ABSTRACT

Title of Document: TOOLS TO SUPPORT TRANSPORTATION EMISSIONS REDUCTION EFFORTS: A MULTIFACETED APPROACH

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The transportation sector is a significant contributor to current global climatic problems, one of the most prominent problems that today's society faces. In this dissertation, three complementary problems are addressed to support emissions reduction efforts by providing tools to help reduce demand for fossil fuels. The first problem addresses alternative fuel vehicle (AFV) fleet operations considering limited infrastructure availability and vehicle characteristics that contribute to emission reduction efforts by: supporting alternative fuel use and reducing carbon-intensive freight activity. A Green Vehicle Routing Problem (G-VRP) is formulated and techniques are proposed for its solution. These techniques will aid organizations with AFV fleets in overcoming difficulties that exist as a result of limited refueling infrastructure and will allow companies considering conversion to a fleet of AFVs to understand the potential impact of their decision on daily operations and costs. The second problem is aimed at supporting SOV commute trip reduction efforts through alternative transportation options. This problem contributes to emission reduction efforts by supporting reduction of carbon-intensive travel activity. Following a descriptive analysis of commuter survey data obtained from the University of Maryland, College Park campus, ordered-response models were developed to investigate the market for vanpooling. The model results show that demand for vanpooling in the role of passenger and driver have differences and the factors affecting these demands are not necessarily the same. Factors considered include: status, willingness-to-pay, distance, residential location, commuting habits, demographics and service characteristics. The third problem focuses on providing essential input data, origin-destination (OD) demand, for analysis of various strategies, to address emission reduction by helping to improve system efficiency and reducing carbon-intensive travel activity. A two-stage subarea OD demand estimation procedure is proposed to construct and update important time-dependent OD demand input for subarea analysis in an effort to overcome the computational limits of Dynamic Traffic Assignment (DTA) methodologies. The proposed method in conjunction with path-based simulation-assignment systems can provide an evolving platform for integrating operational considerations in planning models for effective decision support for agencies that are considering strategies for transportation emissions reduction.

TOOLS TO SUPPORT TRANSPORTATION EMISSIONS REDUCTION EFFORTS:
A MULTIFACETED APPROACH

By

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Chapter 1: Introduction

1.1 Objective and Motivation

There is ample evidence that climate change is the most prominent problem that today's society faces, and the transportation sector is a significant contributor to this problem. In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was founded in an effort to create a global response to the problem, bringing together 194 member countries. Since 1997, the Kyoto Protocol has gathered 190 countries under more legally binding measures with the aim of aiding in reducing national emissions and limiting the rise of global temperatures (UNFCCC, 2010a).

Efforts to mitigate transportation Greenhouse Gas (GHG) emissions and adapt to changing climate have gained increased attention over the last three decades. The transportation sector is the second largest contributor to world GHG emissions. Much of these emissions are produced through the burning of fossil fuels. Among GHGs, carbon dioxide (CO_2) constitutes the largest share of global GHG emissions (76.7% in 2004) and fossil fuel use is responsible for over 56% of the total CO_2 production in the world (UNFCCC, 2010b). The U.S. transportation sector accounts for 5% of global and 29% of national GHG emissions, nearly all of which is from the burning of fossil fuels (97.8% in 2008, (U.S. DOE, 2010)). Fossil fuel consumption not only impacts the environment, but also impacts the economy, security, and quality of life. The U.S. and governments of other industrialized nations recognize that breaking the dependence on foreign oil is necessary for increasing security and economic stability.

Efforts taken in the last two decades have shown that this climate challenge calls for an integrated and multi-faceted approach. Several international (e.g. UNFCCC, Intergovernmental Panel on Climate Change (IPCC), United Nations Environment Programme (UNEP)) and national (e.g. the U.S. Department of Transportation (DOT), the U.S. Environmental Protection Agency (EPA), the U.S. Global Change Research Program (USGCRP), the Federal Highway Administration/American Association of State Highway and Transportation Officials, (FHWA/AASHTO)) organizations have published reports espousing strategies to reduce GHG emissions resulting from the transportation sector's activities. Despite the differences in their classifications or evaluation methods, they all agree that the problem needs to be tackled from several fronts.

A recent report to the U.S. Congress, prepared by the Department of Transportation (DOT) Center for Climate Change and Environmental Forecasting, on the transportation sector's role in climate change identifies four categories of strategies across all modes: (1) introducing low-carbon fuels; (2) increasing vehicle fuel efficiency; (3) improving transportation system efficiency; and (4) reducing carbon-intensive travel activity. The report also suggests strategies, such as aligning transportation planning and infrastructure investments with GHG mitigation objectives, as well as charging for carbon emissions (U.S. DOT, 2010a). Similar strategies are suggested by AASHTO in an effort to help achieve the goal of reducing U.S. GHG emissions by 80% by 2050 from 2005 levels. They suggest a combination of strategies be employed. These strategies target the problem from both supply and demand sides as is required given the complex and interrelated structure of the physical transportation system and the broader socioeconomic system in which it is embedded.

A multi-faceted approach is followed in this dissertation with the aim of supporting GHG emissions reduction efforts both from supply and demand sides. The complex structure of the transportation system and its relations with socio-economics makes developing policies, strategies and analysis methods for transportation problems, including GHG emission reduction efforts, quite challenging. This challenge was described in general terms by Manheim:

"The challenge of transportation system analysis is to intervene, delicately and deliberately, in the complex fabric of a society to use transport effectively, in coordination with other public and private actions, to achieve the goals of that society." (Manheim, 1979).

Some would argue that the societal goals have not changed over the past four decades since Manheim's statement, but with increasing world-wide population and vehicular ownership, the need to achieve these goals, particularly those related to environmental concerns, is now even more urgent. Manheim described what many know term as a systems-based approach to analyzing transportation systems and such a systems-based approach has been suggested by numerous others, including for example works by Lieb (1978) and Sussman (2000). Such approaches advocate for the simultaneous consideration of the many societal goals; that is, for a more holistic approach. Despite agreement in the academic literature that such a holistic approach is necessary, in practice it is often the case that decision-makers focus their actions on myopic objectives, such as building capacity or system maintenance, while neglecting environmental or economic impacts. The increased awareness of the transportation system's impact on the environment, economic activity and land-use calls for a broader perspective that takes into account sustainability of the system. To achieve environmental and economic sustainability goals, there is a need for a change in perspective in transportation analysis, planning and policy-making.

To address this need for a holistic approach to modeling transportation systems both from technological and societal perspectives, new approaches have emerged (Dodder, 2004; Sussman et al., 2005). An example of such approach is CLIOS (Complex Large Integrated Open Systems). CLIOS builds on Manheim's total transportation system definition where the transportation system is described by interrelations among three basic variables: the transportation system (T), the activity system (A), and traffic flows (F) (Figure 1-1.a).

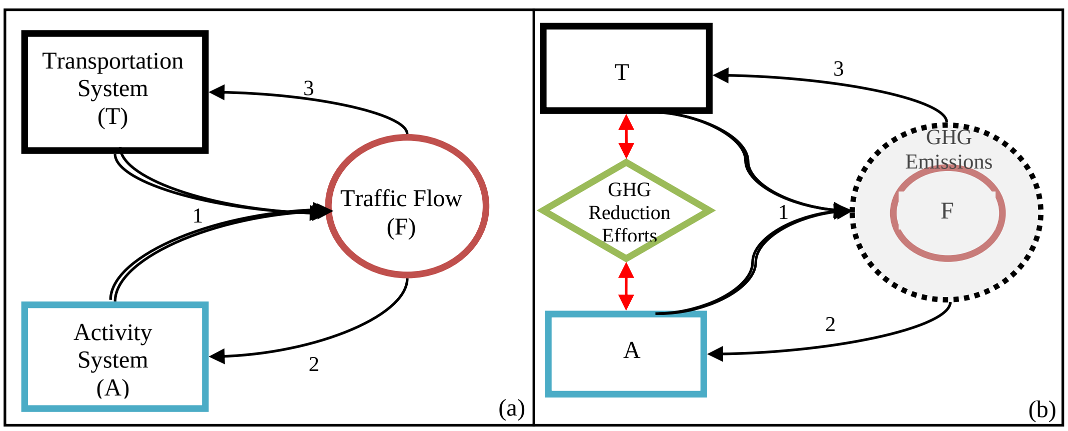


Figure 1-1 (a) Manheim's basic transportation system relations (1979), (b) Transportation system and GHG emissions reduction efforts

One can consider the role of GHG emissions reduction efforts in the context of Manheim's systems framework (Figure 1-1.b). Current traffic flows and resulting GHG emissions are determined by both T and A (relation 1). Changes in flow cause changes in A and T over time (relations 2 and 3, respectively). However, the need to reduce GHG emissions requires changes in A and T be deliberately guided so as to achieve GHG mitigation goals. A combination of policy, technology and behavioral changes are needed to achieve this. GHG emissions mitigation strategies, such as those stated in the U.S. DOT Report (2010a), aim to have this impact. In addition, there is need to trace existing flow patterns, their GHG emissions productions (GHG emission inventories), and changes in traffic flow with corresponding emissions as a result of planned (or implemented) strategies so as to measure the impact of improvements.

The characteristics of T and A are the main factors in GHG emission problems encountered at any scale, from institutional to global levels. For instance, as a result of increased economic activity and existing transportation infrastructure, 75% of the freight tonnage in 2007 was carried by trucks, while rail carried 12 and marine 4%, respectively (ICF, 2008). Trucks were responsible for 19.2% of U.S. GHG emissions, while rail and marine transportation were for 2.8 and 2.3%, respectively, in 2006 (U.S. DOT, 2010a). Despite the fact that rail is typically the least energy-intensive freight mode, due to the limited rail infrastructure and service characteristics, trucking has been the main mode of freight transportation. Similarly, at a local level, for example in a metropolitan area, GHG emissions are a function of interactions between existing transportation systems and person and goods movements. The choice as to how these movements are made is key for the amount of GHG emissions produced. These choices vary from individual decisions taken with respect to departure time, route, mode, residential and work related choices to governmental decisions associated with policies, strategies and services. These decisions ultimately determine the flows on the roads carried by different modes. For example, single occupancy vehicles (SOV) have been the dominant mode of passenger transportation, and are the largest contributor of U.S. GHG emissions, producing nearly 59% of U.S. transportation GHG emissions in 2008 (U.S. DOT, 2010a). Therefore, GHG reduction efforts targeting either freight or passenger transportation need to focus not only on increasing vehicle fuel efficiency and fuel standards to reduce carbon intensity, but also on infrastructure and behavioral changes that can encourage shifts to more energy efficient modes.

GHG emission reduction efforts need to include supply- (T) and demand-side (A) changes. From the supply-side, services and infrastructure for energy efficient modes, both for freight and passenger movements, are needed, as is development of vehicles that are powered by low carbon (e.g. biodiesel, ethanol, natural gas) or zero carbon (e.g. electric and hydrogen) fuels. From the demand-side, reducing demand for transportation itself with mixed-use development, careful land-use planning and pricing carbon can be long-term strategies. At the same time, reducing or shifting demand for carbon-intensive transportation modes to energy efficient, environmentally-responsible modes, such as transit, vanpools, carpools and non-motorized transportation for passenger travel and rail or marine for freight transportation are short- to medium-term strategies.

As indicated in (U.S. DOT, 2010a), no single transportation technology, strategy or policy will be adequate to provide the level of reduction needed. The consensus is that a combination of technologies, strategies and policy actions will need to be employed to engender the level of reduction in GHG emissions that is required.

This dissertation has three main objectives that if attained will contribute to efforts to mitigate GHG emissions resulting from various transportation activities:

(1) **Support AFV fleet operations under current refueling infrastructure and vehicle/fuel availability.** Develop techniques to support companies or agencies that

employ a fleet of vehicles to serve customers or other entities located over a wide geographical region in their decision to transition to alternative fuel use. These techniques will plan for refueling and incorporate stops at AFSs so as to eliminate the risk of running out of fuel while maintaining low cost routes.

(2) **Support large employers in their efforts to reduce SOV commute trips by providing vanpooling services.** Develop econometric models to analyze potential for vanpooling to help cities and large employers, such as universities and government agencies, in their efforts to reduce their GHG emissions through providing alternative transportation options. These models will represent commuter's attitudes towards vanpooling based on commuter survey data. Using data from a commuter survey conducted at the University of Maryland (UMD), an econometric analysis will be performed to better understand interest in vanpooling in the passenger and driver roles. The analysis will be conducted using ordered-response models.

(3) **Support development and analysis of GHG emissions reduction strategies for a selected subarea by providing essential OD trip demand data.** Develop a subarea OD demand estimation procedure to be used in conjunction with network analysis tools to allow consideration and rapid evaluation of a large number of scenarios and to support transportation network planning and operational decisions for GHG emission reduction efforts. The subarea OD demand estimation procedure will support Metropolitan Planning Organizations (MPOs) and other agencies in developing and evaluating strategies that may not require analysis on a complete network representation, but require capturing the vehicular response to traffic conditions resulting from network and operational changes in a subarea.

To achieve these objectives, the dissertation addresses three complementary problems. These problems share the common goal of supporting GHG emissions reduction efforts by providing tools to help reduce demand for fossil fuel through seemingly different, but synergistically related ways. The first problem addresses alternative fuel vehicle (AFV) fleet operations considering limited infrastructure availability and vehicle characteristics, such as vehicle driving range. This problem contributes to GHG emission reduction efforts in two ways: supporting alternative fuel use and reducing carbon-intensive freight activity. The second problem supports single occupancy vehicle trip reduction efforts, targeting commute trips through alternative transportation options. This problem contributes to GHG reduction efforts by supporting reduction of carbon-intensive travel activity. The third problem helps to provide essential input data, origin-destination (OD) demand data, for analysis of various GHG emission reduction strategies. This problem contributes to GHG emission reduction efforts by helping to improve system efficiency and reducing carbon-intensive travel activity.

This dissertation has the following objectives:

1.2 Specific Problems Addressed and Contributions

The three problem classes addressed tackle GHG emission problem from multiple perspectives. They all aim to answer the question “what can be done today/near term to reduce emissions from passenger and goods movements?” and share the common goal of reducing fossil fuel use through existing transportation infrastructure and technology.

1.2.1 Emission Reduction Through Commercial Fleet Operations: The Green Vehicle Routing Problem (G-VRP)

Municipalities, government agencies, nonprofit organizations and private companies are converting their fleets of trucks to include Alternative Fuel Vehicles (AFVs). Some organizations invest in such conversions, because they wish to reduce their environmental impact, while others seek to meet new environmental regulations. However, the lack of a national infrastructure for refueling AFVs in conjunction with limited driving ranges associated with the vehicles present significant challenges to alternative fuel technology adoption by companies and agencies seeking to transition from traditional gasoline-powered vehicle fleets to AFV fleets. The G-VRP is proposed to aid organizations with alternative fuel-powered vehicle fleets in tackling these challenges.

In this dissertation, techniques are developed to aid an organization with an AFV fleet in overcoming difficulties that exist as a result of limited refueling infrastructure. These techniques plan for refueling and incorporate stops at AFSs so as to eliminate the risk of running out of fuel while maintaining low cost routes. The G-VRP is formulated as a mixed-integer linear program (MILP). Given a complete graph consisting of vertices representing customer locations, AFSs, and a depot, the G-VRP seeks a set of vehicle tours with minimum distance each of which starts at the depot, visits a set of customers within a pre-specified time limit, and returns to the depot without exceeding the vehicle's driving range that depends on fuel tank capacity. Each tour may include a stop at one or more AFSs to allow the vehicle to refuel en route. As the G-VRP is computationally intractable, two specialized heuristics are proposed. Numerical experiments were conducted to assess heuristic performance as a function of customer location configuration, and station density and distribution. These techniques were also applied on a large, realistic problem instance to illustrate their utility in real-world operations and to explore the impact of alternative fuel vehicle adoption on vehicle tours and needed fleet size.

1.2.2 Emission Reduction Through Reducing SOV Commute-Trips: Modeling Propensity to Vanpool

Decades of highway and automobile oriented development, along with subsidized oil and automobile industries, in the U.S. have created today's automobile-dependent lifestyle. The transportation sector faces particular challenges in GHG mitigation efforts as a consequence of the limitations that rigid transportation infrastructure, a spread out built environment and the resulting travel behavior induced by such a structure. Therefore, transportation demand management (TDM) has become one of the primary policy objectives for GHG reduction efforts since the early 1990s, with the recognition of global warming as a real danger. The focus of this problem is light-duty vehicles, because automobiles and light-duty trucks (e.g. sport utility vehicles, 2-axle trucks, and minivans) are the largest contributors of GHG emissions, responsible for 58.7% of total U.S. transportation GHG emissions in 2006 (U.S. DOT, 2010a). Moreover, the highest share of vehicle miles traveled (VMT) by purpose was for to/from work trips with a 27.5% share and an average occupancy of 1.2 person per VMT in 2009 (U.S. DOE, 2010a). Despite all the trip reduction efforts through alternative transportation options, such as transit and ridesharing, transit's share of VMT has reduced from 0.4% to 0.2% since 1970 (U.S. DOE, 2010a).

This dissertation contributes to efforts to reduce single occupancy vehicle trips by providing insight related to demand for vanpooling. Companies, agencies and institutions that wish to reduce their GHG emissions will need to consider a portfolio of alternative transportation options, vanpooling among them. In this dissertation, two ordered-response models, a passenger and a driver model, are estimated to understand factors affecting decision to carpool/vanpool and their impact on this decision. These models are estimated with ordered logit and probit models. The models applied on data obtained from the commuter survey conducted at UMD, followed a descriptive analysis of the data. The results showed that the common determinants thought to be affecting carpooling/vanpooling behavior were not necessarily valid in a University setting. The analysis revealed that calibrating two models to study the interest in being a passenger or a driver is a valid approach, as the results indicated that the factors affecting them and their impacts are different. The method can be adopted by other higher education institutions as well as by large-scale employers, cities or metropolitan areas when developing alternative transportation programs. The results provide insight about the potential user characteristics of the service; thus, provide information on the type of service that would yield higher participation. In addition, the econometric method presented in this dissertation helps identify the target groups for marketing purposes.

1.2.3 Emission Reduction Through Transportation System Operations: A Dynamic Subarea OD Trip Demand Estimation Method

The U.S. State Department of Transportation's (DOTs) and metropolitan planning agencies (MPOs) have been developing policies and regulations for GHG emissions reduction. Typically driven by legislation, these agencies are required to demonstrate progress in stabilizing and reducing GHG emissions in their transportation plans. As such, many DOTs and MPOs are in the process of, or are considering, incorporating climate change into their planning processes and are developing strategies for GHG emissions reduction. These requirements introduce many challenges. One such challenge is estimating the potential impact of emissions reduction strategies such as pricing, HOV/HOT lanes, carpooling and vanpooling, from a particular region or sub-region.

In this dissertation, a subarea analysis capability is developed in conjunction with dynamic network analysis models to allow consideration and rapid evaluation of a large number of scenarios and to support transportation network planning and operational decisions for GHG emission reduction efforts. The developed technique has wide applicability, but is described in the context of a meso-scopic simulation tool to be used in conjunction with dynamic network analysis models. Specifically, a two-stage subarea demand estimation procedure is developed. The first stage uses path-based traffic assignment results from the original network to generate an induced OD demand matrix for the subarea network. The second stage incorporates an iterative bi-level subarea OD updating procedure to find a consistent network flow pattern by utilizing the induced OD demand information and archived traffic measurements in the subarea network. An excess-demand traffic assignment formulation is adopted to model the external trips that traverse or bypass the subarea network. This formulation allows vehicular flow to respond to traffic conditions resulting from network and operational changes in the subarea and it can be interpreted in an entropy maximization framework. The resulting OD demand provides essential data for agencies and organizations to design, evaluate and analyze various GHG mitigation strategies for their region.

1.3 Dissertation Organization

The remainder of this dissertation is organized in five chapters. Chapter 2 presents background on transportation emissions, alternative fuels and reduction efforts through alternative fuel use, demand management strategies and improving system efficiency. In Chapter 3, a vehicle routing problem is defined and solution techniques are proposed to aid existing AFV fleet owners or organizations that are planning to switch to AFV fleets in overcoming difficulties that exist as a result of limited refueling infrastructure. Chapter 4, using econometric models, analyzes interest in vanpooling and factors that influence decisions to undertake vanpooling. Chapter 5 focuses on a network modeling tool that facilitates consideration and rapid evaluation of a large number of scenarios in a subarea, a capability that is needed for evaluation and implementation of transportation network planning and operations decisions for GHG emission reduction efforts. Finally, conclusions and extensions are presented in Chapter 6.

Chapter 2: Literature Review

As discussed in Chapter 1, the transportation sector plays a significant role in emissions production, particularly GHG production. Much of these emissions are the result of increased socio-economic activity at both national and global levels. This activity in the socio-economic system puts a high demand on energy required for both passenger and freight transportation. Fossil fuels account for 97% of U.S. transportation use (U.S. DOE, 2010a). To explain the relation between fossil fuel use in transportation and its impacts on air quality and global warming, Section 2.1 provides an overview of transportation emissions and their sources. A comparison of alternative fuels and fossil fuels are also made in regard to emission production. In Section 2.2, an overview of current emission reduction approaches is presented. These approaches are presented from technology and policy perspectives. In Section 2.3, three categories of strategies, namely alternative fuel and vehicle technologies, carbon-intensive travel activity reduction and transportation system efficiency improvements, are considered. Selected strategies are reviewed.

2.1. Overview of Transportation Emissions

This section provides an overview about the various types of emissions resulting from the transportation sector's activities and their impact on health and environment. These impacts are discussed both for light-duty and heavy-duty vehicles. Emissions are typically grouped into three categories: criteria pollutants, greenhouse gases (GHG) and mobile source air toxics (MSAT). It should be noted that while the impact of PM and MSAT are at local level, GHG's impacts are at a global level, making them the primary target of air quality improvement and climate change efforts.

