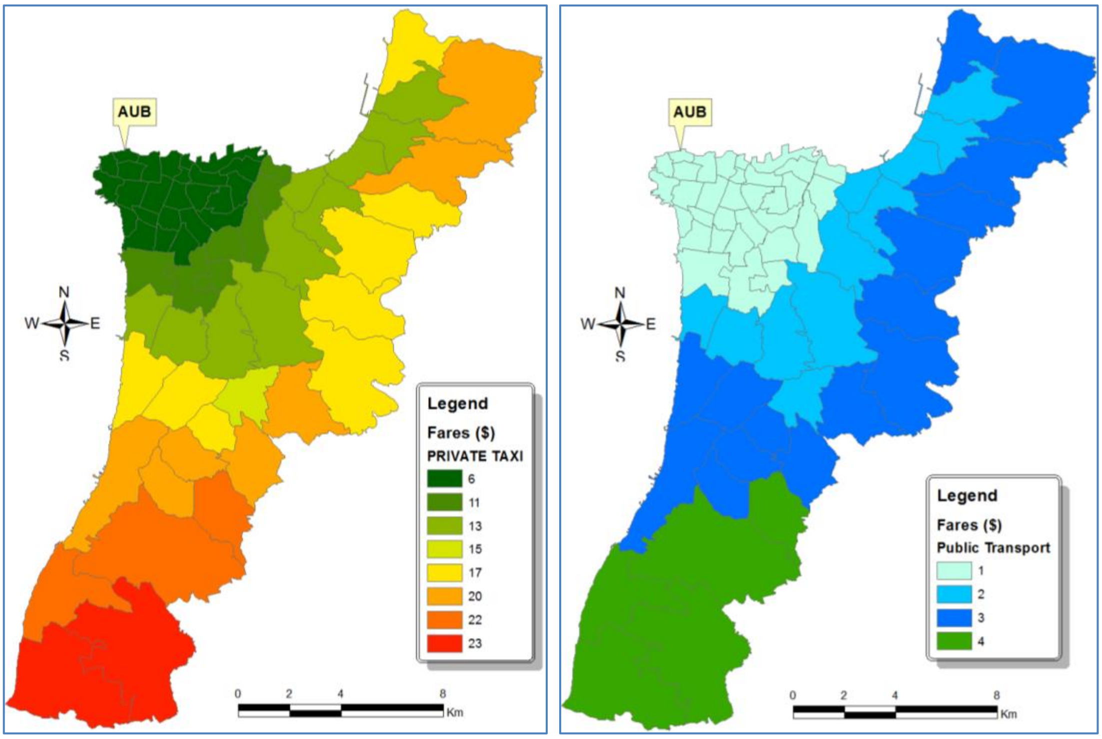

Figure 5.5: Fare Structure of Private Taxi and Public Transport to AUB

A brief market research exercise was conducted to establish the current fare structures for private taxi and public transport (local private taxi Allo Taxi 2014 and LCC 2014 bus operator websites). The value of time was estimated at 13$/hour for students commuting by private car or private taxi, , 10$/hour for students commuting with family member or other student's car, and 3$/hour for students commuting in public transport (based on the values presented in the research paper by Al-Ayyash et al. 2015 for AUB students). The direct "In Vehicle Travel Time" (IVTT) between any two locations on the network was assumed to be the same for all passenger cars (students commuting in their own car, in other student's car, with family member, or in private taxi), and a value higher by 80% was assumed for students commuting in public transport. The "Out of Vehicle Travel Time" (OVTT) was considered as a 7-minute average walking distance from parking locations around campus to the university gate (for students driving their own car). The OVTT of private taxi is considered to be zero since the service is door-to-door. For students commuting in other students' cars or with family members, the OVTT was estimated as a 15-minute average waiting time, while the OVTT for students commuting by public transport was estimated as 20 minutes average waiting and walking time (IBI 2000). It is worth noting that the travel cost of a passenger car is calculated using a time factor ($/hour) and was approximated as 6$/hour (being 5.5$/hour gas + 0.5$/hour maintenance) assuming current gas price of 1.1$/liter and an average consumption of 5 km/liter with an average congested speed of 25 km/hour. A summary of the one-way travel cost and travel time parameters for the five commuting modes is presented in Table 5.3.

Table 5.3: Cost and Travel Time of the Current Commuting Modes

Mode	VOT	Travel Time		Travel Cost
		In Vehicle	Out of Vehicle	
My Car	13$/hr	Direct	7-minute Walk to/from parking	6$/hour + Parking $3
Public Transport	3$/hr	1.8 × Direct	20-minute Waiting and Walking Time	See Figure
Family Member Drop-Off	10$/hr	Direct	15-minute Waiting Time	6$/hour*
In Other Student's Car	10$/hr	Direct	15-minute Waiting Time	50% of My Car
Private Taxi	13$/hr	Direct	-	See Figure

* Average of 'half the cost of a shared trip' and the 'cost of a dedicated 2-way trip' for each drop-off and pick-up

Given the average speed on every road link in the GIS road network model, the direct travel time is calculated for every student home location using the ‘shortest path’ tool of the GIS network analyst module. Figure 5.6 presents the spatial distribution of the direct travel time from any location in GBA to AUB. The direct travel time values, ranging from 3 minutes to 57 minutes, are based on the peak hour average network speeds (considered in this case study as 30, 25, and 15 km/hour for primary, secondary, and local roads, respectively). For practical purposes, the delay at intersections and the time-of-day variability of the average speed on the road network were not reflected in this case study.

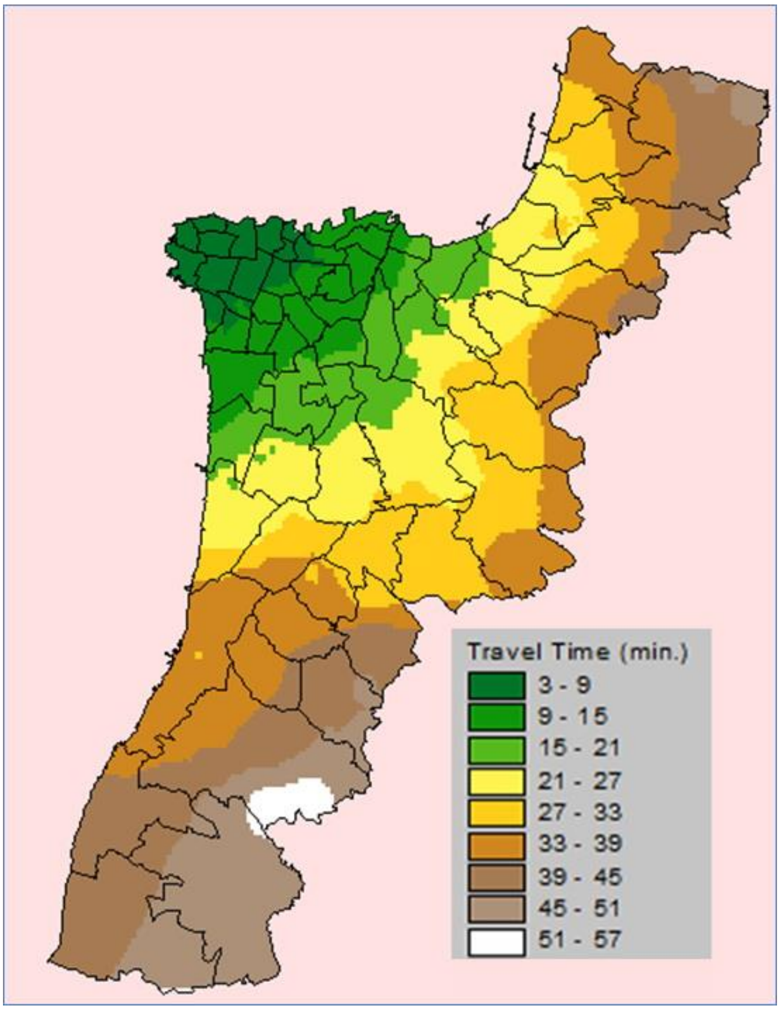

Figure 5.6: Direct Travel Time to AUB

➢ Shared-taxi fare structure

The fare structure of the proposed shared-taxi system is suggested to follow the same zonal breakdown as the private taxi. Different fare scenarios may be investigated by considering it as a fraction of the private taxi fare. For example, if the suggested fare per passenger is 30% of the private taxi fare, a shared-taxi collecting four passengers from the same zone would have revenue of 120% of the private taxi fare. On the other hand, it would have a reduced revenue (90% of taxi fare) if it collects only three passengers from the same zone. Table 5.4 presents the maximum revenue per taxi for different fare scenarios and number of passengers (assuming the same zone for all passengers).

Table 5.4: Maximum Revenue for Different Fare Scenarios

Fare \ Passengers	3	4
20%	60%*	80%*
30%	90%*	120%
40%	120%	160%
50%	150%	200%

* Reduced revenue

➢ Operator's cost structure

For the purpose of this case study, the work is focused on shared-taxi schemes since they have the highest matching opportunities and a greater impact on the parking demand and neighborhood congestion. The operator's cost varies depending on the service design. Two main options may possibly be considered as follows.. These options entail providing shared rides to AUB students by either commissioning those shared trips to already existing taxi operators in Beirut (option 1), or to a new and exclusive operator for AUB (option 2). The operator's cost components for each option are presented in Table 5.5.

Table 5.5: Operator's Cost Components for the Different Options

Option	Online System	Cost Per Mile Driven	Cost of a Dedicated Fleet
1 – ST (existing)	Yes	Yes	No
2 – ST (exclusive)	Yes	Yes	Yes

The following estimates for the operator's cost components are considered for the AUB case study:

- The cost of the online ride matching system is estimated to be US$40,000, and it includes web registration costs, the salaries for an IT developer and a system operator.
- The cost per mile driven is estimated at 6$/hour (see private car in Table 5.3)
- A shared-taxi driver earns 3$/hour
- The annual lease of a dedicated taxi fleet can be considered as 20% of the cost of the cars. The price of a new Japanese sedan car ranges between $20,000 and $30,000. Considering the price of a new 2014 Toyota Corolla (Toyota dealer price in Beirut is $21,500 including tax and registration fees), the average yearly lease can be approximated as $4,500 including maintenance and insurance.
- Other administrative expenditures are presented in Table 5.6 below.