2.1.1 Criteria Pollutants

Criteria pollutants include ground-level ozone (O_3), carbon monoxide (CO), sulfur oxides (SO_x), particulate matter (PM-x, where x represents the size of the particles and typically grouped into two; PM-2.5 for particles smaller than 2.5 microns in diameter and PM-10 for larger particles up to 10 microns in diameter), nitrogen oxides (NO_x), and lead (Pb). They are harmful to health, the environment and even property. The U.S. EPA is required to set National Ambient Air Quality Standards to these six commonly known criteria pollutions to comply with the Clean Air Act (U.S. EPA, 2011a). These pollutants and their major sources are listed in Table 2-1. As seen in Table 2-1, the primary source of these pollutants is fossil fuel use. They are either produced as a result of incomplete combustion of fuel (e.g. CO and PM-x), are included in the fuel itself (e.g. Pb and SO_2), or occur as a result of reaction with oxygen in the air (e.g. O_3 results from a reaction of NO_x, volatile organic compounds (VOC) and sunlight). Among these, lead from transportation is no longer a problem in developed countries where unleaded gasoline is used. However, transportation sector's share in major criteria pollutants, especially through highway modes, has been significant. For example, 50% of CO comes from highway vehicles where the transportation sector's share is 73.2%. Similarly, more than half of VOC and NO_x from transportation are produced by highway vehicles (i.e. 37.7% of O_3 and 57.9% of NO_x). The distribution of these pollutants between light-duty and heavy-duty vehicles is also given in Table 2-1. Gasoline powered light-duty vehicles are responsible for the majority of CO (94.1%) and VOC (91.7%), as well as half of NO_x emissions. Diesel powered heavy-duty vehicles on the other hand are responsible for most of the PM (61.7% of PM-2.5 and 50.3% of PM-10) and NO_x (44%) emissions.

Table 2-1 Criteria pollutants, their sources and distribution between light and heavy duty vehicles

Criteria Pollutants	Source[(a)]	Transportation share[(b)] (2008) (%)	Highway vehicles' share [(c)] (2008) (%)	Light-duty vehicle[(d)] (gasoline /diesel powered) [(e)] (2005) (%)	Heavy-duty vehicle (gasoline /diesel powered) [(f)] (2005) (%)
Carbon monoxide (CO)	Incomplete combustion of fuel	73.2	50	94.1/0.0	4.1/1.8
Nitrogen dioxides (NO_x)	Combustion of fuel at high temperatures	57.9	31.9	49.9/0.2	5.9/44.0
Ground-level Ozone (O_3)	Formed from a reaction between NO_x and VOC under sunlight	37.7	21.5	91.7/0.1	4.2/3.9
Particulate matter(PM-x)	Incomplete combustion of fuel	0.2 (PM-2.5) 3.2 (PM-10)	0.1 1.2	32.1/1.6 44.2/1.0	4.7/61.7 4.4/50.3
Sulfur Dioxide(SO_2)	Fuel	4.5	0.6	NA	NA
Lead (Pb)	Fuel	NA	NA	NA	NA

[(a)] Data is adapted from U.S. EPA (U.S. EPA, 2011a) and Freight and Air Quality Handbook, (U.S. DOT, 2010b)

[(b) (c) (e) (f)] Data is drawn from Tables 12.1 through 12.11 of U.S. DOE, Transportation Energy Data Book, Edition 29 (U.S. DOE, 2010a).

[(d)] Light-duty vehicles include light vehicles, motorcycles and light trucks (less than 8,500 pounds) (U.S. DOE, 2010a).

These pollutants, especially O_3, PM-x and CO have a wide range of negative impacts on health ranging from respiratory diseases to cardiovascular diseases. Thus, they are controlled under the Clean Air Act (U.S.DOT, 2006). In addition, for example, O_3 harms vegetation and impacts forests and ecosystems while PM-x causes damage to materials and reduces visibility.

2.1.2 Greenhouse Gases (GHGs)

Greenhouse gases are atmospheric gases that trap the solar energy within the earth's atmosphere. These gases collectively create greenhouse effect, which is a natural and essential phenomenon to keep earth’s average temperature at levels making life on earth possible. Without this effect, the average temperature on earth would be reduced by 60ºF (U.S. EPA, 2011b). The primary GHGs are water vapor, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases (e.g. chlorofluorocarbons (CFCs), hydrochlorofluorocarbons (HCFCs)). Some of these gases, such as CO_2, N_2O, CH_4 and fluorinated gases, occur naturally and are emitted to the atmosphere through natural processes and human activities. While certain gases such as chlorofluorocarbons (CFCs), hydrochlorofluorocarbons (HCFCs), and sulfur hexafluoride (SF_6) are exclusively produced by human activities.

The primary GHGs that are produced through transportation sector activities are carbon-dioxide (CO_2), methane (CH_4), nitrous oxides (NO_x), sulfur oxides (SO_2) and hydroflourocarbons (HFCs). CO_2 is responsible for the largest share (Table 2.2). Even though CO_2 is constantly sequestered by plants as part of the biological carbon cycle, due to increased economic and social activity, its production rate exceeds what the natural cycle can absorb. Despite the natural sequestration, U.S. CO_2 concentrations in the atmosphere increased approximately 37.5% since pre-industrial era (U.S. EPA, 2011c) and projected to increase 28% from 2010 to 2050 (Greene and Plotkin, 2011).

Since the Industrial Revolution, deforestation has increased to support urban development and agricultural needs, and fossil fuel use has increased to support transportation needs. This led to accumulation of GHGs, especially CO_2, to threatening levels (e.g. annual CO_2 emissions increased by 80% between 1970 and 2004 globally), causing global warming and associated climate change problems (IPCC, 2007). The global nature of GHGs has also made them the primary concern of emission reduction efforts, because unlike criteria pollutants and MSATs, GHGs can remain in the atmosphere for extended periods (e.g. 50 to 200 years for CO_2) (U.S. DOT, 2010a).

Table 2-2 Transportation sector's share in primary GHGs in the U.S. in 2008

GHGs	Source [a]	Transportation share [b] (%)*	Highway vehicles[c] (%)*	Light-duty Vehicles [d] [e] (%)*	Heavy-duty Vehicles [f] (%)*
Carbon dioxide (CO_2)	Combustion of fossil fuel, diesel, biofuel	33.2	84.55	62.2	22.36
Methane (CH_4)	Burning of fossil fuels, livestock, agricultural practices, and decay of organic material	0.62	80	75	5
Nitrous Oxides (NO_x)	Oxides of nitrogen (forms when nitrogen in the air or fuel combines with oxygen at high temperatures	16.2	85.44	82.0	3.45
Hydroflourocarbons (HFC)	Human activities such as burning of fossil fuel, and natural processes	51.6	NA	NA	NA

[a] Data is adapted from U.S. EPA (U.S. EPA, 2011a) and Freight and Air Quality Handbook, (U.S. DOT, 2010b)

[b] [c] [d] [e] [f] Data is drawn from Tables 11.4, 11.5 and 11.7 of U.S. DOE, Transportation Energy Data Book, Edition 29 (U.S. DOE, 2010a).

[d] Light-duty vehicles include light vehicles, motorcycles and light trucks (less than 8,500 pounds) (U.S. DOE, 2010a).

* Percentages are calculated based on values measures in million metric tonnes of CO_2 equivalent (CO_2-e).

As seen in Table 2-2, the transportation sector produced more than half of hydroflourocarbons (51.6%) and approximately one-third of U.S. CO_2 in 2008. Moreover, the majority of these GHGs come from highway vehicles (84.5% of CO_2, 80% of CH_4, 85.4% of NO_x).While light-duty vehicles produce most of CO_2, CH_4 and NO_x (62.2% , 75% and 85.44% respectively), heavy-duty vehicles also had a high share of CO_2 with

22.36% in 2008. The contribution of heavy-duty vehicles to CH_4 and NO_x emissions are less than 5%.

2.1.3. Mobile Source Air Toxics (MSATs)

MSATs include benzene and other hydrocarbons such as 1,3-butadiene, formaldehyde, acetaldehyde, acrolein, and naphthalene (U.S. EPA, 2007). They are emitted by highway vehicles as well as non-road equipment. Both light- and heavy-duty vehicles emit these toxics through the use of fossil fuel. They are not considered as toxic pollutants and are not regulated by NAAQS (National Ambient Air Quality Standard), but they may cause serious health and environmental problems, including cancer, respiratory diseases and birth defects (U.S.DOT, 2006). Therefore, the EPA issued a rule in order to reduce hazardous air pollutants from mobile sources, limiting the benzene content of gasoline and reducing toxic emissions from passenger vehicles and gasoline containers (U.S. EPA, 2007). The EPA has identified 21 MSAT, including diesel particulate matter, benzene and other organic material and metals among 188 air toxics identified by the CAA (Clean Air Act) (U.S. DOT, 2006).

2.1.4. Emissions From Alternative Fuels

Non-petroleum fuels yield substantial energy security and environmental benefits. These fuels are defined as alternative fuels as given in the Energy Policy Act of 1992. Currently, the U.S. Department of Energy (DOE) recognizes the following as alternative fuels: methanol (M), ethanol (E) , and other alcohols; blends of 85% or more of alcohol with gasoline (e.g. M85, M100, E85, E95); natural gas and liquid fuels domestically produced from natural gas (LNG or CNG); liquefied petroleum gas (propane, LPG); coal-derived liquid fuels; hydrogen (H2) and electricity; biodiesel (e.g. B20); and P-series (U.S. DOE, 2009). P-series fuels are blends of ethanol, methyltetrahydrofuran (MTHF), and pentanes plus, with butane added for blends that would be used in severe cold weather conditions to meet cold start requirements.

Some of these fuels contain petroleum in their blends (e.g. biodiesel and ethanol blends with gasoline) while some others emit harmful gases themselves either during the burning process or the production process (e.g. CNG and LNG). Therefore, they also produce emissions. However, the emissions they produce is significantly less than their gasoline counterparts. Table 2-3 summarizes several characteristics of alternative fuels as compared to gasoline and diesel (No.2), including their sources, energy content, impacts on environment and energy security. According to Table 2-3, only electricity and hydrogen can be zero tail-pipe emission alternatives. However, this statement is true only if their lifecycle effects (emissions that are produced during the production and transportation of the fuel, i.e "well to wheel" emissions) are not considered. Even if lifecycle impacts are considered, alternative fuel use is still beneficial in reducing emissions. For example, lifecycle GHG emissions from various biofuels vary between -10% and 79% of their petroleum counterpart (Figure 2-1).

Table 2-3 Comparison of alternative fuels

	Main Fuel Source	Energy Contained in Various Alternative Fuels as Compared to One Gallon of Gasoline	Environmental impacts	Energy Security impacts
Gasoline	Crude Oil	100%	Produces harmful emissions; however, gasoline and gasoline vehicles are rapidly improving and emissions are being reduced	Manufactured using oil, of which nearly 2/3 is imported.
No. 2 Diesel	Crude Oil	1 gallon of diesel has 113% of the energy of one gallon of gasoline.	Produces harmful emissions; however, diesel and diesel vehicles are rapidly improving and emissions are being reduced especially with after treatment devices.	Manufactured using oil, of which nearly 2/3 is imported.
Biodiesel	Fats and oils from sources such as soy beans, waste cooking oil, animal fats, and rapeseed	B100 has 103% of the energy in one gallon of gasoline or 93% of the energy of one gallon of diesel. B20 has 109% of the energy of one gallon of gasoline or 99% of the energy of one gallon of diesel.	Reduces particulate matter and global warming gas emissions compared to conventional diesel; however, NOx emissions maybe increased.	Biodiesel is domestically produced, renewable.
Compressed Natural Gas(CNG)	Underground reserves	5.66 pounds or 126.67 cu. ft. of CNG has 100% of the energy of one gallon of gasoline.	CNG vehicles can demonstrate a reduction in ozone-forming emissions compared to some conventional fuels; however, HC emissions maybe increased.	CNG is domestically produced. The United States has vast natural gas reserves.

Electricity	Coal, nuclear, natural gas, hydroelectric, and small percentages of wind and solar.	33.70 kWh has 100% of the energy of one gallon of gasoline.	EV s have zero tailpipe emissions; however, some amount of emissions can be contributed to power generation.	Electricity is generated mainly through coal fired power plants. Coal is the United States' most plentiful and price-stable fossil energy resource.
Ethanol	Corn, grains, or agricultural waste (cellulose)	1 gallon of E85 has 77% of the energy of one gallon of gasoline.	E-85 vehicles can demonstrate a 25% reduction in ozone-forming emissions compared to reformulated gasoline.	Ethanol is produced domestically.
Hydrogen	Natural gas, methanol, and electrolysis of water.	1 kg or 2.198 lbs. of H2 has 100% of the energy of one gallon of gasoline.	Zero regulated emissions for fuel cell-powered vehicles, and only NOx emissions possible for internal combustion engines operating on hydrogen.	Hydrogen is produced domestically and can be produced from renewable sources.
Liquefied Natural Gas (LNG)	Underground reserves	1 gallon of LNG has 64% of the energy of one gallon of gasoline.	LNG vehicles can demonstrate a reduction in ozone-forming emissions compared to some conventional fuels; however, HC emissions maybe increased.	LNG is domestically produced.

Liquefied Petroleum Gas (LPG)	A by-product of petroleum refining or natural gas processing	1 gallon of propane has 73% of the energy of one gallon of gasoline.	LPG vehicles can demonstrate a 60% reduction in ozone-forming emissions compared to reformulated gasoline.	Approximately half of the LPG in the U.S. is derived from oil, but no oil is imported specifically for LPG production.
Methanol	Natural gas, coal, or, woody biomass	1 gallon of methanol has 49% of the energy of one gallon of gasoline	M-85 can demonstrate a 40% reduction in ozone-forming emissions compared to reformulated gasoline.	Methanol is domestically produced, sometimes from renewable resources.

Source: Available online at U.S. DOE (2011d), AFDC web site, http://www.afdc.energy.gov/afdc/pdfs/afv_info.pdf . Table details are available at http://www.afdc.energy.gov/afdc/fuels/properties_notes.html.

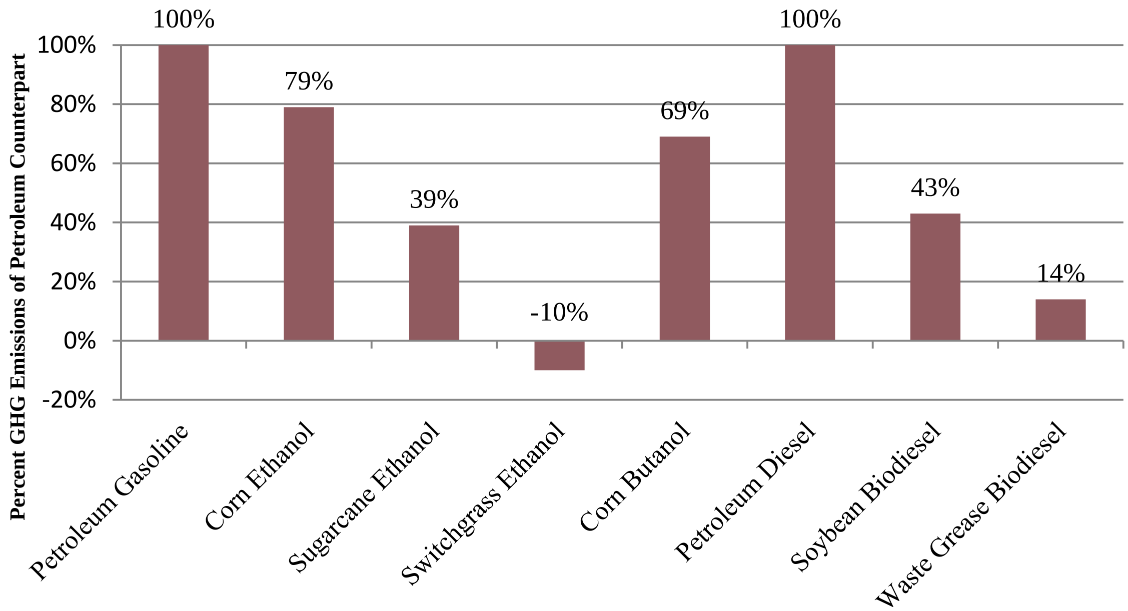


Figure 2-1 Lifecycle GHG Emissions from Biofuels, compared to their petroleum substitutes
Source: Available online at U.S. DOE (2011e), AFDC web site, http://www.afdc.energy.gov/afdc/data/fuels.html .

2.2. Current Trends in Targeting Emissions From Transportation

CO_2 makes up the largest share of global GHG emissions with 76.7% of emissions in 2004. 56.6% of these emissions resulted from fossil fuel use (UNFCCC, 2010b). Overall, the transportation sector's share in GHG emissions is 5% globally and 29% nationally (in the U.S.). Thus, efforts to reduce GHG emissions primarily targeted reducing fossil fuel use. The U.S. is one of the largest petroleum consumers in the world with 24% consumption share globally (Figure 2-2). As seen in Figure 2-2, the U.S. oil production share is much lower than its consumption and its reserves are quite low (2% of world reserves).

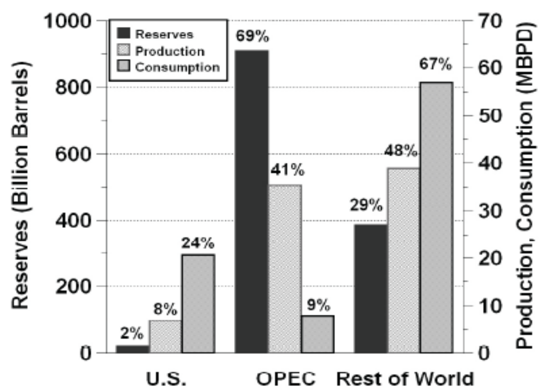


Figure 2- 2 World oil production-consumption 2008, (Transportation Energy Databook, Edition 29, (U.S. DOE, 2010a))

Fossil fuel is a scarce resource. It is inevitable that the world's fossil fuel consumers will need to seek for alternative energy. Dependency on fossil fuel use is problematic for several reasons. There are limited oil reserves and the majority of them are in the Middle East where political instability causes volatility in the oil market. Dependency on oil from this region of the world, thus, affects homeland security. Fossil fuel production and use also negatively impacts the environment, socio-economic systems and health. British Petrol's (BP) oil spill in the summer of 2010 is perhaps the most salient example for the scale of impact that oil production can have on the environment. Similarly, war in Iraq (a member of Organization of Oil Exporting Countries (OPEC)) and recent "unrest", in North African countries, like Libya -an OPEC member as well- have had national economic impact as a consequence of U.S. dependency on foreign oil. Greene and Sanjana (2005) estimated that oil dependence has cost the U.S. economy \$3.6 trillion (constant 2000 dollars). In an earlier work by Greene and Tishchishyna (2000), the cost of oil market upheavals caused by OPEC members between 1970s and 2000 cost the U.S. about \$7 trillion (present value 1998 dollars) in total economic costs. They also stated that major oil price shocks have disrupted world energy markets five times: between 1973-74, 1979-80, 1990-91, 1999-2000, 2008. These concerns for the environment, domestic security and economic stability accelerated recent efforts in developing alternative fuel and vehicle technologies to reduce fossil fuel use. The approaches taken are summarized in section 2.2.1.

Strategies that aim to reduce energy-intensive travel activity have been another approach to reduce fossil fuel use. These strategies aim to reduce highway VMT by reducing the need for travel, increasing vehicle occupancy, shifting travel to more energy efficient modes and improving multi-modal travel opportunities.

2.2.1 Technological Approaches

Alternative fuels and vehicles that are powered by these fuels can play an important role in addressing the challenges of climate change, energy security and air quality. The Energy Policy Act (EPAct) of 2005 includes several requirements for federal and state fleets regarding alternative fuel vehicle (AFV) fleets, alternative fuel use, and GHG emissions reduction. While EPAct requirements do not apply to private fleets, incentives, such as tax credits for purchase of AFVs, alternative fuel infrastructure tax credits, and renewable diesel tax credits, exist to support comparable actions by private companies. Thus, alternative energy and vehicle technology research and development have received significant attention in the U.S. and throughout the world.

Currently, several types of AFVs powered by fuels, such as ethanol, hydrogen, natural gas (liquid or compressed), biodiesel, propane, and electricity, are available. However, their success in the market depends on a number of factors, including vehicle cost and performance and fuel infrastructure availability (see Table 2-3). Adequate refueling availability is one of the most important barriers to successful commercialization[1]. Federal agencies, such as U.S. DOE, EPA and DOT lead and support research and development in both vehicle and fuel technologies to tackle barriers.

2.2.2. Policy Approaches

In 1994, the United Nations Framework Convention on Climate Change (UNFCCC) was founded to curb climate change by addressing the need to reduce GHG emissions (ECMT, 2007). Shortly after the UNFCCC, the Kyoto Protocol brought together over 90 countries under a binding agreement signed by 37 industrialized countries and ratified by 55 nations. The countries signed the protocol, committing to reduce GHG emissions by 5% by 1012 from their 1990 levels. The Framework encourages its participants to

[1] Melaina and Bremson (2008) states that despite 164,300 refueling stations in operation nationwide, from the perspective of refueling availability for AFSs, this nationwide count tends to overstate the number of stations required to support the widespread deployment of AFVs. They characterize a sufficient level of urban coverage and estimate that about 51,000 urban stations would be required to provide this sufficient level of coverage to all major urban areas.

develop market-based mechanisms (like carbon credits), land-use change policies and increase forestry activities (UNFCCC, 2010c). Although the U.S. government has not signed the Kyoto Protocol, it has committed to the UNFCCC. As part of this commitment the U.S. government develops a national emissions inventory annually, recording sources and sinks of emissions from various sectors of the economy in accordance with the guidelines established by the Intergovernmental Panel on Climate Change (IPCC). The U.S. also developed the Copenhagen Change Accord, collaborating with other countries that contribute significantly to global emissions (e.g. China, Brazil, India and South Africa), to initiate global action against climate change. According to the Accord (signed by 138 countries), the U.S. pledges to reduce its emissions levels 17% by 2020 from its 2005 levels (UNFCCC, 2009).

Since the 1970s, the U.S. experienced increased negative impacts on the environment largely resulting from increased travel activity, particularly due to the dominance of SOVs for personal transportation (Meyer, 1999). Federal policies such as congestion mitigation, air quality improvement and transportation system management (TSM) were developed. Recently, GHG emission reduction efforts have also been added to the U.S. federal government agenda. Several governmental organizations, such as the U.S. Department of Transportation (U.S. DOT), the U.S. Environmental Protection Agency (U.S. EPA), the U.S. Global Change Research Program (USGCRP), the Federal Highway Administration/American Association of State Highway and Transportation Officials, (FHWA/AASHTO)), published reports espousing strategies to reduce GHG emissions resulting from the transportation sector's activities.

The U.S. government policy on climate action has several levels. Federal Climate Legislation requires states and Transportation Management Areas/Metropolitan Planning Organizations (TMA/MPO) to develop GHG reduction targets and strategies as part of their transportation plans, to demonstrate progress in stabilizing and reducing GHG emissions. The U.S. EPA has an important role in issuing regulations on transportation GHG goals and standardizing models, methodologies, and data collection. The plans that are developed by states or MPOs are required to develop, submit or publish emission reduction targets and strategies (Mallet, 2010). In addition, the Energy Policy Act of 1992 (EPAct) was passed by the U.S. Congress to reduce dependence on imported petroleum and to increase air quality by requiring certain fleets to acquire alternative fuel vehicles. The U.S. Department of Energy administers the regulations for federal, state and private fleets (U.S. DOE, 2011f).