Table 5.6: Annual Administrative Expenditures for Exclusive Shared-Taxi

Fixed Cost: Administrative Expenditures		
Salaries, wages and benefits (excluding drivers)	$30,000	25.0%
Integrated on-line ride matching system	$40,000	33.3%
Accounting and consulting fees	$10,000	8.3%
Advertising and promotion	$5,000	4.2%
Rent: Office / Depot	$30,000	25.0%
Expenses: Telephone and other	$5,000	4.2%
Total Expenditures:	**$120,000**	**100.0%**

5.3. Demand Estimation

The main objective of this case study is to demonstrate the interaction of the different modules of the evaluation framework (see Figure 3.2) using actual data and simulation of different demand, service design, and policy scenarios. To simulate the demand for the taxi sharing service, a simple deterministic demand model is adopted. The demand estimation is undertaken using a conditional cost function, where a student i is determined to switch to the new ST services if it is cheaper, while considering the ST fare (F_i), the cost of his/her current commuting mode ($C_{CM,i}$), and the value of travel time savings if switching. Switching to ST is considered to take place if the following equation is satisfied:

$F_{\boldsymbol{i}} - C_{CM,\boldsymbol{i}} + VOT_{\boldsymbol{i}} \times (TT_{ST,\boldsymbol{i}} - TT_{CM,\boldsymbol{i}}) < 0$	Eq. 5.1

Where:

$F_{\boldsymbol{i}}$ = ST fare for student ***i*** computed as a fraction of the private taxi fare (Figure 5.5)

$C_{CM,\boldsymbol{i}}$ = out-of-pocket cost of the current commute mode for student ***i*** (Table 5.3)

$VOT_{\boldsymbol{i}}$ = Value of Time for student ***i*** (Table 5.3)

$TT_{CM,\boldsymbol{i}}$ = Travel Time using the current commute mode for student i (Table 5.3)

$TT_{ST,\boldsymbol{i}}$ = Travel Time using the ST for student ***i***, which is the direct travel time (shortest path) plus the average deviation (conservatively estimated as $^2/_3$ of the maximum allowable deviation; the actual deviation for student ***i*** is not used in this equation since the demand model is applied before the routing algorithm). Ideally, the chart in Figure 3.3 indicates a feedback into updating the demand after determining the actual average deviation in the service design module. The results of the average deviations in the service design module indicated slightly lower values than the estimated $^2/_3$ of the maximum allowable deviation, but the demand results were not updated. As such the case study did not implement this iterative process between the service design and the demand modules.

It is important to note however, that a threshold is applied in equation 5.1 for the case of students currently commuting by 'private taxi'. Such a threshold is meant to reflect the extent of saving beyond which the taxi commuter is likely to switch from private taxi to shared taxi (sharing the taxi ride for a substantial saving in cost to compensate extra travel time and less privacy and comfort). This threshold was estimated as 25% of the weighted average of private taxi fares for the different zones ($11.24), or approximately $3. As such, any private taxi (PT) user will not switch to the shared taxi unless the user incurs a saving of $3 or more and the Equation 5.2 below is used instead of Equation 5.1.

$F_{\boldsymbol{i}} - C_{PT,\boldsymbol{i}} + VOT_{\boldsymbol{i}} \times (TT_{ST,\boldsymbol{i}} - TT_{PT,\boldsymbol{i}}) \leq -3$	Eq. 5.2

5.3.1. Scenarios

The deterministic demand model adopted in this case study is based on financial saving and does not include other factors such as availability, reliability, and comfort. As a result, the demand will be determined using two criteria, namely, the savings in the 'out-of-the-pocket expenses' and the savings in 'travel time' (see Figure 3.3). Therefore, scenarios of different ST fare levels and different maximum allowable deviations are investigated. Figure 5.7 presents the demand variation for the different commuting modes (private car, private taxi, drop-off, carpool, and public transport) based on a fixed 'maximum allowable deviation' of 30% and for different fare values ranging from 20% to 90% of the fare of a 'private taxi'. On the other hand,

Figure 5.8 presents the variation of the total demand for the different values of the 'maximum allowable deviation' and 'fares'.

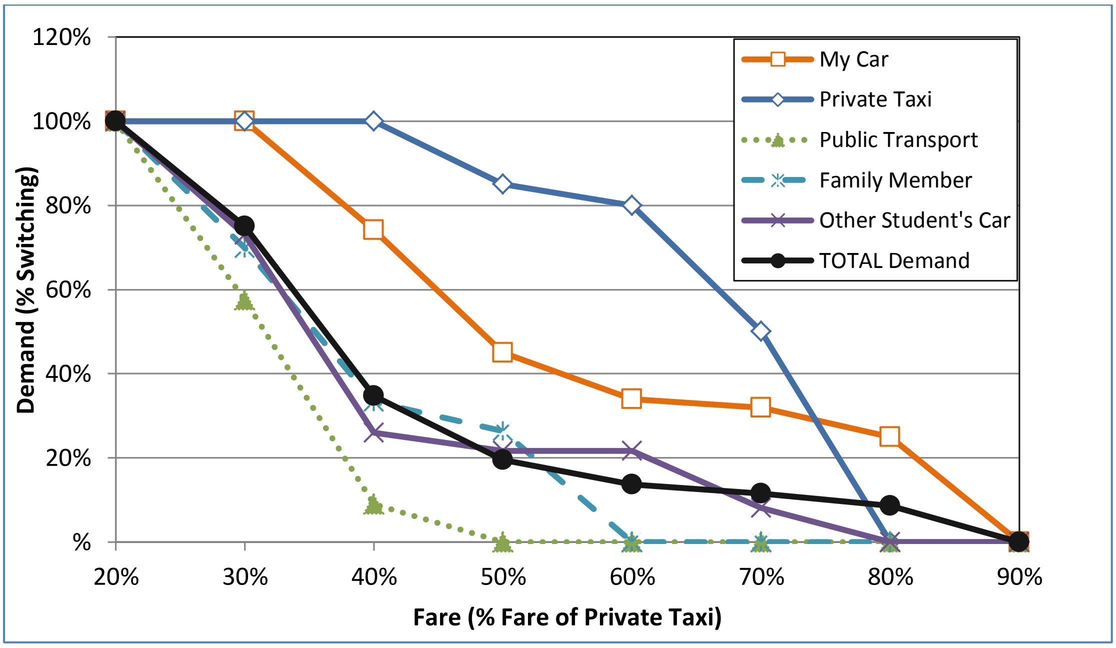

Figure 5.7: Demand Variation by Mode based on Different Fare Values

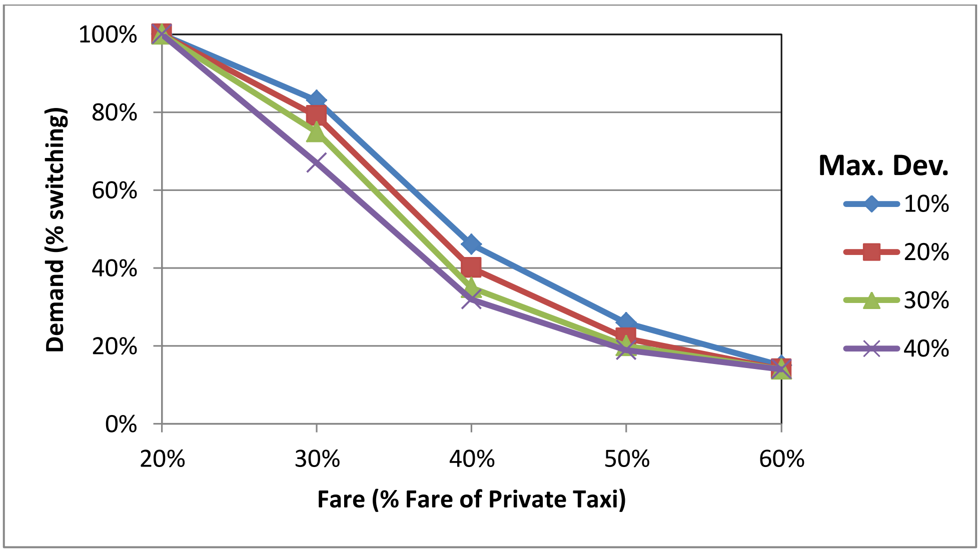

Figure 5.8: Demand Variation based on Different Max. Deviations and Fare Values

As it can be concluded from Figures 5.7 and 5.8, the ST demand is more sensitive to changes in the 'fare' level than to the variation in the 'allowable maximum deviation'. It could also be said from Figure 5.7 that the public transport users are not likely to switch to ST when the fare exceeds 30%.

For the demand analysis, nine scenarios are proposed for further investigation for three 'fare' values (30%, 40%, and 50%) and three 'maximum deviation' values (20%, 30%, and 40%). Table 5.7 below presents the designated scenarios.

Table 5.7: Scenarios for Analysis

Scenarios	Fare = 30%	Fare = 40%	Fare = 50%
Max. Dev. = 20%	S1	S2	S3
Max. Dev. = 30%	S4	S5	S6
Max. Dev. = 40%	S7	S8	S9

5.4. Service Design

After determining the demand for the shared taxi based on all nine scenarios, the best service design scheme is investigated. This process involves three main steps. First, the problem needs to be partitioned into different time groups of students who are expected to be served separately. Second, the students in each time group are matched in taxis to be shared. Finally, a simple taxi dispatch is implemented to match up inbound and outbound trips by cars.

5.4.1. Temporal Pre-Matching

Unlike full time employees, the AUB students have different schedules in terms of starting and ending of classes for each day of the week. Therefore, the total demand needs to be partitioned into temporal groups (different hours of school days) that are considered separately. For example, considering a typical Monday of the Spring 2007 term, the subset of students who may potentially switch to the shared taxi is determined to be 2,393 (out of the weekly 2,788 students in Table 5.2). Based on their course schedules (starting and ending times), these students are then grouped into hourly inbound and outbound clusters as presented in Table 5.8 and further illustrated in Figure 5.9a. This demonstrates a substantial reduction in the size of the ride matching problem since the number of students to be considered in each group is at most a quarter of the total. It can be noted from the student registration records that the accumulated number of students attending the morning classes is much higher than in the afternoon (see Figure 5.9b) yielding in an imbalance in the number of arrival and departure students' trips throughout the day.

Table 5.8: One-Way Partitioning of Students (ST)

Time	Class Schedule Start Time		Class Schedule End Time	
	No. of Students	%	No. of Students	%
8:00	574	24.0%	-	-
9:00	617	25.8%	12	0.5%
10:00	399	16.7%	34	1.4%
11:00	259	10.8%	88	3.7%
12:00	177	7.4%	166	6.9%
13:00	88	3.7%	198	8.3%
14:00	100	4.2%	290	12.1%
15:00	47	2.0%	360	15.0%
16:00	60	2.5%	319	13.3%
17:00	59	2.5%	332	13.9%
18:00	9	0.4%	178	7.4%
19:00	4	0.2%	263	11.0%
20:00	-	-	131	5.5%
21:00	-	-	7	0.3%
22:00	-	-	15	0.6%
TOTAL	**2,393**	**100%**	**2,393**	**100%**

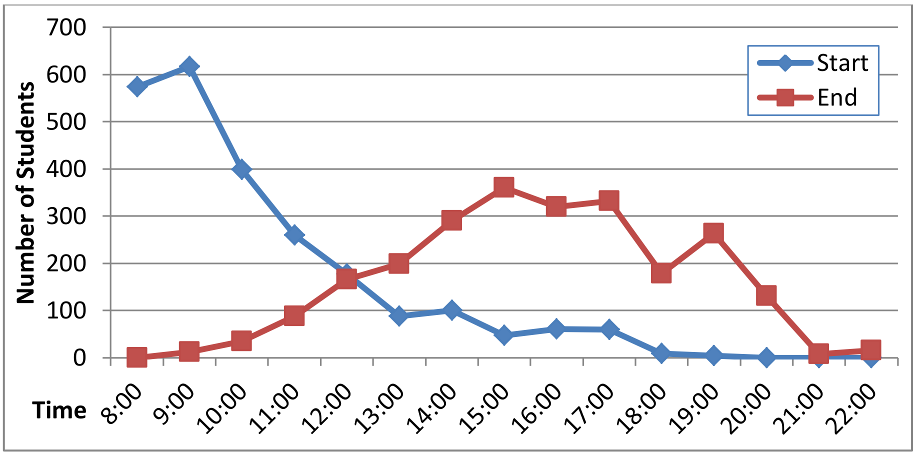

Figure 5.9a: Chart of Students' Schedule Partitions in Table 5.8

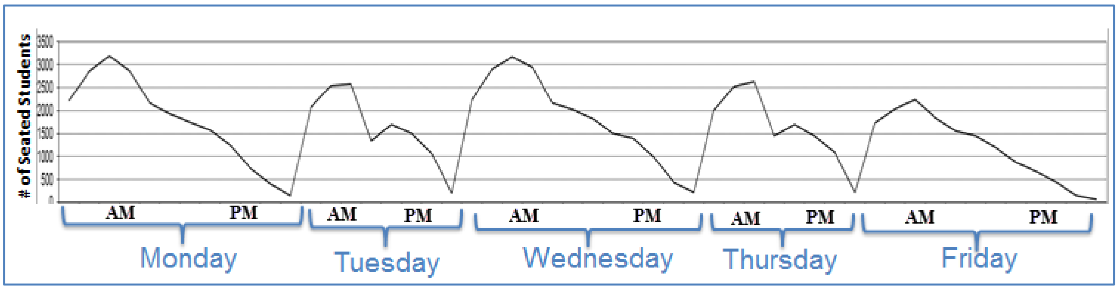

Figure 5.9b: Chart of the Cumulative Number of Students Attending Classes over the Time of the Day

Another more significant problem reduction is expected if the service design was for carpools; a reduction in the problem size limits the matching opportunities. In this case, the students' partitioning should be based on matching both starting and ending times. Although this case study addresses the service design of ST only, for illustration purposes Table 5.9 presents the results of two-way partitioning of students' schedules. Comparing with the results in Table 5.8, the opportunities of matching students in cars are much less in the two-way partitioning (number of groups is almost six times as big, and therefore group sizes are significantly smaller).

Table 5.9: Two-Way Partitioning of Students (CP)

Start \ End	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	Total
8:00	12	22	28	49	40	96	90	66	83	30	46	9	1	2	**574**
9:00		12	33	53	47	90	107	90	87	45	42	10	-	1	**617**
10:00			27	31	58	38	65	57	57	11	34	19	-	2	**399**
11:00				33	24	25	35	37	42	19	22	18	-	4	**259**
12:00					29	24	27	24	13	15	28	17	-	-	**177**
13:00						17	14	18	13	5	14	5	1	1	**88**
14:00							22	24	16	11	21	6	-	-	**100**
15:00								3	16	10	12	6	-	-	**47**
16:00									5	31	19	3	1	1	**60**
17:00										1	25	33	-	-	**59**
18:00											-	5	4	-	**9**
19:00												-	-	4	**4**
Total	**12**	**34**	**88**	**166**	**198**	**290**	**360**	**319**	**332**	**178**	**263**	**131**	**7**	**15**	**2,393**

5.4.2. Ride Matching

The proposed ride matching algorithms in Chapter 4 are implemented in this case study. The simulation includes testing both the PCT and MDT methodologies, and for ‘car capacities’ of 3 and 4 passengers. The testing will include the 9 demand scenarios indicated in Table 5.7, for all 26 groups of students indicated in Table 5.8 (12 inbound and 14 outbound). For illustration purposes, we present the detailed simulation results for the 8:00 AM inbound group consisting of 574 students (potential users). These students share the same class start time, and they all must be on campus at the same time. The service design will determine the number of cars needed and their routing to transport the subset of students who are willing to switch under each of the 9 scenarios. The number of students willing to switch was computed using the proposed demand function as presented in Table 5.10 below. Scenario S1 (lowest fare and lowest deviation) has the highest demand (79% willing to switch) compared to Scenario S9 (highest fare and highest deviation) which has the lowest demand (19% willing to switch).

Table 5.10: Demand for the Monday 8:00 AM Group

Scenarios	Fare = 30%	Fare = 40%	Fare = 50%
Max. Dev. = 20%	454 (79%)	229 (40%)	124 (22%)
Max. Dev. = 30%	430 (75%)	199 (35%)	112 (20%)
Max. Dev. = 40%	385 (67%)	184 (32%)	109 (19%)

The main outcomes of the simulated scenarios include: the number of cars needed, the total travel time (or travel distance), and the observed 'average passenger deviation'; these results are presented in Tables 5.11, 5.12, and 5.13, respectively.

Table 5.11: Number of Required Cars for the AM Peak Hour

Number of Required Cars						
Sc.	**Max. Dev.**	**Fare**	**PCT**		**MDT**	
			Car Cap. 3	**Car Cap. 4**	**Car Cap. 3**	**Car Cap. 4**
S1	**20%**	**30%**	*170*	*145*	*168*	*142*
S2		**40%**	*92*	*81*	*87*	*79*
S3		**50%**	*54*	*48*	*50*	*47*
S4	**30%**	**30%**	*155*	*126*	*151*	*122*
S5		**40%**	*75*	*62*	*73*	*60*
S6		**50%**	*44*	*39*	*42*	*36*
S7	**40%**	**30%**	*133*	*106*	*134*	*102*
S8		**40%**	*66*	*54*	*65*	*53*
S9		**50%**	*40*	*33*	*38*	*32*

Table 5.11 shows that the MDT algorithm resulted in a smaller number of cars than the PCT except for one instance (scenario S7 for car capacity = 3). An equally important observation is that the number of required cars is reduced by 10% to 20% when the car capacity is increased from 3 to 4 passengers/car. This can also be presented in terms of average car occupancy, by dividing the demand (in Table 5.9) by the respective number of trips of each scenario. The chart in Figure 5.10 presents the average vehicle occupancy of scenarios S2, S5, and S8 (where the fare is 40%), and shows that the MDT results in higher occupancy in the case of higher car capacity.

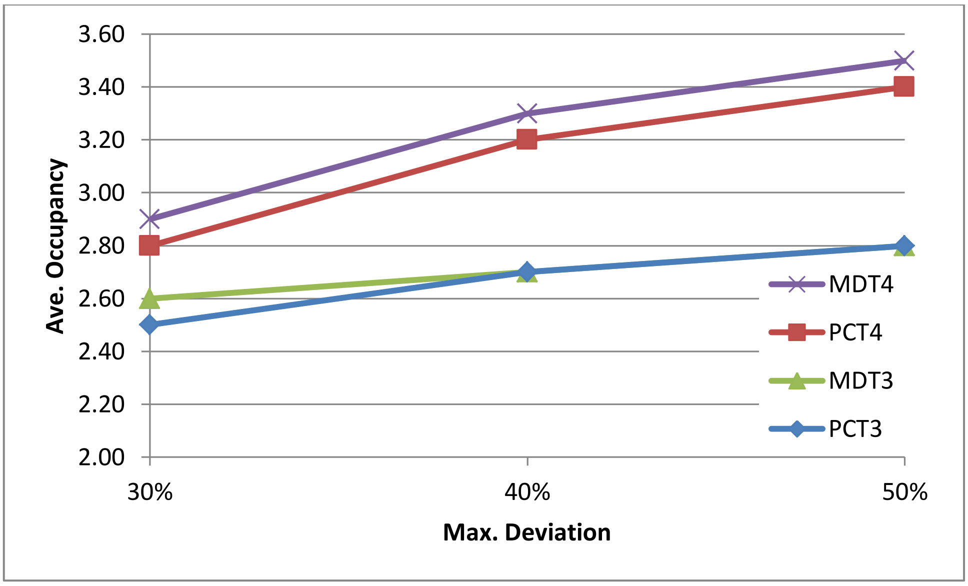

Figure 5.10: Average Car Occupancy Chart (ST Fare is 40% of Private Taxi)

Despite the fact that the PCT algorithm generally results in lower total travel time (as discussed in Chapter 4), the MDT achieves higher matching rates (for narrow time windows constraints) thus requiring a smaller number of cars (as shown in Table 5.11). As a result, Table 5.12 shows that the total travel time using PCT is generally lower than the MDT, with some exceptions for the scenarios requiring relatively fewer cars in MDT than PCT.