2.3. Overview of Strategies to Reduce Transportation GHG Emissions

Recognizing the significant role of transportation in climate change, the U.S. government and other developed nations alike has been developing policies, regulations and strategies that target GHG emissions reductions. This section provides a summary of widely used strategies that are also relevant to the problems addressed in this dissertation.

2.3.1. Vehicle and Fuel Technology Improvements

2.2.1.1. Alternative (low carbon) fuels

Several alternative fuel technologies are available that provide cleaner fueling options for both light-and heavy-duty vehicles. Alternative fuel use in freight transportation has been rather challenging. Applying efficiency standards, like those aimed at light-duty vehicles, is not possible because heavy-duty vehicles vary significantly by engine and manufacturer. Therefore, there are no efficiency standards for heavy-duty vehicles as of yet. The fuels that are available for freight transportation are LPG, natural gas, biodiesel, fuel-borne catalyst and low-sulfur and emulsified diesel. All of these fuels have pros and cons in terms of emissions benefits, availability and ease of conversion. LPG reduces NO_x, PM and GHG. Moreover, the fuel distribution network for LPG is ready. Unfortunately, it has lower energy content than gasoline. Natural gas reduces PM and has similar performance to diesel, but requires special fueling facilities. Biodiesel blends reduce PM and CO while slightly increasing NO_x emissions. However, they require engine modifications for blends that are higher than 20%. Fuel-borne catalysts reduce PM, but may increase some particle emissions. Low-sulfur diesel (reduces PM) and emulsified diesel (reduces PM and NO_x) are also readily available and they do not require engine modification; however, they are more expensive than conventional diesel. Also, emulsified diesel contains less energy per gallon than conventional diesel (U.S. DOT, 2010b). There is the hydrogen option also, but it is not currently available for commercial use.

2.2.1.2. Alternative fuel vehicles (AFV)

The energy efficiency standards for fuels and vehicles, if successfully enforced, can achieve significant reductions in emissions from transportation. For this purpose, the National Highway Transportation Safety Administration (NHTSA) and the U.S. EPA work collaboratively to develop a consistent national program that will yield substantial improvements in fuel economy and emissions reductions from light-duty vehicles.

The availability of light-duty alternative fuel vehicles have increased tremendously in recent years. Currently available light-duty alternative fuel vehicles include: hybrid electric vehicles, flexible fuel vehicles, compressed natural gas and propane vehicles, and the recently introduced all-electric vehicles. The fuel availability is still a significant factor affecting wide use of these vehicles, but progress has been made (e.g. stations selling E85 ethanol are increasing, natural gas fueling station numbers are growing and electric charging is becoming a viable option at home and at some other limited locations) (U.S. DOE, 2011a).

Classification of alternative heavy-duty vehicles is difficult because the use of alternative fuels in such vehicles is typically made possible by making modifications in vehicle engines. Possible modifications depend on the vehicle manufacturer. Therefore, most effort is put in engine and equipment improvements. The available options include hybrid-electric vehicles, improved aerodynamics, more efficient tires and reduced vehicle weight. Other vehicle options, such as vehicles powered by natural gas or biodiesel are available through custom production and typically only for testing for research and development purposes. The available engine, chassis and vehicle combinations (U.S. DOE, 2011b) and examples of heavy-duty AFV fleets (U.S. DOE, 2011c) can be seen at U.S. DOE's Alternative Fuels and Advanced Vehicles Data Center.

2.3.2. Efficient Transportation System Operations

2.3.2.1. Pricing

Using pricing to encourage emissions reduction in transportation is perhaps the most efficient strategy. There are several pricing mechanisms to choose from based on consumer and supplier characteristics. The basic idea is to price the marginal damages on the environment caused by emissions. This forms the basis of cap-and trade or carbon tax policies. Similar market-based strategies include carbon pricing (increasing the cost of fossil fuel use), VMT pricing (applied as tax or pay-as-you drive insurance, or a better way from emissions perspective is pay-at-the-pump insurance), fuel taxes and highway user fees (Greene and Plotkin, 2011).

There are also operational pricing strategies, such as road, congestion and cordon pricing. These strategies are receiving increased attention due to their capability of targeting carbon-related activity, as well as increasing system efficiency. Among other strategies, congestion pricing seems to be more popular in emission reduction efforts, particularly in Europe. This is partially because it addressed multiple objectives facilitating emissions reduction and congestion mitigation, and supporting transit improvements through increased toll revenue and shifted demand to transit modes. The first successful application led to implementations in other cities, including Stockholm and London, was in Singapore that started in 1975 (U.S. FHWA, 2010). Milan and Tokyo (not implemented yet) are the only cities that specifically targeted emission reduction by cordon pricing.

Other pricing examples, although their primary objective was not directly GHG mitigation, also targeted the environmental benefits while the support of transit was secondary objective. The objective of Stockholm and London applications is congestion management. Germany and Czech Republic applications aimed at revenue generation. The Netherlands applied pricing as a nationwide planned strategy to reduce congestion and replace vehicle tax revenue. Only Milan and Tokyo examples specifically targeted emission reduction by cordon pricing (U.S. FHWA, 2010).

2.3.2.2. Incentives through HOV/HOT lane use

Various TDM and congestion management strategies, such as those involving HOV/HOT lanes, bus rapid transit (BRT), corridor management, and information provision, have been implemented or considered by many states and MPOs. Addition of high occupancy vehicle (HOV) or high occupancy toll (HOT) facilities also can support carpooling/vanpooling. In order to increase environmental benefits, HOV/HOT use can be tied to AFV and alternative fuel use through state or local regulations. For example, California enacted AB 171, which grants single occupant vehicles use of HOV lanes for electric and alternative fuel powered vehicles, including zero-emission vehicles, ultra-low emission vehicles, and super-ultra-low emission vehicles in 2000 (Shaheen, 2004).

2.3.2.3. Transportation System Management (TSM) through Intelligent Transportation Systems (ITS)

System efficiency strategies include but are not limited to work zone management, incident management, information provision, corridor management, traffic calming, bottleneck relief, ramp metering and the like. These strategies help reduce energy use and associated emissions by optimizing or improving the design, construction, operation and use of transportation networks (U.S. DOT, 2010a). According to the U.S. DOT (2010a), lowering speed limits on national highways could provide up to 2% reduction in GHG emissions, while traffic management and bottleneck relief could provide up to 3%

reduction. However, these strategies need to be designed carefully as they may cause increases in travel due to induced demand.

2.3.3. Strategies to Reduce Carbon-Intensive Travel Activity

The objective of these strategies is to reduce highway VMT by reducing the need for travel, increasing vehicle occupancy and shifting travel demand to more energy efficient modes (ideally to non-motorized modes). According to the U.S. DOT (2010a), these strategies can collectively yield a 5 to17% reduction in GHGs by 2030.

2.3.3.1 Public transportation improvement

There are many ways to improve public transit and rideshare services, including increased service, HOV priority, improved comfort, lower fares, more convenient payment options, improved user information, marketing programs, transit oriented development, improved security, and special service offerings, such as express commuter buses. High quality transit can attract 5-15% of urban trips and leverages additional travel reductions by stimulating more compact development. People who live in transit-oriented communities typically drive 10-30% less than residents of automobile-oriented areas. AASHTO suggests the reduction in VMT growth to 1% per year and doubling of transit ridership (AASHTO, 2011).

2.3.3.2 Commuter trip reduction programs

Commuter trip reduction programs aim to reduce VMT and SOV mode share of commute trips. Some of the commonly used strategies are telecommuting, carpooling/vanpooling, flexible work start times, transit subsidies, parking management (or pricing) and ridesharing programs. The application of these strategies can be required by employers or can be encouraged by incentives and subsidies. Currently, two states (Oregon and Washington) and two metropolitan areas (Phoenix and Tuscon in Arizona) have employer trip reduction requirements (U.S. DOT, 2010a). Other applications include state, regional or local level TDM programs that employers voluntarily apply (e.g. Atlanta, Washington D.C, and Southern California).

2.2.3.4 Non-motorized transportation improvements

Non-motorized transportation options naturally are the cleanest way of traveling. Encouraging these modes through compact development and improved walking and cycling facilities will help reduce the use of energy-intensive modes for relatively short-distance trips. Walking and cycling have the potential of reducing automobile (and SOV) trips and support transit modes. These strategies include infrastructure improvements for these modes and programs that would promote and foster them. For example, cycling could substitute vehicle trips for short-distance travels, e.g. up to 5 miles, provided that the infrastructure is available both on-road and at the destination.

2.4 Summary

This dissertation addresses three problems that aid in transportation emissions reduction efforts both from freight and passenger travel. In Chapter 3, the G-VRP is proposed to aid organizations with alternative fuel-powered vehicle fleets in tackling challenges introduced by the existing alternative fuel and vehicle availability. The techniques developed plans for refueling and incorporate stops at AFSs so as to eliminate the risk of running out of fuel while maintaining profitable routes. A hypothetical case study is used to demonstrate their utility in real-world operations and to explore the impact of alternative fuel vehicle adoption on vehicle tours and needed fleet size In Chapter 4, an econometric analysis of propensity to carpool/vanpool is made that seeks to contribute to efforts to reduce SOV trips by providing insight related to demand for vanpooling. Commuter survey data from University of Maryland, College Park campus is utilized for the analysis. Chapter 5 presents a network modeling tool that can be used for evaluating impacts of various pricing strategies, HOV/HOT lane impacts, work zones and incident management at a network level. This tool facilitates rapid evaluation of a large number of scenarios in a subarea, a capability that is needed for evaluation and implementation of transportation network planning and operations decisions for emission reduction efforts. Finally, Chapter 6 summarizes and concludes the dissertation.

Chapter 3: The Green Vehicle Routing Problem

3.1 Introduction

In the United States (U.S.), the transportation sector contributes 28% (U.S. EPA, 2009) of national greenhouse gas (GHG) emissions. This is in large part because 97% of U.S. transportation energy comes from petroleum-based fuels (U.S. DOT, 2010a). Efforts have been made over many decades to attract drivers away from personal automobiles and on to public transit and freight from trucks to rail. Such efforts are aimed at reducing vehicle miles traveled by road and, thus, fossil fuel usage. Other efforts have focused on introducing cleaner fuels, e.g. ultra low sulfur diesel, and efficient engine technologies, leading to reduced emissions for the same miles traveled and greater mileage per gallon of fuel used. While each such effort has its benefits, only a multi-faceted approach can engender the needed reduction in fossil fuel usage.

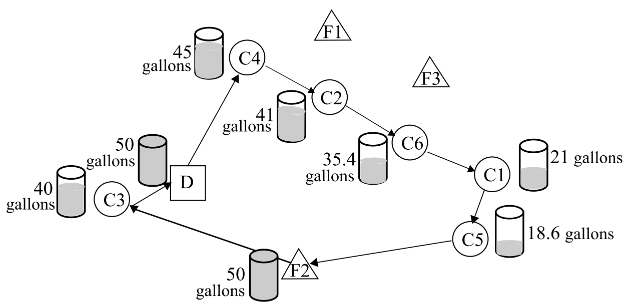
As part of such a multi-faceted approach, renewed attention is being given to efforts to exploit alternative, cleaner fuel sources, namely, biodiesel, electricity, ethanol, hydrogen, methanol, natural gas, (liquid-LNG-or compressed-CNG), and propane (U.S. DOE, 2010). Municipalities, government agencies, nonprofit organizations and private companies are converting their fleets of trucks to include Alternative Fuel Vehicles (AFVs). This focus on truck conversion is desirable. While medium- and heavy-duty trucks comprise only 4% of the vehicles on the roadways (U.S. FHWA, 2008), they contribute nearly 19.2% of U.S. transportation-based GHG emissions (U.S. DOT, 2010a). Moreover, truck traffic has had the greatest growth rate of all vehicles, increasing 77% for heavy-duty trucks and 65.6% for light-duty trucks compared with only 3.3% for passenger cars between 1990 and 2006 (U.S. DOT, 2010a).

Numerous factors are considered in the selection of a particular vehicle type, including fuel availability and geographic distribution of fueling stations in the service area, vehicle driving range, vehicle and fuel cost, fuel efficiency, and fleet maintenance costs. The lack of a national infrastructure for refueling AFVs presents a significant obstacle to alternative fuel technology adoption by companies and agencies seeking to transition from traditional gasoline-powered vehicle fleets to AFV fleets (Melaina and Bremson, 2008). In fact, approximately 98% of the fuel used in the federal government's 138,000 AFV fleet (of which, 92.8% in 2008 are flex-fuel vehicles that can run on gasoline or ethanol based E85 fuel) continues to be conventional gasoline as a result of a lack of opportunity for refueling using the alternative fuel for which the vehicles were designed (U.S. DOE, 2010a). Moreover, existing alternative fueling stations (AFSs) are distributed unevenly across the country and within specific regions. Additional operational challenges exist as a result of the reduced driving range of most AFVs. Similar challenges exist for privately owned AFV fleets. FedEx, in its overseas operations, employs AFVs that run on biodiesel, liquid natural gas (LNG) or compressed natural gas (CNG). In U.S. operations, hybrid vehicles have dominated, while LPG, biodiesel and CNG use is limited to regions with access to appropriate AFSs (Bohn, 2008).

This dissertation is concerned with those companies or agencies that employ a fleet of vehicles to serve customers or other entities located over a wide geographical region. Such companies rely on tools to aid in forming low cost tours, so as to save money and time resulting from travel to customer locations. These routes typically begin at a depot, visit multiple customers and then return to the depot. The problem of assigning customers to vehicles and ordering the customer visits in forming these tours is known as the Vehicle Routing Problem (VRP). A variant of the VRP, the Green Vehicle Routing Problem (G-VRP), is introduced herein that accounts for the additional challenges associated with operating a fleet of AFVs.

In this dissertation, techniques are developed to aid an organization with an AFV fleet in overcoming difficulties that exist as a result of limited refueling infrastructure. These techniques plan for refueling and incorporate stops at AFSs so as to eliminate the risk of running out of fuel while maintaining low cost routes. The G-VRP is formulated as a mixed-integer linear program (MILP). Given a complete graph consisting of vertices representing customer locations, AFSs, and a depot, the G-VRP seeks a set of vehicle tours with minimum distance each of which starts at the depot, visits a set of customers within a pre-specified time limit, and returns to the depot without exceeding the vehicle's driving range that depends on fuel tank capacity. Each tour may include a stop at one or more AFSs to allow the vehicle to refuel en route.

The G-VRP is illustrated on a simple example problem in Figure 3-1. This example involves only one truck with a fuel tank capacity of Q=50 gallons and fuel consumption rate of r=0.2 gallons per mile (or 5 miles per gallon fuel efficiency (Fraer et al. (2005)). Three AFSs are available in the region. The vehicle begins its tour at depot D and must visit customers C1 through C6 before returning to the depot. To visit these customers, a minimum distance of 339 miles must be traversed. Travel of such a distance would consume 67.8 gallons, 17.8 more gallons of fuel than the vehicle's tank can hold. Thus, the vehicle needs to visit at least one AFS in order to serve all customers and return to depot D. The G-VRP takes into account the vehicle's fuel tank capacity limitation and chooses the optimal placement of AFS visits within the tour. Accounting for fuel limitations, the optimal solution to the G-VRP involves a stop at one AFS and requires the traversal of 354 miles. Thus, the tour length is 15 miles longer than the minimum tour length, where fuel tank capacity is assumed to be unlimited.



	D/F_0	C1	C2	C3	C4	C5	C6	F1	F2	F3
D/F_0	0	148	55	32	70	140	73	60	45	75
C1	-	0	93	180	99	12	72	102	80	40
C2	-	-	0	85	20	83	28	45	75	90
C3	-	-	-	0	100	174	99	90	50	93
C4	-	-	-	-	0	85	49	25	60	55
C5	-	-	-	-	-	0	73	89	55	80
C6	-	-	-	-	-	-	0	50	85	64
F1	-	-	-	-	-	-	-	0	100	82
F2	-	-	-	-	-	-	-	-	0	58
F3	-	-	-	-	-	-	-	-	-	0

Figure 3-1 Illustrative example of a solution to the G-VRP

As the VRP is known to be an NP-hard problem (indicating that the computational effort required for its solution grows exponentially with increasing problem size), and the VRP is a special case of the G-VRP, the G-VRP is NP-hard. Thus, exact solution of large, real-world problem instances will be difficult to obtain. Two heuristics, the Modified Clarke and Wright Savings (MCWS) heuristic and the Density-Based Clustering Algorithm (DBCA), along with a customized improvement technique, are proposed for solution of such larger problem instances. These techniques are intended to provide decision support for a company or agency operating a fleet of AFVs for which limited fueling stations exist. Numerical experiments were designed and conducted to assess heuristic performance as a function of customer location configuration, and station density and distribution. The techniques are also applied on a hypothetical problem instance meant to replicate a medical textile supplier company's daily operations in the Washington, D.C. metropolitan area.

3.2. Background

A number of works in the literature present optimization-based approaches designed specifically for siting AFSs. The majority of these works were motivated by the Hydrogen Program that was created during the G. W. Bush administration and supported by a diverse group of governmental and private sponsors (Nicholas et al., 2004; Kuby and Lim, 2005, 2007; Upchurch et al., 2007; Lin et al.,2008a; 2008b; Bapna et al., 2002). Other works focus on military applications and consider issues pertaining to the limited capacity of fuel tanks (e.g. Mehrez et al., 1983; Mehrez and Stern, 1985; Melkman et al., 1986; Yamani et al., 1990; Yuan and Mehrez, 1995). Numerous works address the more general VRP with capacity and distance constraints (e.g. Laporte et al., 1985); however, such works do not consider the opportunity to extend a vehicle's distance limitation as a consequence of actions taken while en route. Of greater relevance is the multi-depot VRP in which vehicles can stop at satellite facilities (also referred to as replenishment or inter-depot facilities) to replenish or unload (e.g. Bard et al., 1998; Chan and Baker, 2005; Crevier et al., 2007; Kek et al., 2008, Tarantilis et al., 2008). Such opportunity for reloading aims to overcome capacity limitations of the vehicles, thus, permitting longer routes and reduced return travel to the central depot. In another related work, Ichimori et al. (1981) addressed a shortest path problem for a single vehicle en route to a single destination in which stops to refuel are explicitly considered.

It appears that no work in the literature directly addresses the G-VRP or a direct variant thereof. While solution techniques developed to address related problems cannot be applied directly in solution of the G-VRP in which fuel tank limits guide distances that can be traveled, the MILP formulation of the G-VRP developed in the next section builds on concepts conceived in (Bard et al., 1998). Bard et al. formulated a VRP with Satellite Facilities (VRPSF) problem as an MILP with capacity and tour duration limitation constraints. Vehicles with capacity limitations have the option to stop at satellite facilities to reload in order to serve customer demand at the nodes. Subtour elimination constraints that employ time relationships, as well as concepts used for tracking capacity utilization, employed by Bard et al., are exploited herein.

3.3 Problem Definition and Formulation

The G-VRP is defined on an undirected, complete graph $G=(V,E)$, where vertex set V is a combination of the customer set $I=\{v_1,v_2,\ldots,v_n\}$, the depot v_0, and a set of $s \geq 0$ AFSs, $F=\{v_{n+1},v_{n+2},\ldots,v_{n+s}\}$. The vertex set is $V=\{v_0\} \cup I \cup F=\{v_0,v_1,v_2,\ldots,v_{n+s}\}$, $|V|=n+s+1$. It is assumed that in addition to the AFSs, the depot can be used as a refueling station and all refueling stations have unlimited capacities. The set $E=\{(v_i,v_j): v_i,v_j \in V, i<j\}$ corresponds to the edges connecting vertices of V. Each edge (v_i,v_j) is associated with a non-negative travel time t_{ij}, cost c_{ij} and distance d_{ij}. Travel speeds are assumed to be constant over a link. In addition, no limit is set on the number of stops that can be made for refueling. When refueling is undertaken, it is assumed that the tank is filled to capacity.

The G-VRP seeks to find at most m tours, one for each vehicle, that starts and ends at the depot, visiting a subset of vertices including AFSs when needed such that the total distance traveled is minimized. Vehicle driving range constraints that are dictated by fuel tank capacity limitations and tour duration constraints meant to restrict tour durations to a pre-specified limit T_{max}, apply. It is assumed that all customers can be served by a vehicle that begins its tour at the depot and returns to the depot after visiting the customer directly within T_{max}. Without loss of generality, to reflect real-world service area designs, it is assumed that all customers can be visited directly by a vehicle beginning and returning to the depot with at most one visit to an AFS. This does not preclude the possibility of choosing a tour that serves multiple customers and contains more than one visit to an AFS.

The formulation distinguishes between visits to AFSs and the depot from customer visits. This is because each AFS may be visited more than once or not at all. In addition, the depot must be visited at the start and end of each tour and can serve, when desired, as an AFS. Customers, on the other hand, must be visited exactly once. To permit multiple (and possibly zero) visits to a subset of the nodes, while requiring exactly one visit to other nodes, graph G is augmented (to create $G'=(V',E')$ with a set of s' dummy nodes, $\Phi=\{v_{n+s+1}, v_{s+2},\ldots,v_{s+s'}\}$, one for each potential visit to an AFS or depot serving as an AFS. $V'=V\cup\Phi$. Associated with each refueling station $v_f\in F$ is n_f dummy nodes for $f=0,\ldots,n+s$. The number of dummy nodes associated with each AFS, n_f, is set to the number of times the associated v_f can be visited. n_f should be set as small as possible so as to reduce the network size, but large enough to not restrict multiple beneficial visits. This technique involving dummy nodes was introduced by Bard et al. (1998) for their application involving stops at intermediate depots for reloading vehicles with goods for delivery.

Additional notation used in formulating the G-VRP is defined next.