Table 5.12: Total Travel Time for the AM Peak Hour

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	111.8	95.3	112.2	96.0
S2		40%	55.3	48.5	54.6	48.7
S3		50%	26.9	24.3	25.9	24.5
S4	30%	30%	99.8	83.4	100.7	84.4
S5		40%	44.3	38.1	44.4	38.5
S6		50%	21.8	19.3	21.6	19.2
S7	40%	30%	83.2	68.5	84.0	67.7
S8		40%	38.6	32.1	39.0	32.6
S9		50%	20.9	17.9	20.6	18.1

In a similar manner, the 'average passenger deviation' is generally less in MDT than in PCT. However, due to the lower vehicle occupancy for PCT in some scenarios (requiring more cars), some values in Table 5.13 are lower for PCT than MDT.

Table 5.13: Average Passenger Deviation

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	**20%**	**30%**	*5.5%*	*7.3%*	*5.2%*	*7.1%*
S2		**40%**	*6.6%*	*8.2%*	*6.1%*	*7.4%*
S3		**50%**	*7.2%*	*8.7%*	*7.7%*	*9.0%*
S4	**30%**	**30%**	*6.7%*	*10.2%*	*7.0%*	*9.8%*
S5		**40%**	*9.3%*	*12.3%*	*7.9%*	*10.7%*
S6		**50%**	*9.5%*	*13.1%*	*9.5%*	*13.5%*
S7	**40%**	**30%**	*9.8%*	*13.0%*	*8.1%*	*11.7%*
S8		**40%**	*10.9%*	*14.0%*	*8.8%*	*13.4%*
S9		**50%**	*12.3%*	*17.4%*	*11.8%*	*17.6%*

The same steps should be repeated for all inbound and outbound groups, and all the results are evaluated in the feasibility module. For practical purposes, we extrapolated the morning demand into a full day demand (using a factor of 8 = 2 way × $^{1}/_{0.25}$ where the 0.25 represents the fraction of the morning peak hour demand).

5.4.3. Taxi Dispatch

The proposed ride matching algorithm solves each group of students presented in Table 5.8 separately; however, the taxicab fleet size needs to be optimally determined taking into account the inter-relationships of the daily inbound and outbound trips and the schedule of the available fleet. Each vehicle completing its designated route within a group needs to be dispatched for another task in another group. The best scenario (in terms of the least relocation distance) for a single vehicle dispatch is when it is assigned to the nearest passenger to be picked up after dropping off the last passenger onboard. This method achieves the highest savings in terms of traveled distance. On the other hand, the optimal dispatch of the overall system may require different arrangements using complex algorithms (allowing extra traveled distances instead of this greedy method that may require a larger number of required cars).

For the purpose of this case study, a simple greedy approach is suggested for the fleet dispatch. It takes into consideration the time and location of every vehicle after completing each task. The depot is practically assumed to be adjacent to the AUB campus; therefore, all outbound trips (AUB to students' residences) are expected to be dispatched to vehicles available at the depot. For the first 8:00 AM group in the morning all required vehicles are dispatched to travel empty to start collecting the passengers and bringing them to AUB based on the temporal pre-matching and ride matching approached described earlier. For the subsequent groups of inbound and outbound time slots, the vehicle is either idle at the depot (due to a lower demand), or in a backhaul operation (delivery then pick-up). Given the demand variation over the whole day as shown in Figure 5.9, the governing number of vehicles is determined in the highest peak hours (where close to 50% of the students start their classes at either 8:00 AM or 9:00 AM). Considering scenario S1, for a car capacity of 4 passengers, the MDT algorithm specifies the need for 142 and 152 cars to respectively serve the 454 and 486 students switching to use the new ST services (with classes starting at 8:00 AM and 9:00 AM).

Having determined the number of cars needed for the highest two consecutive hours, the number of cars that may be dispatched to serve both peak hours can be determined as follows. Since there are no students finishing at 8:00 AM, all 142 cars arriving to AUB at or before 8:00 AM are ready to be dispatched to pick up the students that have classes at 9:00 AM. Those cars can only serve the students who are within 30 minutes of AUB. Figure 5.11 presents the distribution of the 9:00 AM cars doing pick-ups and their associated trip durations, indicating that close to 50% of the pick-ups are within 30 minutes of AUB. Based on this, and anticipating the need for deviations, one may estimate that 40% of the vehicles completing the 8:00 AM drop-offs at AUB may be able to serve the 9:00 AM pick-ups.

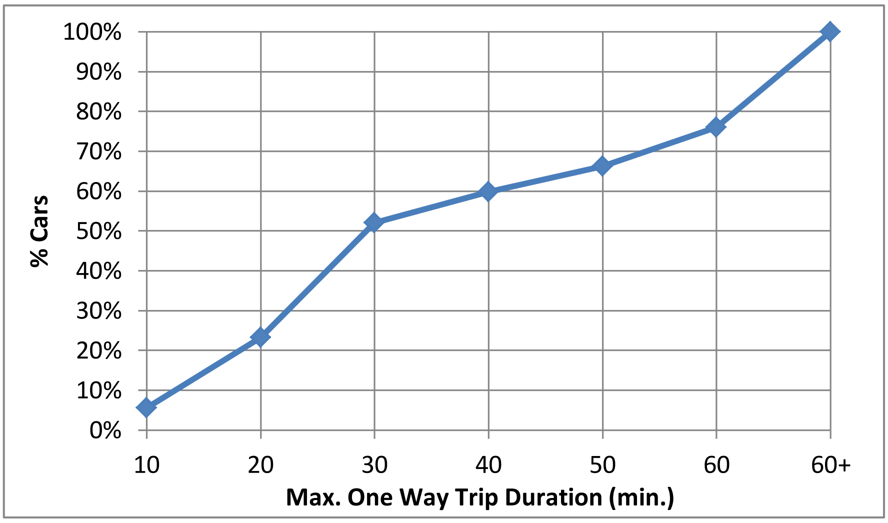

Figure 5.11: Maximum One-Way Trip Durations of Cars

It can be concluded from the above analysis that, the governing number of cars required to serve the peak 2-hour demand for scenario S1 is 227 cars (142 + 85). As shown in Table 5.8 the hourly demand fraction drops by 35% (from 25.8% at 9:00 AM to 16.7% at 10:00 AM) and continues dropping for the rest of the day. As a result nearly 30%* of the car fleet is expected to operate for a single trip in the morning peak hour and stay idle at the depot for the rest of the day.

* *(From the 142 required cars for 8:00 AM, we have 57 operating again at 9:00 AM and 85 ready to operate after 9:00 AM. Therefore, the 145 required cars for 9:00 AM include the 57 cars from 8:00 AM and 88 new cars. At 10:00 AM the required cars are 97 where 85 are available from 8:00 AM cars, and 12 cars are needed from 9:00 AM cars. Therefore, at least 76 of the 88 new cars operating at 9:00 AM will no longer be needed for the rest of the day, 76/227 = 33.4%)*

It was shown in Figure 5.8 that nearly 50% of the car trip durations are less than 30 minutes. As such, 50% of the cars operating at any regular hour of the day (between 9:00 and 18:00) to deliver students from AUB to their residences (outbound trips) may operate in backhaul (picking up new students after finishing dropping off its passengers and before returning to AUB) given a repositioning time that can meet the pick-up time of the first passenger of the new inbound trip. This operation can be optimized using advanced dispatching algorithms resulting in a reduction of the total travel distance (or travel time) of the vehicle fleet to serve the total daily demand. However, and for the purpose of this case study, this reduction was approximated as 20% (being a 40% reduction of the tour distance for 50% of the trip demand).

5.5. Feasibility Analysis

Investigating the feasibility of the different scenarios is essential in determining the viability of the proposed ST initiative. It enables decision and policy making, and setting directions for the design and financing of the ST system for the different fare and maximum deviation scenarios.

This section addresses the financial cost and benefit of operating the ST service based on different scenarios. The analysis time period is for one year including three semesters (Fall, Spring, and Summer). The demand results of the typical Monday are expanded to represent the weekly demand (Monday through Friday) using an approximated factor of 4.86 (given that the students registered for Monday-Wednesday classes are 5,701, for Tuesday-Thursday 5,634, and for Friday 5,061) for the Fall and Spring terms (24 study weeks). In a similar fashion, the Summer term is considered at 40% of the daily demand of the Fall and Spring terms (6 study weeks). As such, the results of the typical weekday may be expanded to one year by multiplying its demand by a factor of ~128 (24 weeks × 4.86 days/week + 6 weeks × 4.86 days/week × 40% demand = 128.3).

Two options for the service delivery are suggested for the analysis. The first option is to commission the service to existing private taxi companies (single or multiple operators), while the second is to consider a completely new service provider operating exclusively for AUB students. The same demand of the 9 scenarios will be investigated for both service delivery options. Option 1 may also be considered as a benchmark for the feasibility of Option 2.

➢ Fare Revenue

Given a specified 'Fare' for each of the 9 scenarios as a fraction of the 'Private Taxi Fare', the fare revenue can be calculated for each student from the respective zone of his/her home location. Table 5.14 presents the fare revenue for each of the 9 scenarios; such fare revenue is the same in both service delivery options. It can be noted from Table 5.14 that the average fare per ride is relatively lower in scenarios S1, S4, and S7 where the fare is the lowest (30%).

Table 5.14: Demand and Fare Revenue for the Typical Day ($)

Scenario	Requests	Fare Revenue	Ave. Rate per Ride
S1	*3,632*	*$ 11,394*	*$ 3.1*
S2	*1,832*	*$ 6,935*	*$ 3.8*
S3	*992*	*$ 3,859*	*$ 3.9*
S4	*3,440*	*$ 10,499*	*$ 3.1*
S5	*1,592*	*$ 5,916*	*$ 3.7*
S6	*896*	*$ 3,341*	*$ 3.7*
S7	*3,080*	*$ 8,798*	*$ 2.9*
S8	*1,472*	*$ 5,389*	*$ 3.7*
S9	*872*	*$ 3,269*	*$ 3.7*

➢ <u>Operator's Cost - Option 1</u>

To benchmark the feasibility assessment of a complete implementation of the AUB ST system with a dedicated vehicle fleet, a first option is evaluated based on the concept of commissioning the AUB ridesharing demand to one or more private taxi companies. In this option the operator is an intermediate link between the existing taxi company/companies and the students, by simply operating the student ride matching system and collecting the fares and then commissioning the student trips to the taxi companies. This option is only viable when the fare collection revenue is higher than the operator's cost. As previously discussed in section 5.2.3 the operator's cost of this option includes the cost of the annual investment for the proposed online ridesharing system (Table 5.6), in addition to the charges of the private taxi company (in other words, the existing taxi company charges the operator for the booked trips and the operator's revenue is from the students' fare collection, therefore, in cases of trips matching only one student the operator collect a fraction of the fee charged by the private taxi company, while in other cases of trips matching multiple students the operator collects fares from the students that exceed the trip cost charged by the private taxi company). The same fare structure defined in Figure 5.5 is adopted while applying a surcharge that is proportional to the extent of vehicle route deviation (the original fare of the commissioned taxi for the direct trip is increased by the same percentage of the route deviation calculated for each car serving more than one passenger). Table 5.15 presents the total charges of the private taxi company for the typical day. This individual charge varies by the zone of the first pick-up student (or the last in drop-off) and the vehicle deviations to pick-up/drop-off additional passengers. As such, these charges would vary for different car capacities and ride matching methods that may lead to different number of trips and total travel distances.

Table 5.15: Charges of the Private Taxi Company for Option 1 (Typical Day)

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	$ 14,962	$ 12,676	$ 14,730	$ 12,592
S2		40%	$ 7,396	$ 6,484	$ 7,168	$ 6,411
S3		50%	$ 3,755	$ 3,422	$ 3,551	$ 3,436
S4	30%	30%	$ 13,350	$ 11,149	$ 13,326	$ 11,164
S5		40%	$ 6,129	$ 5,259	$ 6,051	$ 5,215
S6		50%	$ 3,014	$ 2,726	$ 2,937	$ 2,700
S7	40%	30%	$ 11,181	$ 9,232	$ 11,261	$ 9,030
S8		40%	$ 5,464	$ 4,519	$ 5,419	$ 4,536
S9		50%	$ 2,875	$ 2,442	$ 2,785	$ 2,522

As noted earlier, the MDT achieves the highest matches in general, thus reducing the number of cars needed. As a result, the total charges in Table 5.15 vary between PCT and MDT due to the trade-off between the 'total travel time' and the 'total number of car trips needed'. In other words, the reduction of the needed taxi cars in the MDT method may or may not lead to a lower cost than the PCT depending on the associated total deviation and travel distance.

➢ Operator's Costs - Option 2

In this option the operator is a new ST company dedicated for AUB students. The initial investment cost for this option includes the acquisition cost (lease) of the taxicab fleet as well as the online ride matching system and other items as listed in Table 5.6 (total of $120,000 annually). As discussed in section 5.2.3, the annual lease of a private taxicab is approximately $4,500 (including maintenance and insurance). The total number of cars needed for every scenario is listed in Table 5.16 below (this is the governing number of cars needed to serve the 8:00 and 9:00 AM peak hours demand which comprises 50% of the daily demand and is to be served in 2 hours).

Table 5.16: Number of Required Cars for the Typical Day

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	271	231	268	227
S2		40%	147	129	139	126
S3		50%	86	76	79	75
S4	30%	30%	247	201	241	195
S5		40%	119	99	116	95
S6		50%	70	62	67	57
S7	40%	30%	212	169	214	163
S8		40%	105	86	103	84
S9		50%	63	52	60	51

The operational costs are estimated based on the total travel time (or traveled kilometers) at a rate of 9$/hour (as described in Section 5.2.3: 6$/hour for the vehicle operation and 3$/hour for the driver based on a monthly salary of 600$). The total travel time for the typical day (extrapolated from the 8:00 AM trips) in each scenario is presented in Table 5.17. In general, the MDT resulted in a higher travel time compared to the PCT.

Table 5.17: Total Travel Time for the Typical Day (Hours)

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	715	610	718	615
S2		40%	354	310	350	312
S3		50%	172	155	166	157
S4	30%	30%	638	534	645	540
S5		40%	284	244	284	246
S6		50%	140	123	138	123
S7	40%	30%	533	439	538	433
S8		40%	247	205	249	209
S9		50%	134	114	132	116

➢ Feasibility of Options 1 and 2

The daily charges of the taxi companies in Option 1 and the daily operational costs of Option 2 are expanded from the typical day to a full year horizon, and then added to the annual administrative expenditures of each option. The resulting total cost is then subtracted from the yearly fare revenue of every scenario to determine the net revenue of both options 1 and 2 as presented in Tables 5.18 and 5.19, respectively.

Table 5.18: Net Annual Revenue for Option 1

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	$ (496,809)	$ (204,167)	$ (467,100)	$ (193,430)
S2		40%	$ (98,978)	$ 17,738	$ (69,819)	$ 27,179
S3		50%	$ (26,705)	$ 15,895	$ (632)	$ 14,129
S4	30%	30%	$ (404,882)	$ (123,184)	$ (401,893)	$ (125,121)
S5		40%	$ (67,344)	$ 44,080	$ (57,357)	$ 49,726
S6		50%	$ 1,881	$ 38,716	$ 11,817	$ 42,127
S7	40%	30%	$ (344,995)	$ (95,536)	$ (355,216)	$ (69,623)
S8		40%	$ (49,611)	$ 71,361	$ (43,856)	$ 69,156
S9		50%	$ 10,431	$ 65,948	$ 22,000	$ 55,690

It can be observed from Table 5.18 that feasible scenarios are almost exclusively associated with fares exceeding 30% and car capacities equal to 4. Scenarios S2, S5, and S8 (with fare levels of 40%) seem to present a balance between the fare and the associated demand that results in the highest net profit. On the other hand, a fare of 30% results in the highest demand but least profit per request, and the 50% fare level results in the highest profit per request but the least demand.

Table 5.19: Net Annual Revenue for Option 2

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	$ (705,217)	$ (403,806)	$ (694,605)	$ (391,041)
S2		40%	$ (301,456)	$ (170,016)	$ (260,497)	$ (158,447)
S3		50%	$ (211,279)	$ (147,027)	$ (172,413)	$ (144,130)
S4	30%	30%	$ (623,103)	$ (295,717)	$ (603,355)	$ (275,991)
S5		40%	$ (225,002)	$ (88,911)	$ (211,962)	$ (74,147)
S6		50%	$ (168,049)	$ (113,277)	$ (152,732)	$ (90,152)
S7	40%	30%	$ (561,463)	$ (259,498)	$ (576,204)	$ (226,691)
S8		40%	$ (186,981)	$ (53,833)	$ (181,118)	$ (48,570)
S9		50%	$ (139,344)	$ (67,150)	$ (123,416)	$ (64,643)

Table 5.19 demonstrates the general infeasibility of Option 2 for all nine scenarios. This is evidently caused by the high capital investment in the fleet of taxis (compared to Option 1), and the idle cars after the 8:00 and 9:00 AM peak period. A similar situation is encountered in the infeasibility of dedicating a fleet of low capacity vehicles (or cars) to transport employees on a single trip to work per day basis. Typically, high capacity vehicles (or buses) are likely to be used for the single trip per day scenario (school bus, workers, and employees). The study by Tao and Chen (2007), for the employee based shared taxi service, was based on a scenario similar to option 1. In order to address the infeasibility of Option 2, a number of policies are proposed below.

Service policies:

- Limiting the vehicle fleet size by commissioning the extra peak hour demand (that require additional cars which will operate for one trip per day and will remain idle for the rest of the day) to private taxi operators (considered for analysis as Option 3)
- Denying requests matching fewer than 3 passengers in the peak hours (this option was not considered for analysis as it would also reduce the outbound demand of the denied peak hour inbound trips and which may occur in the off-peak hour, and may have an overall negative impact on TS adoption)
- Imposing a higher acceptable deviation during peak hours to achieve full packing of the vehicles (considered for analysis as Option 4)
- Increasing the vehicle capacity (at least during peak periods) using one of the following:

- Multi-Purpose Vehicles (MPV) offering extra seats (considered for analysis as Option 5)
- Heterogeneous fleet of cars and vans

Demand management / Pricing policies:

- Increasing the fare during peak hours, resulting in shedding of peak demand (considered for analysis as Option 6)

Institutional policies:

- Seeking subsidy/funding from AUB
- Balancing the course distribution and schedules (a large fraction of classes are offered at 8:00 and 9:00 AM) to reduce the high early morning peak demand

Other revenue sources:

- Using the vehicle fleet to serve the AUB students (or other customers) for other trips during holidays and weekends

In what follows we present the results of feasibility analysis for Options 3 to 6.