I_0 Set of customer nodes and depot, $I_0=\{v_0\}\cup I$

F_0 Set of AFS nodes and depot, $F_0=\{v_0\}\cup F'$, where $F'=F\cup \Phi$

p_i Service time at node i (if $i\in I$, then p_i *is* the service time at the customer node, if $i\in F$, p_i is the refueling time at the AFS node, which is assumed to be constant)

r Vehicle fuel consumption rate (gallons per mile)

Q Vehicle fuel tank capacity

Decision Variables

x_{ij} Binary variable equal to 1 if a vehicle travels from vertex i to j and 0 otherwise

y_j Fuel level variable specifying the remaining tank fuel level upon arrival to vertex j . It is reset to Q at each refueling station node i and the depot

τ_j Time variable specifying the time of arrival of a vehicle at node j, initialized to zero upon departure from the depot

The mathematical formulation of the G-VRP is as follows:

$$\min \sum_{\substack{i,j\in V' \\ i\neq j}} d_{ij}x_{ij} \qquad (3\text{-}1)$$

s.t.

$$\sum_{\substack{j\in V' \\ j\neq i}} x_{ij} = 1 \ , \ \forall i\in I \qquad (3\text{-}2)$$

$$\sum_{\substack{j\in V' \\ j\neq i}} x_{ij} \leq 1 \ , \ \forall i\in F_0 \qquad (3\text{-}3)$$

$$\sum_{\substack{i\in V' \\ j\neq i}} x_{ji} - \sum_{\substack{i\in V' \\ j\neq i}} x_{ij} = 0 \ , \ \forall j \in V' \qquad (3\text{-}4)$$

$$\sum_{j\in V'\setminus\{0\}} x_{0j} \leq m \qquad (3\text{-}5)$$

$$\sum_{j\in V'\setminus\{0\}} x_{j0} \leq m \qquad (3\text{-}6)$$

(3-7)

$$\tau_j \geq \tau_i + (t_{ij} - p_j)x_{ij} - T_{max}(1 - x_{ij}),\ i \in V', \forall j \in V' \backslash \{0\} \text{ and } i \neq j$$

$$0 \leq \tau_0 \leq T_{max} \tag{3-8}$$

$$t_{0j} \leq \tau_j \leq T_{max} - (t_{j0} + p_j),\ \forall j \in V' \backslash \{0\} \tag{3-9}$$

$$y_j \leq y_i - r \cdot d_{ij} x_{ij} + Q(1 - x_{ij}),\ \forall j \in I \text{ and } i \in V',\ i \neq j \tag{3-10}$$

$$y_j = Q,\ \forall j \in F_0 \tag{3-11}$$

$$y_j \geq min\{r \cdot d_{j0}, r \cdot (d_{jl} + d_{l0})\}, \forall j \in I, \forall l \in F' \tag{3-12}$$

$$x_{i,j} \in \{0,1\}, \forall i, j \tag{3-13}$$

The objective (3-1) seeks to minimize total distance travelled by the AFV fleet in a given day. Constraints (3-2) ensure that each customer vertex has exactly one successor: a customer, AFS or depot node. Constraints (3-3) ensure that each AFS (and associated dummy nodes) will have at most one successor node: a customer, AFS or depot node. Continuity of flow is ensured through constraints (3-4) by which the number of arrivals at a node must equal the number of departures for all nodes except the depot node. Constraints (3-5) ensure that at most *m* vehicles are routed out of the depot and constraints (3-6) ensure that at most *m* vehicles return to the depot in a given day. A copy of the depot is made to distinguish departure and arrival times at the depot, which is necessary for tracking the time at each node visited and preventing the formation of subtours. The time of arrival at each node by each vehicle is tracked through constraints (3-7). Constraints (3-7) along with constraints (3-8) and (3-9) make certain that each vehicle returns to the depot no later than T_{max}. Constraints (3-8) specify a departure time from the depot of zero ($\tau_0=0$) and an upper bound on arrival times upon return to the depot. Lower and upper bounds on arrival times at customer and AFS vertices given in constraints (3-9) ensure that each route is completed by T_{max}. Constraints (3-10) track a vehicle's fuel level based on node sequence and type. If node j is visited right after node i ($x_{ij}=1$) and node i is a customer node, the first term in constraints (3-10) reduces the fuel level upon arrival at node j based on the distance traveled from node i and the vehicle's fuel consumption rate. Time and fuel level tracking constraints, constraints (3-7) and (3-10), respectively, serve to eliminate the possibility of subtour formation. Constraints (3-11) reset the fuel level to Q upon arrival at the depot or an AFS node. Constraints (3-12) guarantee that there will be enough remaining fuel to return to the depot directly or by way of an AFS from any customer location en route. This constraint seeks to ensure that the vehicles will not be stranded. One could extend this constraint to permit return paths that visit more than one AFS. These constraints are implemented through the Java CPLEX interface using if - then logic. Finally, binary integrality is guaranteed through constraints (3-13).

The main difficulty in solving any VRP is ensuring that subtours will not be created. In traditional VRP formulations, a set of constraints known as subtour elimination constraints are included. In the G-VRP formulation presented herein, subtours are prevented through the combination of constraints (3-2), (3-3), (3-8) and (3-11) acting together.

The formulation of the G-VRP presented in this section builds on the VRPSF formulation by Bard et al.(1998) designed for a delivery routing problem with satellites at which goods can be loaded en route to customers. Similar notation was employed where possible. The G-VRP differs from the VRPSF in several substantial ways. First, the

VRPSF does not consider distance restrictions based on fuel tank capacity. As such, the possibility of running out of fuel en route to a customer is not considered. Second, fuel is consumed along the network edges, while goods are consumed at the network vertices. Thus, capacity limitations associated with the VRPSF cannot serve in modeling fuel usage limitations. Third, determination of upper and lower bounds on arrival times at the vertices are complicated by refueling needs. This is because there are many more combinations of possible vertex sequences than in the VRPSF and the number of AFSs in an instance of the G-VRP will likely exceed the number of satellite facilities in a typical VRPSF. The additional combinations are due to the fact that in the G-VRP, it is possible that refueling will be required even before arriving at a single customer and travel to a refueling station must be considered from every customer en route. This differs from the VRPSF, where reloading at a satellite facility need only be considered when supplies (i.e. goods) must be replenished. Finally, satellite facilities are strategically located, while locations of the AFSs are typically beyond the company's control, possibly affecting the difficulty associated with determining good routes.

3.4 Solution of the G-VRP

The vehicle driving range (or fuel tank capacity) limitations and existence of a subset of vertices (the AFSs) that can, but need not be, visited, as well as the possibility of extending a vehicle's driving range as a result of a visit to a site along the tour, introduce complications that are not present in classical VRPs or most variants thereof. Thus, heuristics designed for the classical VRP or related variants cannot be applied directly in solving the G-VRP. Not only might such heuristics result in solutions that perform poorly, but these solutions may not even be feasible. Two heuristics customized for the

G-VRP are proposed herein for solution of large problem instances: the MCWS heuristic and DBCA. The Clarke and Wright Savings algorithm (Clarke and Wright, 1964) designed for the classical VRP, and customized for its variants, is modified to create the MCWS heuristic so as to tackle the challenges introduced by the G-VRP. The DBCA builds on concepts from the Density Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm proposed in (Ester et al., 1996) for the purpose of discovering clusters of arbitrary shapes in large spatial databases, such as satellite images and x-rays. In addition, two tour improvement techniques involving within-tour edge interchanges and across-tour vertex exchanges designed for the G-VRP that can be applied in series once a tour is constructed are presented herein.

3.4.1. The MCWS Heuristic

MCWS heuristic

Step 1: Create n *back-and-forth* vehicle tours (v_0-v_i-v_0), each starting at the depot v_0, visiting a customer vertex $v_i \in I$ and ending at the depot. Add each created tour to the *tours list.*

Step 2: Calculate the tour duration and distance for all tours in the *tours list*. Check for feasibility of all initial *back-and-forth* tours with regard to driving range and tour duration limitation constraints and categorize them as feasible or infeasible. Place all feasible tours in the *feasible tours list* and the remainder in the *infeasible tour list.*

Step 3: For each tour in the *infeasible tour list*, calculate the cost of an AFS insertion between customer vertices v_i and the depot v_0, $c(v_i,v_0) = d(v_i,v_f) + d(v_f,v_0) - d(v_i,v_0)$

for every AFS ($v_f \in F'$). For every such tour, insert an AFS with the least insertion cost. If both driving range and tour duration limitation constraints are met after the insertion of an AFS, add the resulting tour to the *feasible tours list*. If the driving range constraint is not met with the addition of any AFS, discard the tour. No starting tour containing more than one AFS is considered.

Step 4: Compute the savings associated with merging each pair of tours in the *feasible tours list*. To do so, first identify all vertices that are adjacent to the depot in a tour. *C*reate a *savings pair list (SPL)* that includes all possible pairs of these vertices (v_i,v_j) with the condition that each pair is formed by vertices that belong to different tours. Compute the savings associated with each pair of vertices in the *SPL*, $s(v_i,v_j) = d(v_0,v_i) + d(v_0,v_j) - d(v_i,v_j)$, where (($v_i,v_j$) $\in I \cup F'$). Rank the pairs in the *SPL* in descending order of savings $s(v_i,v_j)$.

Step 5:

While SPL is not empty

Select and remove the topmost pair of vertices (v_i,v_j) in the *SPL* and merge their associated tours.

For the selected (v_i,v_j), check driving range and tour duration limitation constraints.

If both constraints are met, add the resulting tour to the *feasible tours list*.

If the resulting tour duration is less than T_{max}, but violates the driving range constraint, compute the insertion cost $c(v_i,v_j) = d(v_i,v_f) + d(v_f,v_j) - d(v_i,v_0) - d(v_j,v_0)$ for savings pair ((v_i,v_j) $\in I \cup F'$) for every AFS ($v_f \in F'$). Insert the AFS between v_i and v_j with the least insertion cost for which the resulting tour is feasible. Check for redundancy: If the tour contains more than one AFS, consider whether it is possible to remove one or more of the AFSs from the tour. Remove any redundant AFSs.

Add the resulting tour to the *feasible tours list.*

If any tour has been added to the *feasible tours list*, *r*eturn to Step 4. Otherwise, *stop*.

The MCWS heuristic terminates with a set of tours that together form a feasible solution to the G-VRP in which constraints (3-5) and (3-6) are relaxed. The heuristic continues until no tours in the *feasible tour list* can be further merged. The number of tours in the final *feasible tours list* is the smallest that can be attained through the merge process of Step 5. This procedure is consistent with including a secondary objective of minimizing fleet size. If the final number of tours is less than *m*, then the entire set of customers can be served with fewer than *m* vehicles. If it is greater than *m*, then the heuristic was unable to obtain a solution with *m* or fewer vehicles. The best solution obtained, i.e. with the smallest number of required vehicles, is provided. This relaxation of constraints (3-5) and (3-6) in this way, as opposed to declaring infeasibility, permits the decision-maker to consider the impact of conversion to alternative fuels with limited refueling stations on needed fleet size.

An intrinsic quality of solutions of nearly all VRPs and their variants is acyclicity. Moreover, in most variants, every vertex must be visited once and only once. In the G-VRP, cycle formation is allowed and AFS vertices can be visited more than once, by more than one vehicle, or not visited at all. This is illustrated through a series of small examples depicted in Figure 3-2. In Figure 3-2(a), a single vehicle visits F1 twice, forming a cycle. In Figure 3-2(b), there are two vehicles visiting F1 once each. These sequences allow an AFS vertex to be visited by more than one vehicle. In Figure 3-2(c), F1 is not visited at all.

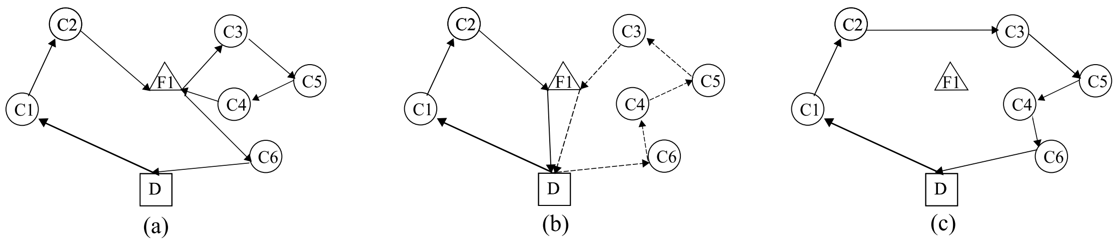


Figure 3-2 Possible feasible G-VRP solutions

Figure 3-3 illustrates additional characteristics of this problem class that affect the merging process. As depicted in Figure 3-3(a), two tours that visit the same AFS can be merged with only a deletion in the links incident on the depot. No additional links are required. Moreover, tours that cannot be merged directly may be merged if an AFS is included as depicted in Figure 3-3(b). When a tour containing an AFS is included in a merge that involves an additional AFS visit, as in 3-3(b), it may be that inclusion of an AFS from an original tour is redundant. This AFS can be dropped from the final post-merge tour, resulting in, for example, the tour depicted in Figure 3-3(c).

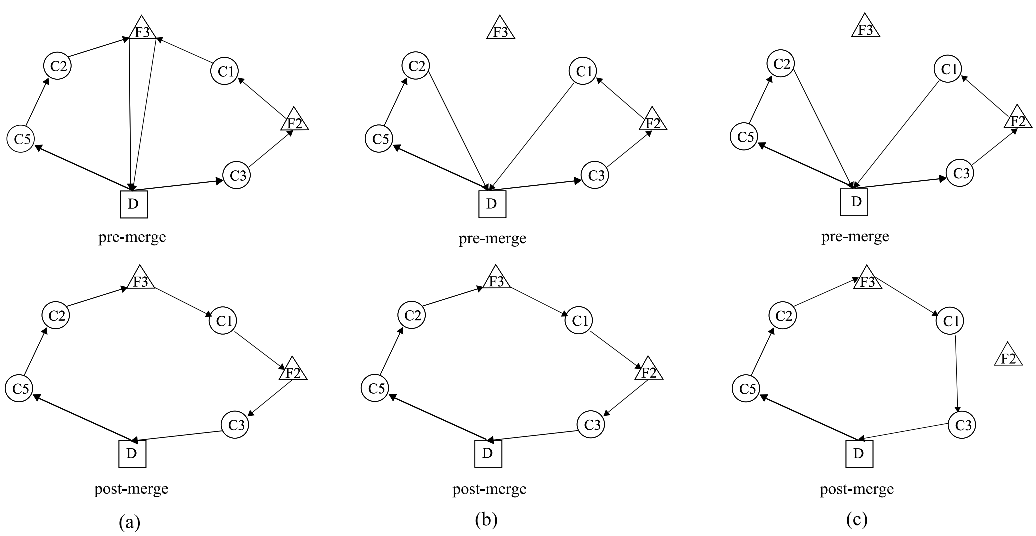


Figure 3-3 Characteristics of Merging in the G-VRP

3.4.2. Density-Based Clustering Algorithm

A second heuristic, the DBCA, is introduced that exploits the spatial properties of the G-VRP. The relative location of customers and AFSs, as well as their distributions over space, significantly affect feasibility and number of required AFS visits. Like many clustering approaches, the DBCA decomposes the VRP into two, clustering and routing subproblems.

The key idea of the DBCA is that for each vertex of a cluster, the neighborhood of a given radius (ε) must contain at least a minimum number of vertices (*minPts*). That is, a density threshold is employed with *minPts*. Figure 3-4 illustrates the DBCA on a 20 customer and three AFS example, where clusters are formed for *minPts* ≥ 4 and $\varepsilon = 30$ miles.

The ε-neighborhood of a vertex v_j, denoted by $N_\varepsilon(v_j)$, is defined by the set of vertices that are within a radius of ε from v_j, $N_\varepsilon(v_j)=\{ v_i \in V' | \, d_{ij} \leq \varepsilon\}$ (*Definition 1*, Ester et al. (1996)). By using ε -neighborhood notation, a cluster can be formed by ensuring that each constituent vertex has at least *minPts* vertices in its ε–neighborhood (e.g. the ε-neighborhood of vertex 5, for ε = 30 miles, includes 4 vertices as depicted in Figure 3-4). A vertex v_i is said to be *directly density-reachable* from a vertex v_j with respect to ε and *minPts* if the following conditions are satisfied (*Definition 2*, Ester et al. (1996)):

i. $v_i \in N_\varepsilon(v_j)$ and

ii. $|N_\varepsilon(v_j)| \geq minPts$

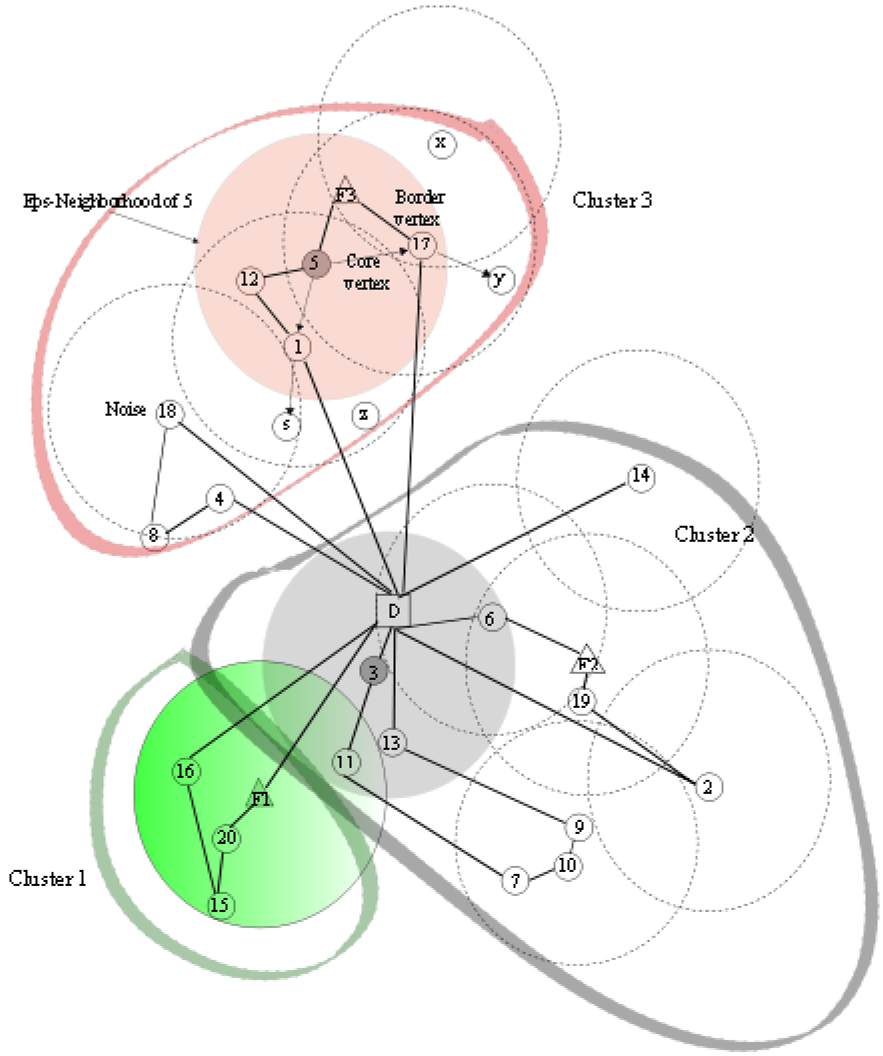


Figure 3-4 Forming Clusters by DBSCAN algorithm

According to this definition v_i is direct-density reachable from v_j, but the opposite may not always be true if $|N_\varepsilon(v_i)| < minPts$ (i.e. condition *ii* is not met). Condition *ii* is called the *core vertex condition*. Vertices that do not satisfy this condition are called *noise* vertices. For example, in Figure 3-4, vertices 17, F3, 12 and 1 are border vertices, and are directly density reachable from vertex 5. However, vertex 5 is not direct-density reachable from any of these vertices. Thus, vertex 5 is a core vertex and is used as a seed to form cluster 3.

A vertex v_i is *density-reachable* from a vertex v_m with respect to ε and *minPts* if there is a chain of vertices that satisfy direct density-reachability for each consecutive vertex pair (*Definition 3,* Ester et al. (1996)). In Figure 3-4, vertices *y* and *x* are density-reachable from vertex 5 via vertex 17. Density-reachability is a transitive, but not symmetric relation. A vertex v_i is *density-connected* to a vertex v_p with respect to ε and *minPts* if there is a vertex v_m such that both v_i and v_p are density reachable from v_m (*Definition 4*, Ester et al. (1996)). For example, vertices *y* and *s* are density-connected through vertex 5 in Figure 3-4. Using these concepts, clusters are formed by identifying sets of *density-connected* vertices based on a core vertex. Elements of each set are assigned a common cluster ID. In Figure 3-4, three core vertices are identified (5, 3 and F1) and three clusters are formed.

Notation used in the DBCA are given next, followed by details of the DBCA.

m	number of required routes corresponding to number of clusters
ε	radius parameter used in determining a vertex' ε-neighborhood
minPts	minimum number of vertices in an ε-neighborhood of a vertex
$[\varepsilon_{min}, \varepsilon_{max}]$	search interval for ε
$[minPts_{min}, minPts_{max}]$	the interval for density threshold for which DBCA searches for different clustering schemes

DBCA ($[\varepsilon_{min},\varepsilon_{max}]$ and $[minPts_{min},minPts_{max}]$)

Step 1: Clustering

For each combination of ε and *MinPts*:

For all v_i in *V*

Determine the ε-neighborhood of vertex v_i with respect to ε and *minPts*

If v_i satisfies core vertex condition (*ii*), v_i is a core vertex. Assign a cluster ID to vertex v_i and all vertices in its ε-neighborhood.

For each vertex v_i with a cluster ID

For each v_j with no cluster ID that is density connected to vertex v_i

Assign the cluster ID of v_i to v_j.

For each vertex v_i with no cluster ID

Assign the cluster ID of the vertex v_j with cluster ID closest to v_i.

This step ends with a set of clusters for each combination of ε and *MinPts* pair. The depot is added to any cluster in which it is not already included.

Step 2: Routing

For each set of clusters corresponding to each pairing of ε and *MinPts*

Run MCWS to construct vehicle tours.

Step 3: Identify Set of Routes

Calculate the total distance traveled by all vehicles for the resulting set of tours corresponding to each (ε,*MinPts*) pair from Step 2 and identify the parameter combination (ε,*MinPts*) that results in the least distance traveled and output the corresponding set of tours.

Like the MCWS heuristic, the DBCA terminates with a set of tours that form a feasible solution to the G-VRP for which constraints (3-5) and (3-6) have been relaxed.

In typical cluster-first, route-second heuristics for the VRP, customers in a single cluster are served with a single vehicle and clusters are formed such that vehicle capacity limitations are not exceeded. However, in the DBCA, clusters are formed without regard for imposed limitations, because there is no simple check to ensure that customers in a cluster can be served by a single vehicle without violating tour duration and vehicle driving range constraints. Thus, more than one tour may be required to serve customers in a given cluster. For example, two tours are formed in cluster 3 and three in cluster 2 as shown in Figure 3-4.