➢ Feasibility of Option 3

This option is a hybrid option between Options 1 and 2 and consists of limiting the number of cars required to serve a single trip per day during the peak hours only. Based on an analysis of the hourly demand levels in Table 5.8 this may be broadly achieved by commissioning 30% of the morning peak demand to an existing taxi company. The results for the feasibility of this option are summarized in Table 5.20 below, and have indicated that this option can be feasible for car capacities equal to 4, fares equal to 40%, and for maximum deviations between 30% and 40%.

Table 5.20: Net Annual Revenue for Option 3

Sc.	Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	$ (421,199)	$ (160,945)	$ (412,192)	$ (152,383)
S2		40%	$ (143,433)	$ (31,322)	$ (111,458)	$ (22,950)
S3		50%	$ (116,361)	$ (63,858)	$ (85,542)	$ (62,323)
S4	30%	30%	$ (362,649)	$ (85,264)	$ (350,233)	$ (73,238)
S5		40%	$ (98,690)	$ 15,301	$ (88,917)	$ 25,331
S6		50%	$ (90,429)	$ (45,102)	$ (78,553)	$ (28,519)
S7	40%	30%	$ (336,578)	$ (82,088)	$ (348,955)	$ (55,873)
S8		40%	$ (76,366)	$ 36,631	$ (72,536)	$ 39,310
S9		50%	$ (70,324)	$ (10,518)	$ (57,760)	$ (9,981)

➢ <u>Feasibility of Option 4</u>

This option imposes a 40% maximum deviation on the peak hour demand. It was assumed that no change in demand shall occur since the overall sensitivity of demand with respect to maximum deviation is limited (see Figure 5.8) and since the rider will continue to experience the original maximum deviation in the off-peak hours. This option enables a higher packing during peak hours, hence limiting the number of cars required to serve a single trip per day during the peak hours only. The results for the feasibility of this option are summarized in Table 5.21 below, and indicate that this option can be feasible for scenario 2 only considering car capacities equal to 4, fares equal to 40%, and for maximum deviations equal to 20%.

Table 5.21: Net Annual Revenue for Option 4

Sc.	Off-Peak Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	$ (427,858)	$ (108,980)	$ (440,840)	$ (84,070)
S2		40%	$ (100,470)	$ 37,936	$ (88,743)	$ 44,306
S3		50%	$ (107,060)	$ (35,940)	$ (87,267)	$ (33,273)
S4	30%	30%	$ (454,319)	$ (140,024)	$ (470,373)	$ (116,846)
S5		40%	$ (160,267)	$ (26,798)	$ (152,495)	$ (21,276)
S6		50%	$ (139,766)	$ (69,804)	$ (124,220)	$ (65,397)
S7	40%	30%	$ (561,463)	$ (259,498)	$ (576,204)	$ (226,691)
S8		40%	$ (186,981)	$ (53,833)	$ (181,118)	$ (48,570)
S9		50%	$ (139,344)	$ (67,150)	$ (123,416)	$ (64,643)

- <u>Feasibility of Option 5</u>

To maintain the same demand of the proposed fare and maximum deviation in the 9 scenarios of option 2, a new option 5 of using a vehicle fleet consisting of higher capacity MPVs is suggested. For the purpose of this case study we suggested the Toyota Avanza MPV (or similar model); this vehicle is commonly used by the taxi companies operating in Beirut and by the AUB escort and security services. This vehicle has seven seats (six passengers and the driver). The dealer price of this model is 16,000$ and the annual lease value is estimated at 3,400$ (including insurance). The feasibility of this option was investigated for scenarios S2, S5, and S8 (with the balanced fare value of 40%). The car capacity was considered as 6 and 4 for the peak and off-peak hours, respectively. The results of the vehicle fleet size and the annual net revenue of option 5 are presented in Tables 5.22 and 5.23, respectively.

Table 5.22: Number of Required Cars for Option 5

Scenario	Max. Dev.	PCT	MDT
S2	**20%**	*123*	*117*
S5	**30%**	*91*	*85*
S8	**40%**	*72*	*74*

Table 5.23: Net Annual Revenue for Option 5

Sc.	Max. Dev.	PCT	MDT
S2	**20%**	*$ (2,653)*	*$ 18,414*
S5	**30%**	*$ 52,187*	*$ 72,754*
S8	**40%**	*$ 95,975*	*$ 84,788*

It can be concluded that Option 5 resulted in a substantial reduction in the cost and thus an increase in the net profit. This demonstrates that the option of operating exclusive taxi service for AUB may also be feasible compared to commissioning the service to an existing Private Taxi operator for maximum deviation equal to or greater than 30%. The key factor is in reducing the initial investment in cars by increasing the seat capacity during peak hours using MPV cars.

➢ <u>Feasibility of Option 6</u>

This option is a demand management policy by increasing the fare during peak hours, resulting in reduced peak demand. This option imposes a 50% fare level for the peak hour demand; the impact on the overall demand was considered (a student coming to AUB during peak hours will consider the average fare between that of the peak hour and the lower price of the returning trip during the off-peak). This option enables leveling the high demand during peak hours, hence limiting the number of cars required to serve a single trip per day during the peak hours only. The results for the feasibility of this option are summarized in Table 5.24 below, and indicate that this option can be feasible for scenarios of 30% and 40% fare in the off-peak. Expectedly, the fare of 50% in the off-peak (scenarios 3, 6, and 9) would lead to the same infeasibility results of Option 2 as both would be the same.

Table 5.24: Net Annual Revenue for Option 6

Sc.	Off-Peak Max. Dev.	Fare	PCT		MDT	
			Car Cap. 3	Car Cap. 4	Car Cap. 3	Car Cap. 4
S1	20%	30%	$ 105,659	$ 247,322	$ 110,646	$ 253,321
S2		40%	$ (132,004)	$ (26,852)	$ (99,236)	$ (17,597)
S3		50%	$ (211,279)	$ (147,027)	$ (172,413)	$ (144,130)
S4	30%	30%	$ 104,947	$ 258,818	$ 114,228	$ 268,089
S5		40%	$ (90,419)	$ 18,454	$ (79,987)	$ 30,265
S6		50%	$ (168,049)	$ (113,277)	$ (152,732)	$ (90,152)
S7	40%	30%	$ 59,173	$ 201,097	$ 52,245	$ 216,516
S8		40%	$ (70,120)	$ 36,398	$ (65,430)	$ 40,609
S9		50%	$ (139,344)	$ (67,150)	$ (123,416)	$ (64,643)

5.6. Recommendations for AUB

The current AUB population is estimated to be 8,000 students and 4,400 employees (including AUBMC). On a typical weekday, nearly 1,400 students' cars are parked in the vicinity of the campus (in public/on-street parking) between 12:00 and 1:00 PM. Moreover, an equal number of employees' cars was identified to park off-campus (Aoun et al. 2012) in addition to the 1,105 available parking spaces on campus. The total parking demand for AUB is approximately 4,000 parking spaces where only 25% of this demand is supplied on campus.

Student commuting surveys were conducted in the years 2007 and 2010 and have indicated a reduction in the students commuting by their private car from 30% to 24%. On the other hand, the students ridesharing in carpools have increased from 3.5% to 12% (between 2007 and 2010). This ridesharing activity was carried out by student and employee initiatives in response to the increased fuel cost and parking deficiencies. AUB should look into schemes for encouraging and expanding such activities through an institution-based ridesharing initiative.

The AUB Neighborhood Initiative has attempted to address the problem of reducing the parking demand and congestion in the neighborhood while maintaining a feasible transportation service to students and employees. AUB researchers have proposed an exclusive, dynamic taxi-sharing service that combines the benefits of a private taxi (professionalism, reliability, vehicle comfort, etc.) with the cost and occupancy of a shared-taxi (Aoun et al. 2012). This will offer a low cost door-to-door trip to students with a minimum route deviation to pick up/drop off other students within proximity or along the way.

This research has investigated the feasibility of different shared-taxi service options for AUB students. A demand analysis indicated that a shared-taxi fare equivalent to 40% of the fare of a private taxi would attract 30% to 40% of the students' trips. Using data from the 2007 students commute survey (70% sample size with known students' schedules, home locations, and current commute modes), the opportunities of matching student trips in shared-taxi cars were assessed (using a developed ride matching tool). Two main service options were considered in the analysis; the first consisted of having a third party operator that would provide an online ridesharing system for students, collect the fees from the students, and commission the matched trips to existing taxi companies, while the second option consisted of having an operator with an exclusive taxicab fleet dedicated to AUB students.

The ride matching analysis considered cars with 3 to 4 passenger capacities and has concluded that the majority of the cars are expected to be nearly fully packed while a relatively smaller portion of the trips will be serving one student per car. To ensure system reliability and availability for students, the single passenger trips were assumed to be served with the same fare as the shared trips and the feasibility was established for the overall car trips.

Analysis of the results has indicated the feasibility of Option 1 for car capacities of 4 passengers, and the infeasibility of Option 2. The main reason behind the infeasibility of the second option is the need for a large taxi-cab fleet where 30% of these cars will operate for a single trip in the morning peak to serve 50% of the students in the morning peak (8:00 to 9:00 AM) and will remain idle for the remaining off-peak hours of the day. This required the investigation of different demand management and service design policies that resulted in the feasibility of this option under certain scenarios.

The results of this study highlight the opportunities for a feasible shared-taxi service for AUB students. This potential business opportunity would attract the interest of private investors. AUB as a nonprofit organization may consider inviting interested private investors and taxi companies to take advantage of this opportunity with a limited role for the AUB administration as a facilitator only. AUB may consider funding further research for market studies and potential risk assessments, as well as increasing the students' awareness and participation. This research has also investigated the success and failure of existing ridesharing systems and highlighted the importance of market studies, proper costing, the phased implementation of the system, and the cooperation of the different stakeholders (AUB, the students, and the shared taxi operator).