3.4.3. Improvement Heuristics

The MCWS heuristic and DBCA construct a set of feasible tours. An improvement technique can be applied on the resulting set of feasible tours in an effort to reduce the total distance that must be traveled. Concepts involving inter-tour vertex exchange and within-tour edge-interchange are customized for the G-VRP. Beginning with a set of tours, inter-tour vertex exchange is applied by considering an exchange of one vertex between every pair of tours. For each pair of tours, two vertices are selected for a position exchange. If the total distance of both tours together is reduced as a result of the exchange and steps can be taken to maintain feasibility, the exchange is executed. Within-tour two-vertex interchange and reordering is applied next in which every pair of vertices is considered for an exchange. The position within the tour of the two chosen vertices is exchanged, creating a new tour ordering. If the new tour ordering is infeasible, the exchange is not performed. Otherwise, if one or both of the chosen vertices for the exchange are AFSs, AFS redundancy is checked and AFS relocation or exchange with an alternate unscheduled AFS is considered so as to minimize the tour length. The improvement heuristic terminates with a set of tours for the G-VRP for which constraints (3-5) and (3-6) have been relaxed. The total distance required to carry out the tours will be no worse than that required of the initial tours to which the procedure is applied.

3.5. Numerical Experiments

Numerical experiments were conducted to assess the quality of solutions obtained through the proposed heuristics on randomly generated small problem instances through comparison with exact solutions obtained through direct solution of the G-VRP formulation. The experiments were devised to allow consideration of the impact of customer and AFS location configuration and AFS density on the solution. A larger, more realistic G-VRP was devised using a medical textile supply company's depot location in Virginia. A customer pool for this company was created based on hospital locations in Virginia (VA), Maryland (MD) and the District of Colombia (DC) using Google Earth. Conversion to biodiesel (B20 or higher) was considered, because of the modest density of biodiesel fueling stations in the region. Such conversion will lead to significant reductions in carbon monoxide, particulate matter, sulfates, and hydrocarbon as compared with diesel fuel, as well as lifecycle GHG emissions (U.S. EPA, 2002). Actual biodiesel stations located in the region in the summer of 2009 were obtained from a U.S. DOE website (U.S. DOE, 2009). Experiments were designed to analyze the impact of fleet conversion for this company to biodiesel using the developed heuristics.

In both sets of experiments, unless otherwise stated, a fuel tank capacity of 60 gallons and fuel consumption rate of 0.2 gallons per mile were set based on average values for biodiesel-powered AFVs (Fraer et al., 2005). The average vehicle speed is assumed to be 40 miles per hour (mph) and the total tour duration limitation was assumed to be 11 hours. Service times were assumed to be 30 minutes at customer locations and 15 minutes at AFS locations.

The construction and improvement heuristics were implemented in Java and compiled using Eclipse. Exact solutions were obtained by implementing the model using ILOG's CPLEX Concert Technology (version 11.2, 2009) in Java, which allowed Java objects to be used in building the optimization model. The experiments were run on a desktop with Pentium (4) CPU, 32-bit platform with 3.20 GHz processor and 2.00 GB of RAM, while ILOG CPLEX runs were made on a Xeon (R) CPU 5160 3.00 GHz processor, 64-bit platform with 16.00 GB of RAM.

3.5.1. Experiments on Small Instances

Random problem instances were generated so as to maintain the properties of one of four general scenario categories as defined in Table 3-1.

Table 3-1 Small instance test scenarios

Scenario	Description	Details
S1	Impact of spatial customer configuration (uniform)	10 randomly generated instances of 20 uniformly distributed customer locations with 3 fixed AFS locations.
S2	Impact of spatial customer configuration (clustered)	10 instances of 20 clustered customer locations with 3 fixed AFS locations.
S3	Impact of spatial AFS configuration	10 instances, half selected from S1 and half from S2, each instance with 6 AFSs generated randomly.
S4	Impact of station density	10 instances, half created from 1 instance of S1 and half from 1 instance of S2, by increasing the number of AFSs gradually from 2 to 10 in increments of 2.

Each instance was randomly generated assuming a grid of 330 by 300 miles based on an area similar in size to MD, VA and the DC. The depot location was fixed and assumed to be located near the center of the grid in all scenarios. Three AFSs were fixed and assumed to be located between the depot and the grid boundaries in westerly, northerly and southeasterly directions for S1 and S2. Specific instances for each scenario are identified by an alternating pattern of numbers and letters indicating e.g in 20c3sU1, the number of customers (20), AFSs (3) how the AFSs are distributed over space (U or C indicating that they are uniformly distributed or clustered, respectively), and instance number (1-10 for each instance) for S1 and S2. For S3 and S4, the pattern indicates the S1 or S2 instance (Scenario 1, instance 2 in S1_2i6s) and number of AFSs (6 AFSs in S1_2i6s).

Table 3-2 S1, impact of spatial customer configuration (uniform) results

	CPLEX			MCWS		DBCA 15≤ε≤150, 1≤minPts≤10	
Sample	***Exact Solution (miles)***	***Number of tours***	***Customers Served***	***Total Cost (miles)***	***Difference (%)***	***Total Cost (miles)***	***Difference (%)***
20c3sU1	1797.51	6	20	1843.52	2.56	1843.52	2.56
				1818.35	1.16	*1797.51*	0.00
20c3sU2	1574.82	6	20	1614.15	2.50	1614.14	2.50
				1614.15	2.50	*1613.53*	2.46
20c3sU3	1765.9	7	20	1969.64	11.54	1969.64	11.25
				1969.64	11.54	*1964.57*	11.25
20c3sU4	1482.00	5	20	1513.45	2.12	1508.41	1.78
				1508.41	1.78	*1487.15*	0.35
20c3sU5	1689.35	6	20	1802.93	6.72	1802.93	6.72
				1752.73	3.75	*1752.73*	3.75[a]
20c3sU6	1643.05	6	20	1713.39	4.28	1713.39	4.28
				1668.16	1.53	*1668.16*	1.53[a]
20c3sU7	1715.13	6	20	1730.45	0.89	1730.45	0.89
				1730.45	0.89	*1730.45*	0.89
20c3sU8	1709.43	6	20	1766.36	3.33	1766.36	3.33
				1718.67	0.54	*1718.67*	0.54
20c3sU9	1708.84	6	20	1718.43	0.56	1718.43	0.56
				1714.43	0.33	*1714.43*	0.33
20c3sU10	1261.15	5	20	1309.52	3.84	1309.52	3.84
				1309.52	3.84	*1309.52*	3.84
Average					***2.79***		***2.49***

([a]) Indicates when a single cluster is formed at the end of the clustering step of DBCA.

The computation time limit in CPLEX was set to 100,000 seconds with an optimal solution tolerance of 10^{-3}. The results are presented in Tables 3-2 through 3-5. In these tables, the values of the objective function obtained for each instance is given in two lines, the first which provides the heuristic objective function value prior to implementation of the improvement techniques and the second which gives the objective function value (in italics) after the improvement techniques have been applied. The computational times required to run the heuristics were on the order of seconds and are not reported here. The DBCA was run multiple times, each for a different (ε, *minPts*)-pair. The best achieved results are provided.

Table 3-3 S2, impact of spatial customer configuration (clustered) results

	CPLEX			**MCWS heuristic**		**DBCA** $15 \leq \varepsilon \leq 150$, $1 \leq minPts \leq 10$	
Sample	***Exact Solution (miles)***	***Number of tours***	***Customers Served***	***Total Cost (miles)***	***Difference (%)***	***Total Cost (miles)***	***Difference (%)***
20c3sC1	1235.21	5	20	1340.36	8.51	1340.36	8.51
				1300.62	*5.30*	*1300.62*	*5.30*
20c3sC2	1539.94	5	19	1553.53	0.88	1553.53	0.88
				1553.53	*0.88*	*1553.53*	*0.88* [a]
20c3sC3	985.41	4	12	1083.12	9.92	1083.12	9.92
				1083.12	*9.92*	*1083.12*	*9.92* [a]
20c3sC4	1080.16	5	18	1135.90[(5)]	5.16	1135.90[(5)]	5.16
				1135.90[(5)]	*5.16*	*1091.78*[(4)]	*1.08*
20c3sC5	2190.68	7	19	2190.68	0.00	2190.68	0.00
				2190.68	*0.00*	*2190.68*	*0.00* [a]
20c3sC6	2785.86	9	17	2887.55	3.65	2887.55	3.65
				2883.71	*3.51*	*2883.71*	*3.51* [a]
20c3sC7	1393.98	5	6	1703.40	22.20	1703.40	22.20
				1701.40	*22.05*	*1701.40*	*22.05* [a]
20c3sC8	3319.71	10	18	3319.74	0.00	3319.74	0.00
				3319.74	*0.00*	*3319.74*	*0.00* [a]
20c3sC9	1799.95	6	19	1811.05	0.62	1811.05	0.62
				1811.05	*0.62*	*1811.05*	*0.62* [a]
20c3sC10	2583.42	8	15	2667.23	3.24	2667.23	3.24
				2648.84	*2.53*	*2644.11*	*2.35*
Average					***5.00***		***4.57***

([a]) Indicates when a single cluster is formed at the end of the clustering step of DBCA.

Table 3-4 S3, impact of spatial AFS configuration results

	CPLEX			**MCWS**		**DBCA 15≤ε≤150, 1≤minPts≤10**	
Sample	***Exact Solution (miles)***	***Number of tours***	***Customers Served***	***Total Cost (miles)***	***Difference (%)***	***Total Cost (miles)***	***Difference (%)***
S1_2i6s	1578.15	6	20	1614.15	2.28	1614.15	2.28
				1614.15	*2.28*	*1614.15*	*2.28*
S1_4i6s	1438.89	5	20	1599.56$^{(6)}$	*11.17*	1599.56$^{(6)}$	*11.17*
				1561.30$^{(6)}$	*8.51*	*1541.46*$^{(5)}$	*7.13*
S1_6i6s	1571.28	6	20	1626.94	3.54	1626.94	3.54
				1616.20	*2.86*	*1616.20*	*2.86*
S1_8i6s	1692.34	6	20	1937.87$^{(6)}$	14.51	1937.87$^{(7)}$	*14.51*
				1902.51$^{(6)}$	12.42	*1882.54*$^{(6)}$	*11.24*
S1_10i6s	1253.32	5	20	1309.52	4.48	1309.52	4.48
				1309.52	*4.48*	*1309.52*	*4.48* [a]
S2_2i6s	1645.8	6	20	1648.24	0.15	1648.24	0.15
				1645.80	*0.00*	*1645.80*	*0.00*
S2_4i6s	1505.06	6	19	1505.06	0.00	1505.06	0.00
				1505.06	0.00	*1505.06*	0.00[a]
S2_6i6s	2842.08	10	20	3127.43	10.04	3127.43	10.04
				3115.10	*9.61*	*3115.10*	*9.61* [a]
S2_8i6s	2549.98	9	16	2724.12	6.83	2724.12	6.83
				2722.55	*6.77*	*2722.55*	*6.77*
S2_10i6s	1606.65 [b]	6	16	2068.93	28.77	2068.93	28.77
				1995.62	24.21	*1995.62*	24.21 [a]
Average					***5.21***		***4.93***

([a]) Indicates when a single cluster is formed at the end of the clustering step of DBCA.
([b]) Best feasible solution found with <11.30% guarantee difference from optimal.

To ensure that the results are comparable, the heuristics were run and the number of tours required for the best found solution was used in constraints (3-5) and (3-6) of the formulation in obtaining the corresponding optimal solution. When the two heuristics obtained solutions with a different number of tours, as was the case in a few instances, the smaller number of tours was employed in the exact solution. In a number of instances (e.g. S2_4i2s), no feasible solution could be obtained. That is, it was not possible to directly visit all customers with one AFS visit, a requirement of the heuristics. Thus, those customers that could not be served directly with a visit to one AFS were eliminated from the problem instance. The number of required tours as identified from heuristic solutions and final number of customers considered in each instance are provided in the tables.

Table 3-5 S4, Impact of station density results

	CPLEX			MCWS		DBCA 15≤ε≤150, 1≤minPts≤10	
Sample	***Exact Solution (miles)***	***Number of tours***	***Customers Served***	***Total Cost (miles)***	***Difference (%)***	***Total Cost (miles)***	***Difference (%)***
S1_4i2s	1582.22	6	20	1589.6	0.47	1589.6	0.47
				1582.2	0.00	*1582.2*	*0.00*[a]
S1_4i4s	1504.1	6	20	1599.6	6.35	1599.6	6.35
				1580.52	5.08	*1580.52*	*5.08*[a]
S1_4i6s	1397.28	5	20	1599.60$^{(6)}$	14.48	1599.6$^{(6)}$	14.48
				1561.29$^{(6)}$	11.74	*1541.46*$^{(5)}$	*10.32*
S1_4i8s	1376.98	6	20	1599.60	16.17	1599.6	16.17
				1561.29	13.39	*1561.29*	*13.39*[a]
S1_4i10s	1397.28	5	20	1568.60	12.26	1568.00	12.22
				1536.04	9.93	*1529.73*	*9.48*
S2_4i2s	1080.16	5	18	1135.8	5.16	1135.89	5.16
				1135.89	5.16	*1117.32*	*3.44*
S2_4i4s	1466.9	6	19	1522.72	3.81	1522.72	3.81
				1522.72	3.81	*1522.72*	3.81[a]
S2_4i6s	1454.96	6	20	1788.22	22.91	1788.22	22.91
				1786.21	22.77	*1730.47*	*18.94*
S2_4i8s	1454.96	6	20	1788.22	22.91	1788.22	22.91
				1786.21	22.77	*1786.21*	*22.77*
S2_4i10s	1454.93[b]	6	20	1787.22	22.84	1787.22	22.84
			20	*1783.63*	22.59	*1729.51*	*18.87*
Average					***10.51***		***9.69***

([a]) Indicates when a single cluster is formed at the end of the clustering step of DBCA.
([b]) Best feasible solution found with <3.5 % guarantee difference from optimal

It is often in the cases for which the original problem is infeasible that the heuristics perform the worst. The heuristics perform well, however, on average with a gap of 2.7, 5, 5, and 10% from optimal for S1, S2, S3 and S4 instances, respectively, as indicated in Tables 3-2 through 3-5. The performance of the heuristics was better for S1 and S2 instances of Tables 3-2 and 3-5 in which there are limited AFSs and their locations are strategically located than for S3 and S4 instances of Tables 3-4 and 3-5 in which there are double the numbers of AFSs, but their locations were randomly chosen. In many instances, the heuristics find the optimal solution, but in the worst-case, the solution is nearly 23% from optimal. The improvement heuristics contributed modestly to improving the solutions obtained (an average of 0.9% reduction in objective function value for MCWS and 1.5% for DBCA).

In general, the results of the two heuristics were very similar; although, whenever there is a difference in solutions obtained, the DBCA finds the better solution. This similarity in the obtained solutions may be a consequence of the small size of the problem instances. That is, there are few feasible solutions and these techniques often narrow in on the same solutions. Moreover, the heuristics are expected to obtain identical solutions when the DBCA produces a single cluster from the first stage. Those instances in which this arises are noted in Tables 3-2 through 3-5. Out of the 13 instances in which the DBCA produces a better solution than the MCWS, the DBCA's solution uses fewer routes to serve the customers in three instances. While there were differences in the number of AFS visits included in the final tours of all three techniques, no consistent pattern was noted. In approximately half the instances, the heuristics employed one fewer or one additional AFS within the final set of tours as compared with the number employed in the optimal set of tours.

The impact of AFS density is examined in S4 (Table 3-5). Results of these instances indicate that more customers could be served as the number of AFSs increased. Thus, the number of infeasible instances was reduced. Note that it was not possible to visit all customers in three of the clustered customer instances (S2_4i6s, S2_8i6s, S2_10i6s) despite the increased number of AFS options and different location configurations (Table 3-4). As the number of AFSs increases, the total cost of the optimal solution decreases for the same number of served customers (Table 3-5). With a larger number of AFS options, the distance required to incorporate needed AFS visits can only decrease. Of course, whether or not an additional AFS will be beneficial depends on its location.

3.5.2. Real-World Case Study

There are 21 publicly available biodiesel stations in VA, MD and DC considered together (U.S. DOE, 2009). Four customer-based scenarios were considered as described in Table 3-6 in which all 21 AFS locations are considered as options unless otherwise specified.

Table 3-6 Real world case study scenarios

Scenario	Description	Details
1	Transitioning to AFV	111 customers
2	Impact of increasing number of customers	Number of customers increased in increments of 50 from 200 to 500, adding customers at random locations within the study area to customer pool from Scenario 1, keeping AFS locations fixed
3	Impact of increased AFS availability	Identical to Scenario 1, but with additional AFSs located strategically, increased in increments of 2 from 22 to 28
4	Impact of driving range limits	Identical to Scenario 1, but driving range increased from 200 miles to 500 miles in 50 mile increments

The MCWS heuristic and DBCA were employed in solving the problem instances. Results from Scenarios 1 and 2 runs are provided in Table 3-7. Additional runs were made to show the heuristic solution when no driving range limitation (i.e. an infinite fuel tank capacity) is assumed. These results are also provided in Table 3-7. Results from Scenario 3 and 4 are provided in Figures 3-5 and 3-6, respectively.

Table 3-7 Heuristic solution results

	Without Driving Range Limit (MCWS)			***Modified Clarke and Wright Algorithm (MCWS)***			***Density Based Clustering Algorithm (DBCA) 15≤ε≤150, 1≤minPts≤30***		
Instance	***Total Cost (miles)***	***Number of tours***	***Customers Served***	***Total Cost (miles)***	***Number of tours***	***Customers Served***	***Total Cost (miles)***	***Number of tours***	***Customers Served***
111c	4745.90	17	109	5750.62	20	109	5750.62	20	109
	4731.22			*5626.64*			*5626.64*		
200c	9358.63	32	196	10617.02	35	190	10617.83	36	191[a]
	9355.56			*10428.59*			*10413.59*		
250c	11691.43	40	244	11965.10	41	235	11965.10	41	236[a]
	11668.388			*11886.61*			*11886.61*		
300c	14782.08	50	293	14331.30	49	281	14331.30	49	282[a]
	14762.41			*14242.56*			*14229.92*		
350c	17677.70	59	343	16610.25	57	329	16610.25	57	329
	17661.00			*16471.79*			*16460.30*		
400c	19968.97	67	393	19568.56	67	378	19196.71	66	373
	19936.75			*19472.10*			*19099.04*		
450c	23168.02	77	443	21952.48	75	424	21952.48	75	424
	21336.91			*21854.17*			*21854.19*		
500c	25032.38	83	492	24652.15	84	471	24652.15	84	471
	25024.94			*24527.46*			*24517.08*		

([a]) Indicates when a single cluster is formed at the end of the clustering step of DBCA.

The original instance (111c) results in Table 3-7 are compared with and without driving range limitations. Given the AFS infrastructure, the results indicate that 20 AFVs are required to serve the same number of customers served by 17 vehicles for which no driving range limitations would apply. Additionally, an increase by 19% in driving distance is required to serve the same set of customers when driving range limitations are imposed (i.e. through vehicle fleet conversion to biodiesel AFVs). As the number of customers increased from 200 to 500, the difference between those customers that could not be served when no driving range limitations were enforced as compared to when such limitations were required increased from 2 to 21.

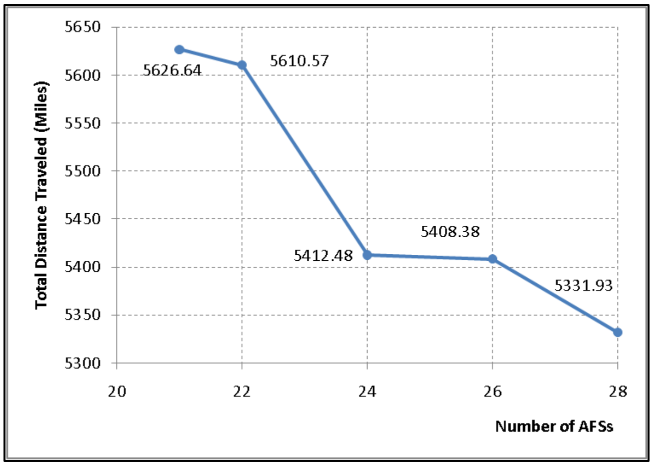
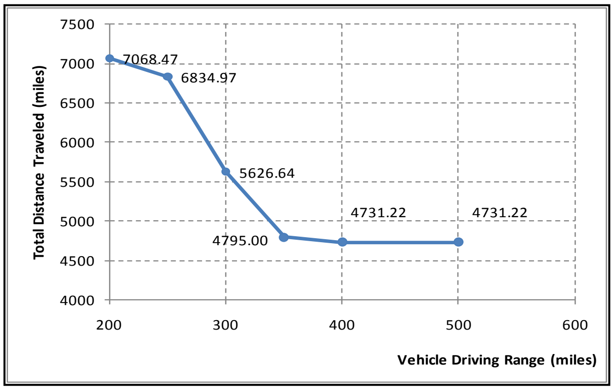


Figure 3-5 Effect of Increasing AFSs for Instance 111c

The graph in Figure 3-5 indicates that as the number of AFSs increases from 21 to 28 (a roughly 33% increase), the total distance traveled decreases by 295 miles (a roughly 5% decrease). Increased AFS availability can reduce AFV fleet operational costs; however, cost savings depends highly on the specific locations of the added stations. This is illustrated in the numerical experiments. An increase by three AFSs from 21 to 24 led to a reduction in travel distance by 213 miles as indicated in Figure 3-5, but an increase from 24 to 26 AFSs resulted in only a four mile reduction. Thus, it may be beneficial for the company to seek partnerships with agencies or companies that own private fueling stations in well-positioned locations or maintain one or more of its own refueling facilities located strategically within an operational area.



Driving range (miles)	Total Cost (miles)	Number of tours	Customers Served
200	7068.47	28	98
250	6834.97	25	107
300	5626.64	20	109
350	4795.00	17	109
400	4731.22	17	109
500	4731.22	17	109

Figure 3-6 Effect of Vehicle Driving Range on Total Distance Traveled

As indicated in Figure 3-6, as the driving range is increased from 200 to 400 miles, the required travel distance decreased by 2,337 miles. Any increase in driving range beyond 400 miles did not result in an improved solution, indicating that all customers could be served given the 21 AFSs located in the region. For example, a fleet of 25 vehicles each with a 250 mile driving range can serve 107 customers traveling 6,835 miles. A fleet of only 17 vehicles would be required to serve all 109 customers if the driving range of the vehicles is increased to 400 miles. Moreover, the total distance required to serve the customers would decrease to 4,731 miles based on the heuristic solutions.