5.7. Summary and Conclusions

This case study aimed at presenting the mechanism of the proposed evaluation framework for an actual case study. It can be concluded that a ST ridesharing service can offer a feasible solution for AUB students and the university. A suggested ST fare of 40% of the fare of a private taxi would attract 30% to 40% of the students commuting in private cars to switch to the new ST service. Considering a benchmark scenario of commissioning the trips to existing taxi companies (Option 1) has shown that the AUB demand can be feasibly served using taxicab cars with capacities of four passengers. Given the high peaking demand of the incoming trips to AUB in the morning peak, around 30% of the required number of cars will only serve a single trip per day. A critical component in the feasibility of a dedicated taxicab fleet for AUB is the acquisition cost (lease) of the vehicle fleet. Nine demand scenarios (using maximum deviation values of 20%, 30%, and 40% with fare values of 30%, 40%, and

50%) were tested considering the lease of a dedicated taxi fleet option (Option 2) and have shown the infeasibility of the nine scenarios. The mechanism of the proposed evaluation framework enables the investigation and testing of service, demand management/pricing, and institutional policies. Four additional options were further analyzed using hybrid scenarios of different service and pricing policies and have indicated the best feasible scenario for these options.

The following subsections summarize the general conclusions and service impact and indicate the limitations of this case study.

5.7.1. General Conclusions

- Any increase in the 'Fare' and/or the 'Maximum Deviation' results in a decrease in the demand. The 'Fare' variation has a much higher impact on the demand compared to the 'Maximum Deviation'.
- 'Maximum Deviation' variations have a bigger impact on the ride matching process and car occupancy levels than the 'Fare' variations (translated in demand variation).
- The MDT algorithm results in higher 'travel times' (or 'travel distances') but lower 'number of cars required' than the PCT.
- Saving in 'travel time' has less financial benefit compared to reduction of the 'required number of cars'; as a result, MDT has offered a better overall feasibility than the PCT despite its higher 'travel time' results.
- The MDT algorithm generally achieves lower 'average passenger deviation' than the PCT algorithm (depending on the spatial distribution of the passengers whether random or clustered as discussed in Chapter 4).

- Opportunities for two-way ride matching for carpooling are substantially less than the one-way matching for ST.
- Most public transport users would likely switch to ST when the fares are low (less than 30%) or subsidized.
- In order to address the infeasibility of service options, a number of policies were identified and proposed as follows: service policies, demand management / pricing policies, institutional policies, and other revenue sources.

5.7.2. Service Impact

In addition to the cost benefit analysis, other important impacts should also be considered with respect to the students, the operator, the university, and the community. These service impacts are summarized in Table 5.25 below.

Table 5.25: Service Impacts

Impact / Criterion	Students	Operator	AUB	Community
Fare	Higher Demand, Cost Savings	Less Profit per user	Reduction in Parking Demand, Need for Subsidy	Reduction in Parking and Congestion
Least Deviation	Higher Demand, Travel Time Savings	More cars Less Profit	-	-
Higher Car Capacity	Less comfort	Less cars More Profit	-	Less trips to AUB (Reduce Congestion)

5.7.3. Limitations

An important limitation in this work lies in the deterministic nature of the demand model used and which included cost and travel time savings only.

Considerations for additional factors are recommended, including comfort, service availability, and reliability. Al-Ayyash et al. (2015) have used stated preferences survey data to estimate an integrated choice and latent variable model for a shared ride taxi service for AUB. The service reliability may include a 'Guaranteed Ride Home' option in any emergency or in case of unscheduled class. This option can be priced differently or limited to a certain number of times per semester. In addition, this case study did not consider dynamic (real time) requests or cancellation, and the impact of technological enablers.

Other limitations in the service design module of this case study include:

- Simplification of the average speed on each road segment and its time-of-day variability (same for peak and off-peak hours)
- Delays at intersections were not considered
- Simplification of the vehicle dispatch optimization method
- The iterative process between the service design and the demand modules was not implemented.

CHAPTER 6

SUMMARY AND FUTURE RESEARCH

6.1. Summary

This dissertation presented a feasibility framework for the evaluation of ridesharing services in an organization-based context encompassing all impacts and evaluation criteria and can be used as a decision support tool. This framework consisted of three main modules: the demand estimation module, the service design module, and the feasibility module. Each of the three modules was analyzed taking into account the essential components, methods, and the needed data. The interrelationships between these modules (and their components) were established showing an iterative feedback between the three modules. This has enabled analysis of "what if" scenarios for the demand, the service design, and the feasibility modules.

In general, researchers have addressed each of the three modules of the framework independently and a gap was found in the literature for the ride matching methods for the organization-based ridesharing problem. This problem is a variant of the CVRPTW that is characterized by unit demand, asymmetric network, and narrow time windows with common arrival/departure time to/from the organization location. The solution for this problem is identified to have two main objectives that are generally conflicting (minimizing total cost and minimizing the user deviation). In this regard, this work introduced the formulation and development of a new ride matching algorithm using hierarchical spanning trees. Two tree types were defined in the proposed heuristic algorithm (PCT and MDT), where the PCT is based on the proximity clustering strategy for total cost minimization while the MDT is based on the route deviation strategy for user deviation minimization. This new algorithm was tested against optimal solutions for small problems and has provided high quality solutions in a substantially shorter processing time. Moreover, for large size problems it was demonstrated to achieve higher ride matching opportunities and for different vehicle capacities with fast processing compared to known methods in the literature.

A case study was presented to illustrate the implementation of the developed framework using actual data from the American University of Beirut; such data was also documented for future research. The most feasible ridesharing alternative to the current travel mode was determined using a simple deterministic demand module and a full implementation of the proposed ride matching algorithm taking into consideration service delivery scenarios and varying the involved parameters. The analysis included system feasibility assessment in terms of cost and revenue as well as service impact on parking demand and congestion. The results of this case study have shown that the high peak hour demand requires up to 30% extra number of cars (compared to the regular off peak requirements) that will only operate for a single trip in the morning and will remain idle for the rest of the day. Different feasible solutions were recommended for AUB that consisted of different hybrid scenarios related to service design, demand management, pricing, and institutional policies.

6.2. Research Contribution

The significance of this research lies in the development of a comprehensive framework encompassing all factors and criteria for evaluating the feasibility of different potential alternative services for an organization-based ridesharing context. Previous researches have addressed specific parts of this framework independently, and have given little input on the big picture. One main contribution is the incorporation of the demand side in the service design process, while previous service design literature assumed a fixed demand independent of the outcomes of the service design.

The developed framework defines the modeling elements of alternative service options, the associated parameters and factors, and the database needed. It can be used as a decision aid tool that analyzes in a comparative manner the feasibility of various service design alternatives with the option of varying key parameters using an iterative approach. This framework calls for an iterative process between three main modules, being the demand estimation, the service design, and the feasibility.

This research investigates various ride matching methods and algorithms that were previously developed by researchers for their applicability in a university or large institution context (“many-to-one”, with one known destination for a subset of a determined users’ database). The research introduces a new proposed ride matching algorithm that is context-related to the organization-based ridesharing problem as a special case of the Capacitated Vehicle Routing Problem with Time Windows (VRPTW). The advantage of this algorithm lies in its capability to fast solve large problems with two types of solution strategies, matching passengers within proximity clusters and matching passengers along minimum route deviations. This algorithm can be used for investigating different vehicle capacities and maximum deviation constraints.

This research implements a complete case study for the American University of Beirut using the three modules of the developed framework and provides a documentation of the used database for future research benchmarking. The original demand, based on which the service design step is undertaken, is based on broad service design parameters.

6.3. Future Research

The evaluation framework presented in this dissertation is generic and its importance lies in the interrelationships among the various elements of ridesharing studies. Each of the three main modules of the framework can be either implemented using simplified methodologies or sophisticated models. The following subsections discuss the recommended future research for each of the three modules.

6.3.1. Future Research for the Demand Module

A deterministic demand model was used in this research for the purpose of presenting the mechanism of the proposed evaluation framework for an actual case study. Advanced demand models using stated preference data can be further developed based on the works presented by Amey (2010), Deakin et al. (2010), and Al-Ayyash et al. (2015). Additional factors which may need to be included in such models are comfort, service availability, and reliability. In addition, the demand model needs to reflect the probabilistic nature of the decision to switch to the shared taxi service.

6.3.2. Future Research for the Service Design Module

The service design module is the most challenging component of the framework. This research presented a fast heuristic algorithm that achieves higher matching opportunities than the previous methods identified in the literature. Despite this important contribution to the service design module, additional work is identified here for future research including:

- A new method combining both PCT and MDT trees as a single solution may be investigated
- Developing additional steps in the proposed ride matching algorithm for problems with dynamic ridesharing (new or canceled requests in real time)
- This research is focused on the evaluation of shared taxi (all users are passengers) and can be modified to be used for the classical carpool problem (matching drivers with passengers)
- Expanding the many-to-one ride matching algorithm to many-to-few for consideration of more than a single destination node (e.g. large campus with multiple gates or when considering ridesharing for multiple organizations within close proximity)
- Improving travel time calculations by considering more accurate average speed on each road segment and its time-of-day variability (different peak and off-peak hours), in addition to the consideration of the delay at intersections
- Development of an advanced dispatching optimization algorithm
- Additional research is needed for the "technological enablers" component and the associated impact on the demand, the service design, and the system cost.

6.3.3. Future Research for the Feasibility Module

The feasibility module can be expanded to include a more sophisticated cost-benefit financial model and a broader impact assessment. Consideration of long term impact of the ridesharing service may include changes in car ownership of the users and their preference for home locations. Future research may also investigate additional policy scenarios that reflect the interests of various stakeholders.