3.6. Concluding Remarks

In this dissertation, the G-VRP is formulated and techniques were proposed for its solution. These techniques seek a set of vehicle tours that minimize total distance traveled to serve a set of customers while incorporating stops at AFSs in route plans so as to eliminate the risk of running out of fuel. Numerical experiments showed that these techniques perform well compared to exact solution methods and that they can be used to solve large problem instances. The ability to formulate the G-VRP, along with the solution techniques, will aid organizations with AFV fleets in overcoming difficulties that exist as a result of limited refueling infrastructure and will allow companies considering conversion to a fleet of AFVs to understand the potential impact of their decision on daily operations and costs. These techniques can help companies in evaluating possible reductions in the number of customers that can be served or increase in fleet size needed to serve an existing customer base, as well as any increase in required distance traveled as a result of driving range limitations and added fueling stops.

The formulation and solution techniques are applicable for any fuel choice. The techniques account for service times at the stations and, thus, the proposed approach is directly relevant in modeling conversion to electric vehicles in which significant time may be spent at stations for the purpose of recharging the battery and for possible programs that would permit the trading of a depleted battery for a fully charged one while en route. Moreover, this approach can be used in seeking optimal tours for gasoline or diesel powered fleets that involve special refueling arrangements.

The developed formulation and solution techniques presume that fuel usage is directly related to distance traveled. The model could be extended to consider more complex fuel-usage models, consideration of fuel prices and heterogeneous fleets in which vehicles may have different driving range limitations or be powered by different sources of fuel. The model could be extended to consider optimal station locations jointly with tour finding in future studies.

Chapter 4: Analysis of Demand for Vanpooling and Implications on GHG Mitigation

4.1 Introduction

The Executive Order on Federal Sustainability, signed by President Obama in 2009, commits the Federal Government to lead by example and reduce greenhouse gas emissions by 28% by 2020, increase energy efficiency, and reduce fleet petroleum consumption. Achieving this 28% reduction will reduce federal energy use by 646 trillion BTUs (British termal unit), which is equivalent to 205 million barrels of oil, or taking 17 million cars off the road for one year. This is also equivalent to a cumulative total of $8 to $11 billion in avoided energy costs through 2020 based on current energy prices (Executive Order, 2009).

Decades of highway and automobile oriented development, and subsidized oil and automobile industry, will make the attainment of this objective extremely difficult. The U.S. has 20.3% of the world's cars. The share of households that own more than three vehicles increased from 2.5% to 18.3% between 1960 and 2000 (U.S. DOE, 2010). In 2008, automobiles and light-duty trucks traveled 53.2% and 36.5% of the total vehicle miles traveled (VMT), respectively, while buses represented only 0.2% (U.S. DOE, 2010). In the 1970's, these percentages were 82.6% (for cars), 11.1% (for light-duty trucks) and 0.4% (for buses). Light-duty vehicles were responsible for 59% of the U.S. transportation GHG emissions in 2006 (U.S. DOT, 2010a). Moreover, the highest VMT share by purpose was due to work trips, representing the 27.5% of the total share, with 1.2 persons per VMT in 2009 (U.S. DOE, 2010).

Recognizing the significant role of light-duty vehicles in emissions production, policies and regulations that encourage the development and the application of Transportation Demand Management (TDM) strategies with the objective of reducing transportation GHG emissions has become a priority in the U.S. government agenda (see e.g. The Congestion Mitigation and Air Quality Improvement Program (CMAQ); Safe, Accountable, Flexible, and Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU); the Presidential Climate Action Project, 2010; U.S. DOT, 2010).

TDM strategies emerged in the U.S. during the 1970's for different but related reasons: as a response to the occurring energy crisis and to the declining funding for new transportation infrastructure. Starting from the 1970's, environmental effects of increased travel activity gained importance as single occupancy vehicles (SOVs) dominated as the preferred and in many instances only practical mode for personal transportation (Meyer, 1999). Federal policies that take aim at congestion mitigation, air quality improvement and transportation system management (TSM) have been carried through today with the addition of a GHG emission reduction objective. The transportation sector confronts the dilemma of global warming from a particular disadvantaged position; the rigid transportation infrastructure, the spread out built-environment that defines much of America, the automobile industry's creation and recreation of consumer demand, and the travel behavior resulting from such a social structure makes finding solutions to GHG emissions mitigation challenging but ever important.

Changing travel behavior has been and will be difficult but given the emergency of the climate change problem, the status quo is not an option. The challenge is to overcome the barriers of the urban-suburban-exurban geography and to identify opportunities within given transportation systems, finding the right combination of alternative options, policies and structures that will lead the transition to more environmentally sound strategies. Para-transit services with the help of advanced information and communication technologies can have a significant role in making that change happen. Para-transit (or ride-sharing) modes such as carpooling, vanpooling and subscription bus services (SBS) are traditionally seen as in-between modes that can bridge the gap between automobile use and transit services. Kirby et al. (1974) proposed an effective but quite deterministic way (based on distance) to identify the market for para-transit services. Recent advances in technology might have a significant role in the expansion of para-transit services and might contribute to their integration into a multi-modal system that works effectively as a whole (Figure 4-1).

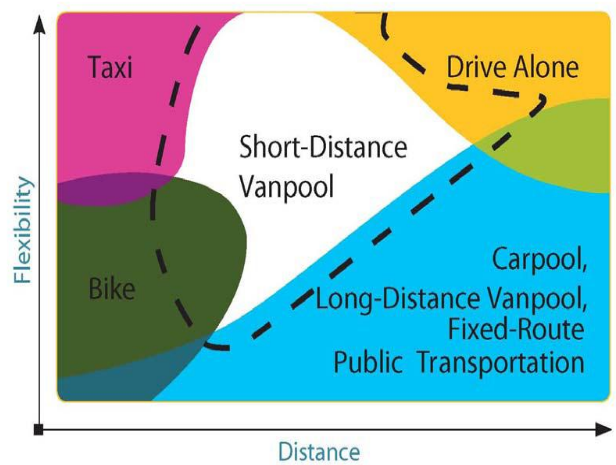


Figure 4-1 Vanpooling and other alternative transportation options, adopted from SANDAG Short-Distance Vanpool Transportation Feasibility Study (SANDAG, 2009)

For example, Geographic Positioning Systems (GPS), cellular phones, availability of emerging vehicle sharing systems such as Zipcar, and internet and social networking services have the potential to make dynamic ride-sharing type of services more flexible and convenient.

This research focuses on vanpooling programs aiming at reducing carbon-intensive work travel from the perspective of large employers. According to research conducted by the Federal Transit Administration (FTA), vanpooling is identified as the greenest motorized mode for urbanized areas with 0.22 CO_2e per passenger mile while the corresponding value for SOVs is 0.96 (2009 FTA values in U.S. DOT, 2010a). Expanding vanpool programs across the country might be an effective way to tackle the GHG emission problem. In fact, a study conducted in Massachusetts found that there was an average of 66% fuel use reduction per vanpool participant (Evans and Pratt, 2005). Another study, based on the Connecticut's vanpool program which included over 3,000 participants in 2006, estimated a total of 1,250 tons reduction in GHG emissions (0.42 tons per vanpooler) (U.S. DOT, 2010a). If these reduction values are applied to a 2% participation rate (as opposed to current vanpooling share of 0.3%) in the 50 largest metropolitan areas, a 1.22 million new vanpoolers would be created and a 1.33 mmt of CO_2e (CO_2 equivalent) would be mitigated (see U.S. DOT, 2010a for details of these estimations).

Federal, regional and local level regulations combined with subsidies and incentives can be used to enlarge market base as well as to influence operations, fuel and vehicle types used for the existing and future programs. In 2005, vanpooling accounted for 0.3% of all work trips at the national level (Evans and Pratt, 2005). However, in the period from 1974 to 1980, the interest in vanpooling was higher due to government policies and incentives. Vanpooling doubled each year reaching 15,000 programs in the

U.S. (Evans and Pratt, 2005). However, with the end of the energy crisis, vanpooling shares and their growth rates have declined. In 1999, there were about 8,500 vanpool programs and 10,000 more in 2005. This trend needs to change in order to achieve U.S. GHG emission targets (i.e. keeping the VMT growth to 1% annually and reducing GHG emissions by 80% by 2050 from 2000 levels).

Companies, agencies and institutions that are trying to reduce their GHG emissions either voluntarily (e.g universities) or in need of meeting regulatory requirements (of states, federal agencies) are required to evaluate options from a portfolio of possible alternatives. Vanpool can be a viable part of such a portfolio; targets commuters that do not have access to transit or need connectivity to transit stations as well as commuters who do not have a feasible alternative. From the perspective of an institution with the objective of reducing GHG emissions (to meet certain target levels), quantifying the benefits of each prospective alternative in terms of GHG emissions is a critical part of the decision making process. Identifying the best option presents several challenges. A market-based study is needed to determine if an adequate demand exists and whether the program would yield to significant GHG reductions. In order to calculate market share, the factors that influence decision to vanpooling need to be identified. Improvement of an existing program also requires understanding behavioral response, preferences, and attitudes of the potential and existing users of the service. Due to specific characteristics of each city, region, etc., user preferences and attitudes are likely to be different from place to place. Therefore, models developed for one city or institution may not be transferable. Surveys, analysis and models need to be developed for specific cases (e.g. Beaton et al., 1995). However, a general approach or procedure can be developed and serve as a guide.

This dissertation considers behavioral aspects of carpool/vanpool market potential and user attitudes and preferences. It seeks to contribute to efforts to reduce GHG emissions from commute trips by better understanding factors affecting decision to vanpool. This understanding will help companies, agencies and other institutions in developing policies, programs and strategies to reduce automobile commute trips, especially with SOVs, which is one of the main sources of institutional GHGs. Survey data collected by the University of Maryland (UMD) on the transportation patterns of commuters are analyzed, with a specific emphasis on carpooling/vanpooling.

Following a background on previous studies on vanpool market potential and on user attitudes and preferences described in Section 4.2, an overview of the case study and of the survey conducted at the UMD College Park campus are given in Section 4.3. In Section 4.4, descriptive statistics and results from a detailed data analysis associated with the case study are reported. The methodology used in analyzing factors that influence behavior, preferences and attitudes toward vanpooling are presented in Section 4.5. The analysis of the estimation results are presented in Section 4.6. Finally, findings and discussion of the models on how these results can be used to design a better service policy is presented in Section 4.7.

4.2 Background

In this section, literature on vanpool programs with particular focus on the analysis of demand and, where available, on the estimated environmental impacts of the proposed programs is presented. Not surprisingly most of the early works in the literature date back to the 1970s and 1980s, when issues related to high fuel price and shortage of oil reserves were relevant. However, these works were mainly limited to survey data analysis and did not utilize econometric methods, thus were not able to capture multivariate interactions among factors that affect the analysis (Hupp, 1981; Dowling et al., 1991; Christiansen et al., 1993; Burns, 1995; Davidson, 1995, for a review of the methods proposed for ridesharing demand analysis including vanpooling see, Kostyniuk 1982). The number of recent work on vanpooling is very limited. Most work in this area focuses on carpooling or ridesharing. The literature can be grouped into two categories: studies that focus on behavioral aspects (user preferences, attitudes, etc.) and studies that focus on physical aspects of the trip (e.g. delay caused by the pooling, trip distance between poolers, work start-end times). This review focuses on literature that studies behavioral aspects and the studies that consider environmental impacts (for physical aspects see for example Tsao and Lin (1999) and Amey (2011)).

Few early studies looked into environmental benefits of vanpooling. Morris (1981) analyzed impacts of a third-party vanpool program in Massachusetts. This study concluded that the program was beneficial and the cost savings of the users were far higher than the cost of the program. It also considered fuel consumption and emission impact. It was found that the vanpool program analyzed was not only cost efficient but also effective in reducing emissions at local level relative to other modes; however, its contribution to area wide reductions was small due to the limited market size and the predicted growth. However, Rose (1981) criticizes earlier studies that state vanpooling is the most energy efficient commuting mode. He bases his criticism on the methods used to compare alternative modes. Although he accepts that vanpooling can play a significant role in reducing GHGs, he concludes that efficient brokered-carpools could save up to 60% of the energy used by vanpools and presents them as competing modes. This fits to deterministic approach of the period, ignoring the fact that there is potential for both modes and that they are complementary.

On the behavioral side, most studies focused on factors affecting carpool and vanpool behavior. For example, Heaton et al. (1981) analyzed effectiveness of third-party vanpool programs on four existing projects from various angles such as organizational, operational and financial. Their results showed that vanpoolers in all projects were mostly people who do not need a car during the day, have fixed schedule, rarely work over time and commute relatively long distances. Bailey (1983) estimated vanpooling market share in the Baltimore region using simulated work trips. He found that vanpooling is preferred for trip distances that are equal-cost or longer (thus less costly) compared to drive alone alternative. He estimated about 200 vanpools can be formed with this cost based analysis. However, those distances shorten if there are factors that increase perceived driving cost such as higher gas price and parking and up to 2000 vanpools could be formed.

The studies that utilize econometric analysis to determine factors affecting decision to vanpool are limited. Koppelman et al. (1993) looked at the effectiveness of demand reduction strategies to encourage ridesharing modes including vanpooling. Their analysis suggested that a positive propensity towards ridesharing requires incentives in increased service quality and disincentives for automobile use (i.e. increase in parking cost in the Midwest suburban setting). They also found that gender and number of cars owned in the household plays a role in ridesharing propensity. Specifically, women and individuals in households with fewer autos were more likely to share ride. Whereas, people with variable work schedules, trip chaining and higher income are not likely.

Few recent researches focused on analyzing effect of service availability, price and subsidies on vanpooling behavior. Outwater (2003), stated that, unlike demand for transit and drive alone, demand for vanpooling depends on the service availability rather than on time and cost factors. Therefore, the author focused on vanpool prior-choices and estimated a multinomial logit model (MNL) to determine shifts from automobile and transit to currently available vanpool programs. The analysis is based on data from the Puget Sound Region, King County. The model results showed that significant determinants for switching to vanpool were: drive alone operating cost, employment accessibility by transit, number of workers and vehicles per household. Transit accessibility was found to be significant indicating that when the workplace is accessible by transit, the likelihood of commuter's shifting from transit to vanpool was high. Number of workers per household had a significant and negative coefficient which was attributed to different work schedules, locations or limited vehicle number in the household. Finally, the model showed that as the number of vehicles increase in a household, the propensity to drive alone, carpool and vanpool was higher than ride transit. Concas et al., (2005) investigated the effect of price and subsidies on vanpool demand by using discrete choice modeling techniques. A conditional discrete choice model was estimated on the 1999 employer and employee survey data collected under the commute trip reduction program of the Puget Sound region (Washington). The results showed that vanpool demand was relatively inelastic with respect to fare changes and that distance is an important factor in vanpool demand. While individual elasticities were equivalent to the aggregate estimate for shorter commutes (shorter than 30 miles), they become inelastic for longer distances (i.e. beyond 60 miles). An important result of their analysis was that subsidies have a great impact on demand; when offered, the vanpooling choice probability doubles. This work concludes that even though pricing and subsidies are important factors, other factors such as employee profile, industry sector, employer size, parking policies, and travel patterns must be considered when designing a vanpooling program. Winters and Cleland (2011) investigated impact of pricing on vanpool market potential. A stated preference method was used on data from four cities in Florida and a revealed preference approach was used on data from Puget Sound area of Washington to analyze user response to different pricing and service combinations. They employed logistic regression for analysis. The stated preference model results indicate that a 50% reduction in fares from $50 (2 mile pick-up distance and without any incentives) vanpool use would increase ~5%. The increase would be 22% if service was free. The revealed preference results indicated that a 15% increase in demand can be obtained for each 10% price reduction, within the range of prices modeled.

On the model transferability, Beaton et al. (1995) tested stated preference approach on demand management strategies in two different sites and found that even though the strategies are same due to different external conditions, models are not transferable. This highlights the need for a general approach that can be applied to different places.

This research contributes to the existing literature on commute trip reduction strategies in general and attitudes towards carpooling/vanpooling in particular. It introduces an econometric modeling approach that investigates potential for carpooling/vanpooling and that can be adopted by large-scale employers to provide better transportation services to their employees. It helps to answer decision questions that are vital for developing new alternative services or improving existing ones, such as whether the commuting behavior can be changed. If so, what is the magnitude of that change and which factors affect these changes? Answering these questions will help develop commute trip reduction strategies, such as vanpooling, that would provide the highest amount of participation, thus leading to greater environmental benefits. Two ordered response models are estimated and analyzed on data obtained from a commuter survey conducted at UMD.

4.3 Data and Survey Background

The UMD is a major public research university located on 1,250 acres of land on the Baltimore-Washington, D.C. corridor in suburban College Park area. Based on Fall 2009 figures, the university population is 46,753 of which 58% undergraduate students, 23% graduate students, 8% faculty and 11% staff (UMD, 2010). Although a good portion of (~41%) of undergraduate students is accommodated on-campus, majority of campus members live throughout the Washington-Baltimore metropolitan area and commute to/from campus. The data used for this research is obtained from the survey designed with the partnership of the Department of Transportation Services (DOTS), the Office of Sustainability, the Center for Integrative Environmental Research (CIER) and the Student Affairs Assessment Committee of the UMD (for survey questions, see Appendix).

The survey was conducted in Spring 2010 as part of the University's GHG emission reduction efforts. In May 2007, the president of the University signed the American College and University Presidents' Climate Commitment (ACUPCC, 2009), pledging to reduce GHGs and to achieve carbon neutrality. According to the University's GHG inventory, transportation is the second largest contributor to the University's GHG emissions with 31% after combined heat and power plant, which are responsible for 41% of the total emissions (Tilley et al., 2009). The inventory, which included GHG emissions from 2002 to 2008, indicated that 27% of the transportation GHG emissions are due to student commuters, 23% to faculty/staff commuters and 7% to the university fleet and Shuttle-UM while the rest (43%) was derived from air travel. Therefore, the DOTS developed a plan that commits to attain a 3,450 unit reduction in the number of commuter permit holders by 2015. As part of this plan, the Green Initiatives Program was developed, aiming to reduce the number of commuters by car and shifting demand to alternative transportation modes, including bicycling, carpooling, park and rides, and transit. In addition to these existing options, the university is considering the provision of a vanpooling service that potentially will shift 500 SOV commuters to vanpools.

4.3.1 The Data and the Survey

The Transportation Survey was conducted online in two phases. Participants to the first phase of the survey (ran for three weeks) were selected randomly and offered a cash incentive ($50). During this phase, 6,500 student emails were randomly selected by the Registrar's Office, which was directed to send one initial email and three reminder emails over the course of the survey. Faculty and staff were selected for survey participation in a different manner; a list-serve with 4,000 randomly selected employee emails was created. The second phase (lasted four weeks), was made available to all campus community on the DOTS website (a flash screen appeared upon entry) and was announced by a posting to the campus-wide list-serve. The format used was identical to the first phase with exceptions of the introductory text and incentives (i.e. no incentive).

The survey questions were designed to: (1) understand commuting behavior, (2) evaluate existing transportation programs, (3) analyze attitudes towards existing services and prospective alternative transportation programs. The survey had three parts aiming to collect the following information:

Part 1. General commuter information including: status classification, arrival/departure time, travel time, residential distance from campus, commute mode and frequency, and on-campus modal preferences. This part also included specific questions about driving, as driving is currently the main mode of commuting to/from campus.

Part 2. Attitudes towards alternative transportation options, such as bicycling, carpooling/vanpooling and transit (mainly Shuttle-UM). These questions are designed to evaluate existing programs (i.e. bicycling and carpooling) and analyze potential for new programs (such as vanpooling).

Part 3. Demographics, such as age, gender, driver license, type of the appointment at the University etc.

Questions in Part 2, regarding the potential program related questions, including carpooling and vanpooling, are the focus of the analysis in this research.

4.3.2. Sample Formation and Analysis Context

A total of 2,531 respondents participated in the survey (1,927 in Phase-I and 604 in Phase-II). Among these respondents, 2,015 (1,642 in Phase-I and 373 in Phase-II) provided complete data. Data were carefully examined to ensure consistency between reported travel modes, times and distances. Additional testing on both Phases-I and -II data were necessary to assess if the two datasets could be used jointly. In fact, two different procedures were applied to recruit the respondents. Phase-II was conducted through the DOTS website via a flash screen appearing upon entry, thus, the data from Phase-II had potential for selectivity bias. Therefore, when modeling the pooled data, a scaling of residuals of Phase-II to those of Phase-I was performed to test whether the two datasets were significantly different in relation to interest in carpooling/vanpooling. Based on the test results, the two data sets were not found to be significantly different and the two data sets (Phase-I and -II) were combined for the econometric analysis. However, it should be noted that the test results might have shown significant difference regarding other questions, such as mode choice.

In the next section, a descriptive analysis of the commuters' characteristics and their attitudes towards carpooling/vanpooling is given. The term carpooling and vanpooling were explicitly defined considering the possible unfamiliarity of the respondents to those services in the survey. Carpooling was defined as commuting by private car with one or more people (up to four), whereas, vanpooling was defined as commuting by van with five or more people. Furthermore, a hypothetical vanpooling service is described, where the van is provided by the university. One volunteer member is responsible for driving the van and keeping it at home in the evenings and the other participants to the service are requested to pay a monthly fee.

Respondents were asked to state their interest in carpooling/vanpooling to campus as driver or as passenger; responses were given on a 5-point ordinal scale: not at all interested (NAI), not very interested (NVI), moderately interested (MI), very interested (VI) and extremely interested (EI). Other questions regarding vanpooling include: current carpooling and vanpooling frequency (Q34 in Appendix), willingness to pay a monthly fee for a daily vanpool as passenger (Q37 in Appendix), effect of the removal of the vanpooling fee on willingness to be driver (Q38 in Appendix). In addition, questions regarding the reasons that make respondents inclined to carpool or vanpool (Q39-Q46 in Appendix) and barriers to carpooling and vanpooling (Q47-Q58 in Appendix) are included in the survey.

4.4. Descriptive Statistics

An overview of survey population characteristics is presented in Table 4-1. In both phases, undergraduate students are underrepresented while, graduate students, faculty and staff are overrepresented compared to their actual shares 58%, 23%, 8% and 11%, respectively. In both phases, nearly 93% of the respondents live off-campus, while the remaining 7% live on-campus. Of these 93% off-campus respondents, 41% live further than 10 miles from campus in Phase-1 while this percentage is about 20% in Phase-II. This difference is likely due to the larger share of faculty and staff in Phase-1 compared to the Phase-II sample. Similar differences can be observed, possibly due to the same reason, in the percentage of respondents with a U.S. driver’s license: 93.5% in Phase-I, while 84.8% in Phase-II. Similarly, 36% of the respondents are under age 25 and 66% are under age 35 in Phase-I, while these percentages are 55% and 86%, respectively, in Phase-II. In both phases, the gender distribution is slightly skewed towards female (about 56% female versus 43% male) respondents. Finally, in both phases, the majority of the trips are shorter than 45 minutes (73% in Phase-I and 77% in Phase-II). Approximately

25% of commutes last longer than 45 minutes which demonstrates a viable market potential for a vanpool program.

Table 4-1 Basic demographics and travel statistics

	Phase- I		Phase-II	
	N	*%*	*N*	*%*
Status				
Undergraduate Student	363	22.11	165	44.24
Graduate Student	568	34.59	120	32.17
Faculty	255	15.53	25	6.70
Staff	456	27.77	63	16.89
(Total)	(1642)		(373)	
Work classification				
Part-time	185	11.27	21	5.63
Full-time	1457	88.73	352	94.37
Location				
On-campus	110	6.70	23	6.17
Off-campus	1532	93.30	350	93.83
Distance from campus(miles)				
On-campus	110	6.70	23	6.17
<1 mile	104	6.33	38	10.19
1-5 miles	434	26.43	163	43.70
6-10 miles	313	19.06	73	19.57
11-15 miles	202	12.30	23	6.17
16-20 miles	135	8.22	14	3.75
>20 miles	344	20.95	39	10.46
Average commute time (minutes, door-to-door)				
<15 min	270	16.44	56	15.01
15-30min	528	32.16	139	37.27
30-45 min	397	24.18	93	24.93
45-60 min	280	17.05	46	12.33
61-90 min	131	7.98	28	7.51
>90 min	36	2.19	8	2.14
Gender				
Male	633	43.12	164	43.97
Female	832	56.67	207	55.50
Transgender	3	0.20	2	0.54
New in Maryland				
Yes	322	22.92	96	25.74
No	1083	77.08	277	74.26
License to drive in the U.S.				
Yes	921	93.50	235	84.84
No	64	6.50	42	15.16

Age				
18-25	592	36.05	191	55.36
26-35	496	30.21	107	31.01
36-45	211	12.85	15	4.35
46-65	316	19.24	29	8.41
>65	27	1.64	3	0.87

4.4.1. General Commuting Characteristics

Mode choice of the campus community (living off-campus only) is analyzed to better understand commuting patterns. Modal split is calculated by taking into account trip frequency and distance information. For each respondent, first, the total number of trips made in a week is calculated (all modes considered). Then, the percentage by each mode and the mode with maximum share are obtained. While this process gave the most frequently used mode for each respondent, the consistency of the results were ensured by checking the distance, travel time and other characteristics when necessary. This consistency check was especially needed when more than one mode shared the same percentage for a respondent.

The analysis is based on two factors: (1) the status of the respondent and (2) the one-way commute distance from campus. According to the analysis by status for Phase-I, majority of the trips are made alone by car for all groups (Table 4-2). Driving alone share, on average, is 72.8% for faculty-staff and 49.5% for students. This result is expected as students tend to live closer to campus; thus, they can use alternative or non-motorized transportation options such as bicycling and Shuttle-UM. While ~40% of the students (graduate and undergraduate) use Shuttle-UM, the percentage of faculty and staff riders is low (~8%). The carpool share is higher for undergraduate students and staff (7.9% and 7.2% respectively). Car and Shuttle-UM (park and ride) and MetroRail/MARC and Shuttle-UM also have a relatively high share among other combinations of modes. In Phase-II, Shuttle-UM has a significant share, higher than drive alone which is likely due to the high rate of undergraduate students in the sample.

Table 4-2 Mode split to/from campus by status (for off-campus members)

Phase 1	Undergraduate Student %	Graduate Student %	Faculty %	Staff %
Bike	3.8	7.3	3.5	1.6
On foot	4.9	7.8	2.0	4.7
Alone by car	49.8	49.2	72.9	72.7
With others by car (carpool/vanpool)	7.9	3.9	5.9	7.2
Scooter/Motorcycle	1.1	0.5	0.0	0.4
Shuttle-UM	19.6	20.2	5.9	2.2
Other bus	1.5	1.2	0.8	2.5
MetroRail/MARC and Shuttle-UM/bus	2.3	5.0	4.3	2.0
By car and Shuttle-UM (Park & Ride)	6.8	2.3	3.1	3.6
Shuttle-UM/bus and bike	0.4	0.7	0.4	0.0
Car and bike	1.1	1.2	0.4	1.6
Other	0.8	0.7	0.8	1.6
Total N	*265*	*565*	*255*	*447*
Phase II	%	%	%	%
Bike	10.5	9.2	16.0	3.3
On foot	11.2	8.3	4.0	3.3
Alone by car	24.5	15.0	8.0	54.1
With others by car (carpool/vanpool)	3.5	2.5	12.0	3.3
Scooter/Motorcycle	1.4	0.8	0.0	0.0
Shuttle-UM	40.6	54.2	32.0	14.8
Other bus	2.1	4.2	8.0	6.6
MetroRail/MARC and Shuttle-UM/bus	1.4	3.3	8.0	6.6
By car and Shuttle-UM (Park & Ride)	3.5	1.7	12.0	3.3
Shuttle-UM/bus and bike	1.4	0.0	0.0	1.6
Car and bike	0.0	0.0	0.0	1.6
Other	0.0	0.8	0.0	1.6
Total N	*143*	*120*	*25*	*61*

In Table 4-3, the modal share is analyzed based on distance from campus. It can be seen that non-motorized transportation modes' share is relatively high for distances up to five miles; as distance increases, drive alone's share reaches 76.3 % (in Phase 1). The results show that drive alone has the highest share for all distance groups off-campus. Carpooling share also grows as the distance from campus increases (e.g. 11.1% for 16-20 miles and 9.9% for >20 miles). Shuttle-UM is mostly used by respondents who live within 10 miles from campus; although shares remain over 5% distances up to 15 miles. The reason that shuttle and other public transportation mode shares are very low for longer distances are probably due to the limited public transportation service available to commuters. In line with this reasoning, the park and ride option has a higher share for distances over 15 miles. This shows that when service is available, people tend to use public transportation and possibly a vanpool service.

Table 4-3 Mode split to/from campus by distance (in miles) (for off-campus members)

Phase 1	<1 %	1-5 %	6-10 %	11-15 %	16-20 %	>20 %
By Bike	20.2	11.1	1.6	0.5	0.0	0.0
On foot	23.1	11.5	0.0	0.0	0.0	0.0
Alone by car	26.0	47.0	62.3	74.3	76.3	74.4
With others by car	1.0	4.4	2.9	5.0	11.1	9.9
Scooter/Motorcycle	0.0	0.9	13	0.0	0.0	0.0
Shuttle-UM	25.0	21.0	19.5	5.4	0.7	2.9
Other bus	1.0	2.5	1.6	2.5	0.7	0.3
MetroRail/MARC and Shuttle-UM/bus	0.0	0.2	7.7	6.4	4.4	4.1
By car and Shuttle-UM (Park & Ride)	1.0	0.2	2.9	4.5	5.2	5.2
Shuttle-UM/bus and bike	1.0	0.2	0.3	0.0	0.0	0.0
Car and bike	1.9	0.9	0.0	0.0	0.0	1.5
Other	0.0	0.0	0.0	1.5	1.5	1.7
Total N	*104*	*434*	*313*	*202*	*135*	*344*
Phase II						
By Bike	15.8	14.7	2.7	4.3	0.0	0.0
On foot	36.8	3.7	0.0	0.0	0.0	0.0
Alone by car	2.6	16.0	30.1	47.8	57.1	57.9
With others by car	2.6	3.1	5.5	0.0	0.0	7.9
Scooter/Motorcycle	0.0	1.2	1.4	0.0	0.0	0.0
Shuttle-UM	42.1	50.3	43.8	13.0	35.7	13.2
Other bus	0.0	6.1	2.7	4.3	7.1	2.6
MetroRail/MARC and Shuttle-UM/bus	0.0	0.6	6.8	13.0	0.0	5.3

By car and Shuttle-UM (Park & Ride)	0.0	1.2	5.5	8.7	0.0	7.9
Shuttle-UM/bus and bike	0.0	1.8	0.0	0.0	0.0	0.0
Car and bike	0.0	0.0	0.0	0.0	0.0	2.6
Other	0.0	1.2	1.4	8.7	0.0	2.6
Total N	*38*	*163*	*73*	*23*	*14*	*38*

4.4.2. Driving Behavior and Attitudes Towards Carpooling and Vanpooling

As discussed in Section 4.4.1, driving alone has the highest share among all modes for all status and distance groups over 5 miles (Tables 4-2 and 4-3, Phase 1). Faculty and staff share of driving alone (~73%) is higher than students (~50%). Drive alone's share based on distance vary from 26% to 76.3% (Table 4-3, Phase 1). In order to evaluate current carpooling behavior, reported vehicle occupancies are presented in Table 4-4.

Table 4-4 Number of passengers reported as the carpool and vanpool size

	Phase-I (N=1437)	Phase-II (N=325)	All (N=1762)	Phase-I %	Phase-II %	All %
Drive Alone	1041	197	1238	72.44	60.62	70.26
+1 person	303	100	403	21.09	30.77	22.87
+2 person	58	15	73	4.04	4.62	4.14
+3 person	22	7	29	1.53	2.15	1.65
+4 person	5	2	7	0.35	0.62	0.40
+5 or more	8	4	12	0.56	1.23	0.68

According to the survey results, 27% of the respondents (in Phase-I) who answered the question reported that they usually ride with other people when they drive to campus. The majority of these carpools are made with one other person only (21.09%). However, there is a possibility that these carpools are formed with a family member, such as dropping children or riding with spouse.

Table 4-5 Existing carpooling and vanpooling pattern

Frequency	Phase-I N=1615	Phase-II N=356	Both N=1824	Phase-I %	Phase-II %	Both %
Most everyday	126	21	147	7.80	5.90	8.06
At least Once per week	96	27	123	5.94	7.58	6.74
At least Once per month	83	33	116	5.14	9.27	6.36
Rarely or never	1310	275	1585	81.11	77.25	86.90

According to Phase-I results, 7.8 % of the respondents carpool or vanpool most every day; 5.94% carpool at least once a week (Table 4-5). Carpooling share increases with distance from campus (Table 4-3). However, the majority of the respondents (81.11%) stated that they rarely or never carpool. Understanding the reasons for carpooling and barriers to carpooling will help making adjustments in the current University Carpooling Program as well as designing a new vanpooling program.

In order to understand propensity of the respondents to vanpool in case such service is provided by the university, questions that are discussed in Section 4.3.2 are analyzed. The two main questions are used to understand whether being passenger or driver makes any difference in respondents' interest in carpooling or vanpooling. As it can be seen in Table 4-6, where data from both Phases-I and -II are presented, interest in carpooling and vanpooling is not very high but there is a considerable potential (if moderate to extreme interest is considered). The interest as passenger is slightly higher than as driver. The interest increases as the distance from campus increases. People who reside approximately farther than 10 miles from campus can be regarded as potential vanpool participants.

Table 4-6 Interest in carpooling and vanpooling as passenger or as driver based on distance (miles)

	As Driver (N=1097)				As Passenger (N=1126)			
	6-10 N=357 %	11-15 N=216 %	16-20 N=147 %	>20 N=377 %	6-10 N=379 %	11-15 N=220 %	16-20 N=147 %	>20 N=380 %
Not at all Interested	33.89	34.72	40.14	32.10	29.55	34.09	36.73	31.58
Not Very Interested	29.13	34.26	27.21	25.20	25.86	27.73	23.81	21.84
Moderately Interested	29.41	21.30	23.81	28.91	31.40	23.18	25.85	28.16
Very Interested	4.76	7.41	6.80	9.28	8.44	8.64	11.56	10.26
Extremely Interested	2.80	2.31	2.04	4.51	4.75	6.36	2.04	8.16

The same data is analyzed from another perspective and classified by status (Table 4-7). Faculty and graduate students have higher interest for being a driver while both graduate and undergraduate student interest are higher for being a passenger. Staff members' interest was lower compared to other groups for both passenger and driver roles.

Table 4-7 Interest in carpooling and vanpooling as passenger or as driver based on status

	As Driver (N=1142)				As Passenger (N=1126)			
	UGS N=214 %	GS N=315 %	Faculty N=205 %	Staff N=363 %	UGS N=216 %	GS N=326 %	Faculty N=210 %	Staff N=374 %
Not at all Interested	28.97	31.11	63.90	36.09	25.93	25.46	38.10	37.97
Not Very Interested	30.84	25.71	52.68	29.75	24.54	20.86	27.14	26.47
Moderately Interested	27.57	31.75	46.34	26.17	31.02	35.28	23.33	22.46
Very Interested	7.94	8.25	8.78	4.96	9.72	11.35	7.14	9.09
Extremely Interested	4.67	3.17	5.37	3.03	8.80	7.06	4.29	4.01

-UGS and GS stand for undergraduate and graduate student respectively

Currently, the university does not have an official vanpooling service. The prospected program assumes that one volunteer member is responsible for driving the van and keeping it at home in the evenings; other members pay a monthly fee to participate in the vanpool. Then, the willingness to pay for such a service was investigated. Table 4-8 summarizes the survey results regarding willingness to pay for a vanpool service provided by the University. Consistently, all status groups and distance groups agreed to pay $10-$20 per month. Another interesting observation is that, as the distance from campus increased, the respondents were willing to pay more for the service; this shows that, the long commute and corresponding high cost affect the perception of the respondents on vanpooling program.

Table 4-8 Willingness to pay for a vanpool service provided by the university

$ per month	By Classification (N=1103)				By Distance (N=1103)			
	UGS N=213 %	GS N=324 %	Faculty N=203 %	Staff N=363 %	6-10 N=372 %	11-15 N=214 %	16-20 N=143 %	>20 N=374 %
Not at all	38.49	34.25	48.27	45.73	39.78	45.79	42.66	40.11
< $10	16.43	20.06	10.83	10.46	20.70	15.42	8.39	10.16
$10-$20	25.82	25.61	16.25	20.66	24.19	23.36	27.27	17.91
$20-$30	14.08	11.72	14.28	13.49	11.83	9.81	15.38	15.78
$30-$40	5.16	8.33	10.34	9.64	3.49	5.61	6.29	16.04

-UGS and GS stand for undergraduate and graduate student respectively

The survey also inquired if the removal of the monthly participation fee would impact the willingness to be the primary driver. As Table 4-9 suggests, in all status groups and all distance groups, the majority of the respondents were indifferent to the fee removal.

Table 4-9 Interest in being primary driver in case monthly fee is removed

	By Classification (N=1097)				By Distance (N=1094)			
	UGS N=213 %	GS N=320 %	Faculty N=202 %	Staff N=362 %	6-10 N=369 %	11-15 N=211 %	16-20 N=142 %	>20 N=372 %
Much more likely	8.92	6.25	2.97	5.25	5.15	5.21	4.93	7.26
Slightly more likely	5.63	4.69	1.49	2.76	5.42	2.37	2.82	2.96
No change	50.70	56.88	73.27	69.61	62.60	68.25	64.79	59.95
Slightly less likely	22.54	22.19	13.37	11.05	20.05	15.17	15.49	14.78
Much less likely	12.21	10.00	8.91	11.33	6.78	9.00	11.97	15.05

-UGS and GS stand for undergraduate and graduate student respectively

The survey also included questions aiming at understanding reasons that would make the respondents more inclined to carpool or vanpool. According to the analysis by member status (Table 4-10), frequent pick-up and drop-off times are extremely important. Students are sensible to increase in the cost of gasoline and more convenient parking options. Faculty and staff ranked very high a more convenient Guaranteed Ride Home Program and an increase in the cost of gasoline. Based on these responses, we can conclude that frequent and flexible pickup and drop-off times would encourage many campus members to use the service. It should be noted that the university already has a Guaranteed Ride Home service through Commuter Connections, which is a regional network of transportation organizations coordinated by the Metropolitan Washington Council of Governments (MWCOG). Emphasizing and marketing this service intensively might help faculty and staff members to be more inclined to vanpool.

Table 4-10 Reasons that would make campus members more inclined to carpool or vanpool (by status)

Reasons	UGS N=700	GS N=430	Faculty/Staff N=610
Web application that matched me with potential carpool partners	7.29	6.05	5.25
More convenient parking options	13.14	8.84	4.92
Increase in the cost of parking	7.43	7.44	9.84
Increase in the cost of gasoline	9.14	9.07	8.20
Finding good company to ride with	10.71	8.14	6.72
Less expensive parking than the days when I drive alone	5.43	3.95	5.25
A more convenient Guaranteed Ride Home Program	6.57	7.44	10.00
Frequent pick-up and drop-off times	31.14	38.14	29.67

-UGS and GS stand for undergraduate and graduate student respectively

Analyzing the same factors by distance, we obtain additional information about the preferences of the campus community (Table 4-11). For all distance groups, again frequent pick-up and drop-off times is the most important factor affecting the interest in vanpooling. Interestingly, the 11-15 mile group ranked this option with a greater share. Web application that matches commuters with a potential partner was not highly ranked but its ranking increased as distance from campus increased. This suggests that, as the member's distance from campus increase, their location may disperse to a larger area and finding a carpool or vanpool partner may become more challenging. In addition, because of the long commute time, members maybe more concerned about their pool partners. More convenient parking options were valued most by 6-10 mile group but other groups' shares were also close. The increase in the cost of parking received the highest ranking from 16-20 mile group. As expected, >20 mile group ranked the increase in the cost of gasoline the highest. Finding good company option was third important reason for 6-10 mile group, while it had the highest share among other distance groups. Counter intuitively, this reason was the fifth important for the >20 miles group.

Table 4-1 Reasons that would make campus members more inclined to carpool or vanpool (by distance, in miles)

Reasons	6-10 N=224 %	11-15 N=152 %	16-20 N=93 %	>20 N=236 %
Web application that matched me with potential carpool partners	3.57	3.95	7.53	7.63
More convenient parking options	7.14	6.58	5.38	5.51
Increase in the cost of parking	8.04	4.61	15.05	6.36
Increase in the cost of gasoline	8.48	8.55	6.45	13.98
Finding good company to ride with	8.93	8.55	7.53	7.20
Less expensive parking than the days when I drive alone	4.46	3.29	3.23	4.66
A more convenient Guaranteed Ride Home Program	10.27	4.61	7.53	8.05
Frequent pick-up and drop-off times	34.82	37.50	32.26	31.78

The survey also included questions about barriers to carpooling and vanpooling. Learning what prevent campus members from carpooling and vanpooling will help improving the current carpool program as well as developing a future vanpool program. According to the analysis by status (Table 4-12) the most important barrier is the need of a specially equipped vehicle. After a careful investigation, we concluded that the respondents might have meant child seat as special equipment (see shares of "I need to pick-up/drop-off my children” and “I need a specially equipped vehicles”). For the faculty-staff group, the second highest reason stated is not having a car. This is useful information that this group does not already have a car and there is a high potential for them to become member of a carpool or vanpool service. Similarly, more than half of the student groups also do not have car and thus suggesting a promising market potential. These results also suggest that if the University would provide a larger day-care service or an elementary/middle school option on-campus, the majority of the campus members may not need to drive alone.

Table 4-2 Barriers to carpooling and vanpooling (by status)

Barriers to carpooling and vanpooling	Student(Both) N=700 %	Faculty/Staff N=610 %
I do not have a car.	55.71	72.46
I need my car for off-campus trips.	23.71	17.70
I have a constrained or irregular schedule.	9.57	8.52
I need a specially equipped vehicle.	77.57	80.16
I need to pick-up/drop-off my children.	77.57	61.15
I do not have a way to find a carpool or vanpool group.	36.29	45.25
I do not have time to wait on others.	11.71	11.31
I do not like to depend on others I do not know well.	10.00	10.33
I am concerned about my safety.	26.57	33.28
I prefer to ride alone.	25.71	27.38
I am concerned about becoming stranded on campus.	17.71	18.03

The barriers to carpooling and vanpooling by distance also show a similar pattern (Table 4-13). Specially equipped vehicle is the most important barrier to all distance groups. Picking up and dropping-off the children and not having a car are the next important barriers to all distance groups.

Table 4-3 Barriers to carpooling and vanpooling (by distance, in miles)

Barriers	6-10 N=224 %	11-15 N=152 %	16-20 N=93 %	>20 N=236 %
I do not have a car.	64.29	45.54	76.34	74.58
I need my car for off-campus trips.	24.55	12.95	18.28	19.92
I have a constrained or irregular schedule.	6.25	4.91	4.30	7.63
I need a specially equipped vehicle.	79.46	50.45	81.72	82.20
I need to pick-up/drop-off my children.	66.52	38.84	66.67	67.37
I do not have a way to find a carpool or vanpool group.	38.39	23.21	49.46	36.02
I do not have time to wait on others.	8.48	7.59	12.90	8.47
I do not like to depend on others I do not know well.	7.59	7.14	10.75	8.90
I am concerned about my safety.	29.91	19.64	36.56	25.85
I prefer to ride alone.	29.46	16.07	25.81	24.58
I am concerned about becoming stranded on campus.	20.54	11.16	16.13	11.86

4.5 Modeling Approach

The type of questions where the answers are given in an ordinal scale, such as the questions explained in Section 4.3.2, are called ordered-responses. The modeling approach, where the dependent variable is in ordered form, is typically Ordered Choice Modeling within the Discrete Choice Modeling framework (e.g. Train, 2009; Greene and Hensher, 2009; Bhat and Pulugurta, 1998). Other approaches are also available and they differ based on the treatment of the dependent variable. For example, it is possible to specify an unordered model such as nested logit, mixed logit, or probit model but they would not fit the structure of the data properly, because such models are derived from specification of a utility function for each alternative. In ordered models, this would mean each response alternative has a utility and the respondent chooses the one with highest utility (Train, 2009).

In ordered models, the dependent variable is treated as an unobserved, continuous latent variable (y*) and the ordinal responses j=1,.,J represent measurements of this unknown latent variable, and y_i=j represents the ordered outcome for person i. This latent variable can be considered as the utility or opinion of the respondent about the subject in question. The respondent answers to the question based on that opinion. Because the given options are discrete in ordered response questions, there may not be a value that exactly represents the respondent's utility or opinion. Therefore, the value y_i* is determined by J-1 thresholds (μ_1, $\mu_{2,\dots,}\mu_{J-1}$) (Train, 2009). The observed y_i values represent the value of y_i* depending on the threshold interval y_i falls to. For example, in this study, j=1,..,5, where 1=NAI, 2= NVI, 3=MI, 4=VI and 5=EI. An observation of y_i =1 means that for person i, the value of y* is less than or equal to μ_1. Similarly, y_i=2, if $\mu_1 < y^* \leq \mu_2$, y_i =3, if $\mu_2 < y^* \leq \mu_3$, y_i =4, if $\mu_3 < y^* \leq \mu_4$, y_i =5, if $y^* > \mu_4$.