REFERENCES

Agatz, N.A.H., A.L. Erera, M.W.P. Savelsbergh, and X. Wang, (2011), "Dynamic Ride-Sharing: A Simulation Study in Metro Atlanta", Transportation Research Part B, Vol. 45, pp. 1450-1464.

Agatz, N., A. Erera, M. Savelsbergh, and X. Wang, (2012), "Optimization for Dynamic Ride-Sharing: A Review", European Journal of Operational Research, Vol. 223, Issue 2, pp. 295-303.

Al-Ayyash, Z., M. Abou-Zeid, and I. Kaysi, (2015), "Forecasting Students' Demand for a Shared-Ride Taxi Service Using an Integrated Choice and Latent Variable Model", Submitted for presentation and publication at the 94th Annual Meeting of the Transportation Research Board, Washington, DC.

Allo Taxi, (2014), Allo Transport SAL, website: http://www.allotaxi.com/.

Amey, A., (2010), *Real Time Ridesharing: Exploring the Opportunities and Challenges of Designing a Technology-Based Rideshare Trial for the MIT Community*, Master's Thesis, Massachusetts Institute of Technology.

Amey, A., J. Attanucci, and R. Mishalani, (2011), "Real time Ridesharing: Opportunities and Challenges in Using Mobile Phone Technology to Improve Rideshare Services", Transportation Research Board Transit 2011, Vol. 2, pp 103-110.

Araque, J.R., L.A. Hall, and T.L. Magnanti, (1990), Capacitated Trees, Capacitated Routing, and Associated Polyhedra, discussion paper, *Center for Operations Research and Econometrics*, Catholic University of Louvain, Belgium.

Aoun, A., M. Abou-Zeid, I. Kaysi, and C. Myntti, (2013), Reducing Parking Demand and Traffic Congestion at the American University of Beirut, *Transport Policy*, Vol 25, pp. 52-60.

AUB Neighborhood Initiative Research, (2007), The Student Commuting Survey, Web Publication, http://www.aub.edu.lb/ni/research/Pages/commuting.aspx.

Bonsall, P., (1981), "Car Sharing in the United Kingdom", *Journal of Transport Economics and Policy*, Vol. 15, No. 1, pp. 35-44.

Buliung N., K. Soltys, C. Habel and R. Lanyon, (2009), Driving Factors Behind Successful Carpool Formation and Use, Journal Transportation Research Record: Journal of the Transportation Research Board, No. 2118, pp. 31-38.

Chan, N. and S. Shaheen, (2012), Ridesharing in North America: Past, Present, and Future, *Transport Reviews*, Vol. 32, No. 1, pp. 93-112.

Christofides, N., S. Mingozzi, and P. Toth, (1981), Exact Algorithms for the Vehicle Routing Problem Based on Spanning Tree and Shortest Path Relaxations, *Mathematical Programming*, Vol. 20, pp. 255-282.

Caulfield, B., (2009), "Estimating the Environmental Benefits of Ride-Sharing: A Case Study of Dublin", *Transportation Research Part D*, Vol. 14, pp. 527-531.

Chevrier, R., A. Liefooghe, L. Jourdan, and C. Dhaenens, (2012), "Solving a Dial-a-Ride Problem with a Hybrid Evolutionary Multi-Objective Approach: Application to Demand Responsive Transport", Applied Soft Computing, Vol. 12, pp. 1247-1258.

Ciari, F., and K.W. Axhausen, (2012), "Choosing Carpooling or Carsharing as a Mode: Swiss Stated Choice Experiments", Transportation Research Board Annual Meeting, Washington, D.C.

Comsis Corporation (1993), Implementing Effective Travel Demand Management Measures: Inventory of Measures and Synthesis of Experience, USDOT and Institute of Transportation Engineer

Dantzig, G. B., and J.H. Ramser, (1959), The Truck Dispatching Problem, Management Science, Vol. 6, No. 1, pp. 80–91.

Deakin, E., K.T. Frick, and K.M. Shively, (2010), Markets for Dynamic Ridesharing, The Case of Berkeley, Transportation Research Record: Journal of the Transportation Research Board, No. 2187, pp. 131–137, Transportation Research Board of the National Academies, Washington, D.C.

Desrosiers, J., Y. Dumas, M.M. Solomon, and F. Soumis, (1995), Time Constrained Routing and Scheduling, In: Ball M, Magnanti T, Monma C, Nemhauser GL, editors. Network Routing. Amsterdam, The Netherlands: Elsevier Science Publishers B.V. (North-Holland); vol. 8 Handbooks in operations research and management science. pp. 35-139.

Di Febbraro, A., N. Sacco, and M. Saeednia, (2012), "One-way Car-Sharing: Solving the Relocation Problem", Transportation Research Board Annual Meeting, Washington, D.C.

Enoch, M., S. Potter, G. Parkhurst, and M. Smith, (2006), “Why Do Demand Responsive Transport Systems Fail?”, 85th Annual Meeting of the Transportation Research Board, Washington, D.C.

Evans, J. E. and R.H. Pratt, (2005), Transportation Research Board of the National Academies, “Vanpools and Buspools: Traveler Response to Transportation System Changes”, TCRP Report 95, Transit Cooperative Research Program, Washington D.C.

Ferguson, E., (1997), “The Rise and Fall of the American Carpool: 1970-1990”, *Transportation*, Vol. 24, No. 4, pp. 349-376.

Fisher, M.L. and R. Jaikumar, (1978), A Decomposition Algorithm for Large-Scale Vehicle Routing, Working Paper 78-11-05, Department of Decision Sciences, University of Pennsylvania.

Homberger, J. and H. Gehring (2005), A two-phase hybrid Metaheuristic for the Vehicle Routing Problem with Time Windows, *European Journal of Operational Research*, Vol. 162, pp. 220–238.

Huang, H, and S. Gao, (2012) Optimal paths in dynamic networks with dependent random link travel times, *Transportation Research Part B: Methodological*, Vol. 46, No.5.

IBI Group, (2000), *Ridership Analysis Report,* Beirut Suburban Mass Transit Corridor Feasibility Study, Beirut, Lebanon.

iTrans (2007), Vanpool Program Feasibility Study Final Report, prepared for Smart Commute Association, Centre for Sustainable Community Development (www.sustainablecommunities.fcm.ca)

Jozefowiez, N., F. Semet, and E.G. Talbi (2008), From Single-Objective to Multi-Objective Vehicle Routing Problems: Motivations, Case Studies, and Methods, The Vehicle Routing Problem: Latest Advances and New Challenges, Operations Research/Computer Science Interfaces, Vol. 43, pp. 445-471.

Kaysi, I., B. Younan, and A. Bassam, (2007), “Jitney Operations in City Traffic: Observations and Analysis for a Congested Developing City”, in *Proceedings of the 11th World Conference on Transport Research,* Berkeley, California.

Khattab, M., M. Abou-Zeid, and I. Kaysi, (2012), Neighborhood Initiative Congestion Studies: Analysis of 2010 AUB Student and Employee Travel Surveys, American University of Beirut, Final Report.

Kocur, G. and C. Hendrickson, (1983), “A Model to Assess Cost and Fuel Savings from Ride Sharing”, Transportation Research Part B, Vol. 17, No. 4, pp. 305-318.

Laporte, G., and Nobert, Y. (1987), "Exact algorithms for the vehicle routing problem", in: S. Martello, G. Laporte, M. Minoux and C. Ribeiro (eds.), Surveys in Combinatorial Optimization, North-Holland, Amsterdam, 147-184.

LCC, (2014), Lebanese Commuting Company SAL, website: http://www.lccworld.com/

Perugia, A., L. Moccia, J.F. Cordeau, and G. Laporte, (2011), Designing a Home-to-Work Bus Service in a Metropolitan Area, Transportation Research Part B, Vol. 45, pp. 1710-1726.

Raubal, M., S. Winter, S. Teβmann, and C. Gaisbauer, “Time Geography for Ad-hoc Shared-ride Trip Planning in Mobile Geosensor Networks”, ISPRS Journal of Photogrammetry & Remote Sensing, Vol. 62, pp. 366-381, 2007.

Sarraino, J., “Spatial Analysis of Commuting Patterns at the University of Toronto's St George Campus: Identifying Ridesharing and Public Transportation Potential”, University of Toronto Sustainability Office, University of Toronto, 2008.

Shaheen, S., A. Cohen, and M. Chung, “North American Carsharing: 10-Year Retrospective”, Transportation Research Record No. 2110, Transportation Research Board of the National Academies, pp. 35-44, 2009.

Stasko, T.H., A.B. Buck, and H.O. Gao, “Impacts of Carsharing in a University Setting: Changes in Vehicle Ownership, Parking Demand, and Mobility in Ithaca”, NY, Transportation Research Board Annual Meeting, Washington, D.C., 2012.

Solomon, M.M., (1987), Algorithms for the Vehicle Routing and Scheduling with Time Windows Constraints, Operations Research, Vol. 35, pp. 45-65.

Tao, C.C. and C.Y. Chen, (2007), Heuristic Algorithms for the Dynamic Taxipooling Problem Based on Intelligent Transportation System Technologies, Fourth International Conference on Fuzzy Systems and Knowledge Discovery, Haikou.

Team International, (1999), *Beirut Urban Transport Project, Preparation Study*, Beirut, Lebanon, Volume 1, Main Report.

Tsao, H. J., and D.J. Lin, (1999), "Spatial and Temporal Factors in Estimating the Potential of Ridesharing for Demand Reduction", Institute of Transportation Studies, UC Berkeley.

US Census Bureau (2004), "Commuting Characteristics by Sex. 2004 American Community Survey 1-Year Estimates", (Washington, DC: US Census Bureau).

US Census Bureau (2005), "Commuting Characteristics by Sex. 2005 American Community Survey 1-Year Estimates", (Washington, DC: US Census Bureau).

Yan, S., C.Y. Chen, and C.C. Wu, (2012), "Solution Methods for the Taxi Pooling Problem", Transportation, Vol. 39, Issue 3, pp. 723-748.