The functional form of Ordered Choice Model takes the following form:

$$y_i^* = \boldsymbol{\beta}'\mathbf{x_i} + \varepsilon_i \text{ , } i = 1,.....,n, \tag{5-1}$$

where $\boldsymbol{\beta}\boldsymbol{x}_i$ represents the observable part and ε_i represents the unobservable error term of respondent i's utility y_i*. The vector $\boldsymbol{x_i}$ represents a set of K explanatory variables that are assumed to be independent from ε_i. Parameters vector $\boldsymbol{\beta}$ represent the impact of explanatory variables and thresholds on respondents' ranking, in this case, interest in vanpooling as passenger/driver (μ=1,..,J). The unobserved factors ε_i are considered random and their distribution determines the probability for the possible responses of NAI, NVI, MI, VI, and EI. Ordered models have proportional odds (or parallel regression) assumption which means the relationship between all outcome groups is same. Models considered in this study do not consider heterogeneity across individuals.

The probability of a respondent choosing one of these responses can be calculated based on the distribution of ε_i chosen. In this research, logistical distribution with cumulative distribution of F(ε_i) = $exp(\varepsilon_i)/(1+exp(\varepsilon_i))$ is assumed for ε_i. Accordingly, the probability of an answer $y_i=j$ is computed as follows (Train, 2009):

$$\Pr(y_i = j|\boldsymbol{x_i}) = \Pr(\varepsilon_i \leq \mu_j - \boldsymbol{\beta' x_i}) - \Pr(\varepsilon_i \leq \mu_{j-1} - \boldsymbol{\beta' x_i}), j = 1,.., j. \tag{5-2}$$

$$\Pr(y_i = j|\boldsymbol{x}_i) = \frac{e^{\mu j - \boldsymbol{\beta' x_i}}}{1+e^{\mu j - \boldsymbol{\beta' x_i}}} - \frac{e^{\mu_{j-1} - \boldsymbol{\beta' x_i}}}{1+e^{\mu_{j-1} - \boldsymbol{\beta' x_i}}}, j = 1,... j. \tag{5-3}$$

These probabilities take the following form for Ordered Probit Model where ε_i is assumed to have standard normal distribution (Train, 2009).

$$\Pr(y_i = j|\mathbf{x}_i) = \Pr(\varepsilon_i < \mu_j - \boldsymbol{\beta'}\mathbf{x}_i) - \Pr(\varepsilon_i < \mu_{j-1} - \boldsymbol{\beta'}\mathbf{x}_i), j = 1,.., J. \tag{5-4}$$

$$\Pr(y_i = j|\mathbf{x}_i) = \phi(\mu_j - \boldsymbol{\beta'}\mathbf{x}_i) - \phi(\mu_{j-1} - \boldsymbol{\beta'}\mathbf{x}_i), j = 1,...J. \tag{5-5}$$

where Φ represents the standard cumulative normal function.

Parameter estimation is performed solving a maximum likelihood estimation problem. The log likelihood function for ordered logistic regression model is (Greene and Hensher, 2009):

$$Log\ L = \sum_{i=1}^{n}\sum_{j=1}^{j} m_{ij} log\left[F(\mu_j - \boldsymbol{\beta'}\mathbf{x}_i) - F(\mu_{j-1} - \boldsymbol{\beta'}\mathbf{x}_i)\right] \tag{5-6}$$

subject to μ_0=-∞, $\mu_1=0$, μ_j=+∞, where m_{ij} is an indicator that takes value 1 if $y_i=j$ and zero otherwise.

4.5.1 Model Specification

Two different models, a passenger and a driver model, have been estimated to explain interest in carpooling/vanpooling from the perspectives of the passenger and driver. A sequential factor elimination procedure is applied to select the independent factors that affect the ordered discrete perception categories. The following factors are included in the final model specifications:

The continuous dependent variables

1. Interest in carpooling/vanpooling as driver (from 1 to 5 in increasing order).
2. Interest in carpooling/vanpooling as passenger (from 1 to 5 in increasing order).

Commuter characteristics

3. Status and willingness to pay interaction variables (undergraduate student, graduate student, faculty and staff interactions with willingness to pay (dollars per month) variable).

Commute characteristics

4. One way commute distance from campus, obtained from zip code (two dummy variables that take value one: for Distance 5-to-15 miles and Distance > 15 miles).
5. Location of the commuter (two dummy variables, Washington Area and Baltimore Area).
6. Commuting alone by car frequency (a dummy variable for driving alone four or more times a week).
7. Carpooling behavior (a dummy variable that takes value one if respondent rarely or never carpool/vanpool to campus).

Variables related to attitudes and preferences

8. Effect of removal of the participation fee (dummy variable takes value one if extremely increase the interest, zero otherwise).

9. Reasons that would make them more inclined to vanpooling (dummy variables that take value one if following reasons are selected as one of top three reasons, zero otherwise: Web application, Convenient parking, Cost of parking, Cost of gas, Good company, Cheap parking, Convenient ride home service, Frequent pickup/drop off service).
10. Barriers to vanpooling (dummy variables that take value one if following are selected as one of top three barriers, zero otherwise: Do not have a car, Need to pick up children, Like independency).

Demographic variables

11. Age (two dummy variables are used for age groups of 35-to-45 and greater than 45).
12. Gender (dummy variable that takes value one male, zero if female)
13. Whether licensed to drive or not (dummy variable that takes value one if licensed, zero if not).

4.6. Model Estimation

Table 4.14 presents the empirical results obtained by modeling interest in vanpooling/carpooling from the perspective of the passenger and driver. Estimations are based on ordered logit and ordered probit formulations and are performed using software package STATA 9.2 (StataCorp, 2005). These models are estimated with ordered logit and probit models to investigate if assumptions on the error terms have a significant impact on the estimation results.

4.6.1 Ordered Logit Model Estimation Results of Interest as Passenger and as Driver

The interaction variables that combine respondents' status and willingness-to-pay for a university provided vanpooling service are significant factors determining the interest in vanpooling as passenger. Status can be considered a proxy for income, which is unfortunately not available. Graduate students are those with the highest propensity to pay for the service under analysis (with coefficient estimate 0.823 in passenger model in Table 4-14); other groups show similar behavior. A similar pattern is observed in the driver model; however, a decrease in the coefficient values is observed for all status groups. These coefficients represent the rate of change in the dependent variable for a one unit change in the independent variable of interest, in the ordered log-odds scale while all other independent variables kept constant in the model. For example, a unit increase in faculty & willingness-to-pay variable will increase the log-odds of being in a higher level of interest to be a passenger by 0.771 (while all other variables are held constant at their mean values) (Table 4-14). Higher coefficients of the status and willingness-to-pay interaction variables in the passenger model indicate that interest in being a passenger is higher. Graduate students' coefficient is higher, indicating higher log-odds for being in a higher level of interest to be a passenger (by 0.823). Although this may seem contradictory to their low income levels, it may be a function of factors, such as perception of driving cost and high education level. Faculty and graduate students have higher coefficients in driver model, which maybe a function of their flexible or irregular schedule, and the need for independence. In passenger and driver models, staff members have lower coefficients than other groups. On the other hand, one would expect that staff would have high interest in being a passenger (or even driver) as they have a regular schedule. In this case, some other demographic factors, such as age, having young children, and residential distance etc. may be playing an important role in their choices.

Interest in vanpooling/carpooling is higher for commuters who live 15 miles or more from campus; whereas, distances shorter than 15 miles are not a determinant of interest. People who live farther from campus expect to save time and money especially during rush hours. The interest in driving is higher than the interest in being a passenger for distances over 15 miles. This can be explained by the fact that users might still want to maintain a certain independency. This factor (see “like independence” factor in Table 4.13) has negative sign and supports the previous interpretation.

In order to analyze the impact of residence areas, dummy variables derived from the aggregation of residential information in two metropolitan areas (Washington and Baltimore) are introduced. According to the results, residing in Washington is a significant determinant for being a passenger while, it is not a significant factor in the driver model. However, the effect of this variable has a negative sign, indicating that Washington area residents are not likely to participate in such a program as the passenger. The respondents who live in the Baltimore area, however, are interested in being the driver while this factor is not significant for the passenger model. The Washington area is served by a good public transportation system and that the access to campus is possible through the green metro line might explain this finding. On the other hand, results obtained for the Baltimore area confirm that when the distance increases, interest in using carpooling/vanpooling in the role of driver also increases.

Commuting frequency by car, factor “SOV > 4 times per week” is found to be not significant in the passenger model while it is significant for the driver model. Therefore, respondents who commute to campus most days of the week are more likely to participate in a carpooling/vanpooling program. The factor “rarely or never carpool/vanpool” is a significant determinant for both passenger and driver models; however, its impact is higher in the passenger model.

As expected, removal of the participation fee is not significant for the passenger model as it was targeting driver interest, while it is a significant factor in the driver model; interest in carpooling/vanpooling increases when the participation fee is removed. It appears that respondents who are already interested in being a passenger are more likely to drive when the service is free.

A number of factors have been derived from the reasons that would make people more inclined to vanpooling, these include: web application, convenient parking, cost of parking, cost of gas, good company, cheap parking, convenient ride home service and frequent pickup/drop off service. With the exception of the coefficient related to the convenient ride home service which is not significant for the driver model, those factors were found to be significant in both models. Among these factors, web application, parking convenience and cost, cost of gas and convenient ride-home service are most important. Providing these services will significantly increase the propensity to vanpool both as passenger and driver.

The factors that are potential barriers to carpooling/vanpooling have greater impact on the passenger model than on the driver model. All three factors, not having a car, need to pick up/drop children and independence, are significant in the passenger model, while only independence is significant for the driver model. As expected, not having a car increases the interest of being a passenger, while the necessity to pick up/drop of children and independence negatively affects interest in carpooling/vanpooling. The need to stop by other locations and the preference for independence make it inconvenient to participate in a vanpooling program.

The impact of demographic characteristics of the respondents is also analyzed. Gender is not a significant factor while age, estimated on two categories (35-45 and >45), negatively affects service preferences. Being licensed to drive is not a significant determinant in either model.

Finally, thresholds for the latent variables, interest as passenger and driver, are given in Table 4.14, as well as model statistics. According to the Likelihood Ratio (LR) Chi-square test (with 26 degree of freedom and 0.000 p-value) and Log-likelihood at convergence values, all model forms are successful functional forms for explaining the relationship between the independent and dependent variables.

Table 4-4 Ordered Logit and Probit Model estimation results

	Passenger Model				Driver Model			
	(Logit)		**(Probit)**		**(Logit)**		**(Probit)**	
Variables	Coeff.	z-stat*	Coeff.	z-stat*	Coeff.	z-stat*	Coeff.	z-stat*
Undergraduate&Willingness to pay	0.772	13.4	0.439	13.7	0.556	10.0	0.315	10.0
Graduate&Willingness to pay	0.823	16.1	0.465	16.3	0.607	12.2	0.342	12.2
Faculty&Willingness to pay	0.771	12.1	0.452	12.3	0.619	9.5	0.358	9.7
Staff&Willingness to pay	0.763	14.1	0.437	14.1	0.584	10.9	0.339	11.0
Distance 5-to-15 miles	-0.176	-1.3	-0.101	-1.3	-0.087	-0.6	-0.056	-0.7
Distance>15 miles	-0.342	-2.2	-0.169	-1.9	-0.558	-3.6	-0.291	-3.2
Washington Area	-0.267	-2.1	-0.148	-1.9	-0.152	-1.2	-0.066	-0.9
Baltimore Area	0.022	0.1	-0.011	-0.1	0.427	2.5	0.241	2.4
SOV>4 times per week	-0.173	-1.6	-0.100	-1.6	0.267	2.4	0.158	2.5
Rarely or never carpool/vanpool	-0.812	-6.4	-0.480	-6.6	-0.551	-4.3	-0.352	-4.8
Removal of vanpool fee	0.254	2.0	0.165	2.3	0.606	4.7	0.371	5.1
Web application	0.645	5.5	0.377	5.5	0.577	4.9	0.334	4.9
Convenient parking	0.477	4.3	0.279	4.3	0.397	3.5	0.257	4.0
Cost of parking	0.278	2.4	0.172	2.6	0.359	3.1	0.209	3.1
Cost of gas	0.547	4.8	0.322	4.9	0.677	5.9	0.390	5.9
Good company	0.271	2.4	0.138	2.1	0.426	3.8	0.239	3.7
Cheap parking	0.469	4.0	0.243	3.6	0.513	4.4	0.303	4.5
Convenient ride home service	0.496	4.2	0.298	4.4	0.154	1.3	0.103	1.5
Frequent pickup/drop off service	0.314	2.9	0.165	2.7	0.218	2.0	0.119	1.9
Do not have a car	0.588	4.2	0.353	4.4	0.088	0.6	0.045	0.6
Need to pick up children	-0.508	-3.3	-0.254	-2.8	0.013	0.1	0.028	0.3
Like independency	-0.268	-2.7	-0.149	-2.6	-0.234	-2.4	-0.133	-2.3
Gender (Male)	-0.183	-1.9	-0.095	-1.7	0.076	0.8	0.048	0.9
Age 36-to-45	-0.303	-1.7	-0.183	-1.8	-0.443	-2.5	-0.274	-2.7

Age>45		-0.406	-2.7	-0.260	-2.9	-0.520	-3.4	-0.332	-3.7
Licensed to drive		-0.203	-0.9	-0.116	-0.9	-0.003	0.0	-0.023	-0.2
Thresholds		Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
	1	0.266	0.318	0.143	0.868	0.868	0.329	0.472	0.189
	2	1.756	0.323	1.014	2.329	2.329	0.333	1.342	0.191
	3	3.694	0.330	2.131	4.360	4.360	0.345	2.505	0.195
	4	5.066	0.342	2.856	5.601	5.601	0.364	3.117	0.200
Number of observations		*1644*		*1644*		*1629*		*1629*	
Log likelihood at intercept		*-2404.28*		*-2404.28*		*-2231.33*		*-2231.33*	
Log likelihood at convergence		*-2021.69*		*-2029.37*		*-1993.81*		*-1990.46*	
LR Chi Squared		*765.19*		*749.82*		*475.03*		*481.73*	
Mc-Faddens R2		*0.1591*		*0.1559*		*0.1064*		*0.1079*	

* Significance level=0.05, two-sided

4.6.2 Ordered Probit Model Estimation Results of Interest as Passenger and as Driver

The results obtained with the probit model specification are not significantly different from those obtained by using the logit specification both in terms of the values of the coefficients and of the overall model statistics (i.e. log likelihood and Chi-squared values) (Table 4-14). Therefore, analysis of the estimates is not repeated for the probit model. The probit model presents a slightly better value of the final log-likelihood for the driver model, while logit does substantially better in terms of goodness of fit for the passenger model. The difference observed in the model coefficient estimates are due to an inherent difference in the scaling of the associated variable. The probit model coefficient estimates are approximately 1.8 times smaller than the logit counterparts as expected (Greene and Hensher, (2009)). The shape of the distributions (i.e. logistic in logit and standard normal in probit model), is also a factor (Greene and Hensher, 2009) that might explain differences across the results of the probit and logit models. It should be noted that in ordered models the analysis of coefficient estimates is not very informative because the model describes the probabilities of the outcomes (i.e NAI, NVI, MI, VI, and EI). Thus, ordered models do not describe a direct relationship between explanatory variables ($\boldsymbol{x}_i$) and the dependent variable (y_i^*). In order to better assess the model results, marginal effects (elasticities) of each explanatory variables and predicted probability outcomes are utilized, as described next.

4.6.3. Probability Predictions

Table 4-15 presents the predicted probabilities of the outcomes (NAI, NVI, MI, VI and EI) for both passenger and driver models. The predicted probabilities from logit and probit models are obtained by keeping the explanatory variable values at their means. Logit and probit model predictions are given side by side for comparison. No significant difference is reported across the two sets (logit and probit models) of results.

Table 4-5 Predicted probabilities

Passenger Model									
		Logit				**Probit**			
Variable	Obs	Mean	Std.Dev	Min	Max	Mean	Std.Dev	Min	Max
P(NAI)	1644	0.296	0.22	0.003	0.865	0.306	0.24	0.001	0.894
P(NVI)	1644	0.248	0.08	0.011	0.342	0.255	0.08	0.015	0.337
P(MI)	1644	0.282	0.12	0.030	0.434	0.282	0.12	0.016	0.424
P(VI)	1644	0.107	0.09	0.004	0.317	0.099	0.09	0.001	0.283
P(EI)	1644	0.065	0.08	0.001	0.738	0.058	0.09	0.000	0.609
Driver Model									
		Logit				**Probit**			
Variable	Obs	Mean	Std.Dev	Min	Max	Mean	Std.Dev	Min	Max
P(NAI)	1629	0.336	0.21	0.025	0.885	0.339	0.21	0.015	0.884
P(NVI)	1629	0.283	0.07	0.074	0.350	0.284	0.06	0.083	0.336
P(MI)	1629	0.282	0.13	0.025	0.468	0.280	0.12	0.019	0.439
P(VI)	1629	0.065	0.06	0.003	0.288	0.063	0.05	0.001	0.236
P(EI)	1629	0.033	0.04	0.001	0.257	0.034	0.05	0.000	0.315

The probability of interest in being a passenger is higher than the interest of being a driver for the outcomes VI and EI. If probabilities of having moderate to extreme interest are summed, interest as passenger probability is 0.45 while interest as driver probability is 0.38. Although they are somewhat low, they are still promising especially if we consider that respondents stated their preferences on a hypothetical vanpooling program.

Figures 4-2 through 4-4 give probability profiles for status variables and distance variable (distance>15 miles) to better assess the impact of these variables on the probabilities of outcomes. These factors are selected because they are thought to be major factors when designing a vanpool service. Intpas and Intdrv stand for interest in carpooling/vanpooling as a passenger and as the driver respectively. Probability outcomes 3, 4 and 5 represent moderately interested (MI), very interested (VI) and extremely interested (EI) ordered outcome groups. For example legend Pr(Intpas=3) reads as "probability of interest as passenger for outcome group three (MI)".

Undergraduate student interest in carpooling/vanpooling as passenger shows a higher profile than as driver (see outcome 4 and 5 profiles in Figure 4-2). It is also observed that the probability of interest in the role of passenger is higher for the higher willingness to pay levels. Also, a higher probability of interest to serve as driver is observed for moderate interest outcome (outcome 3). Graduate student profiles also shown to behave similar. It is interesting to see that in lower willingness to pay levels the interest to be driver is (moderately) higher for both student groups.

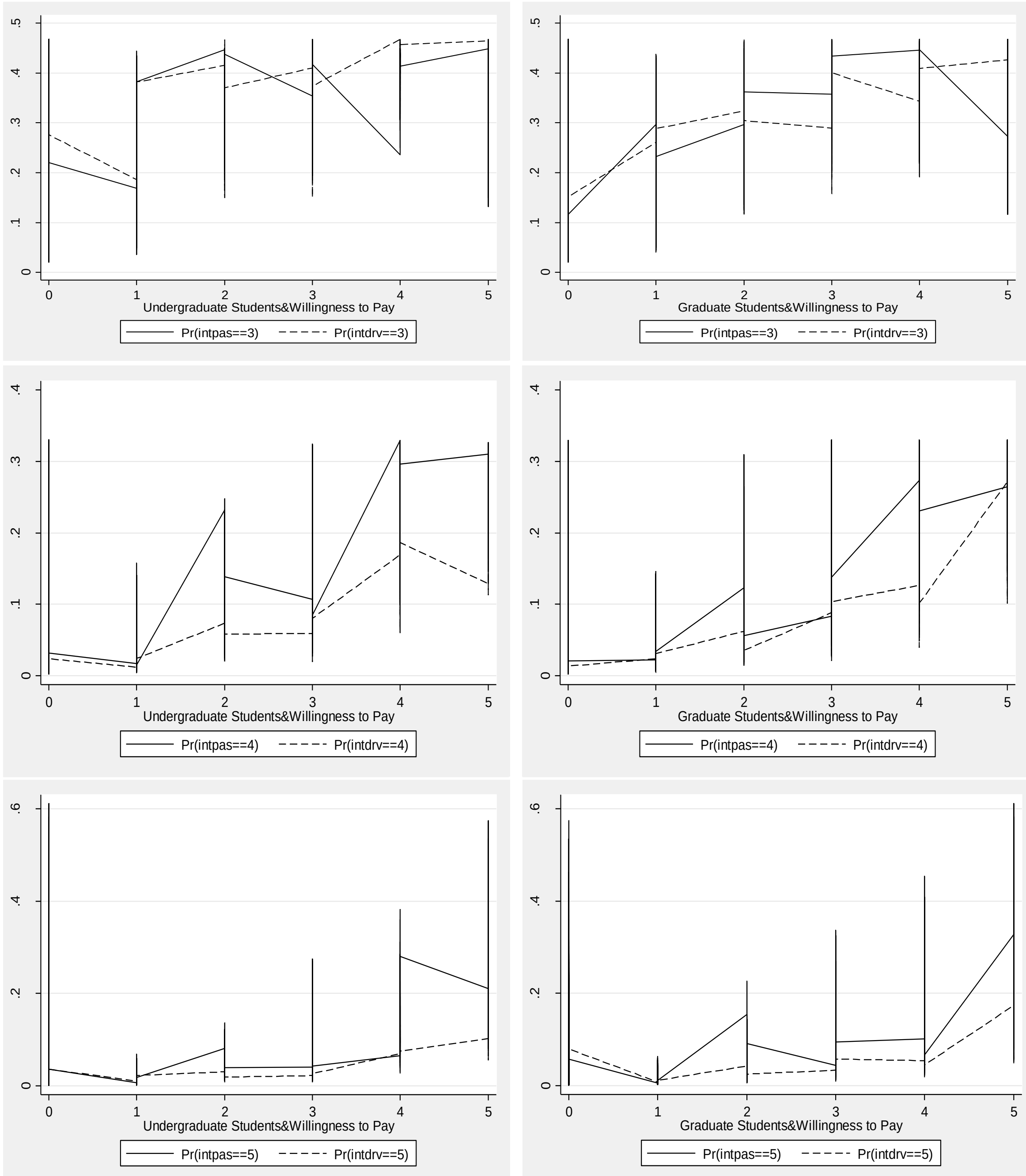


Figure 4-1 Probability profiles for interaction variables: undergraduate student& willingness to pay and graduate students and graduate students & willingness to pay.

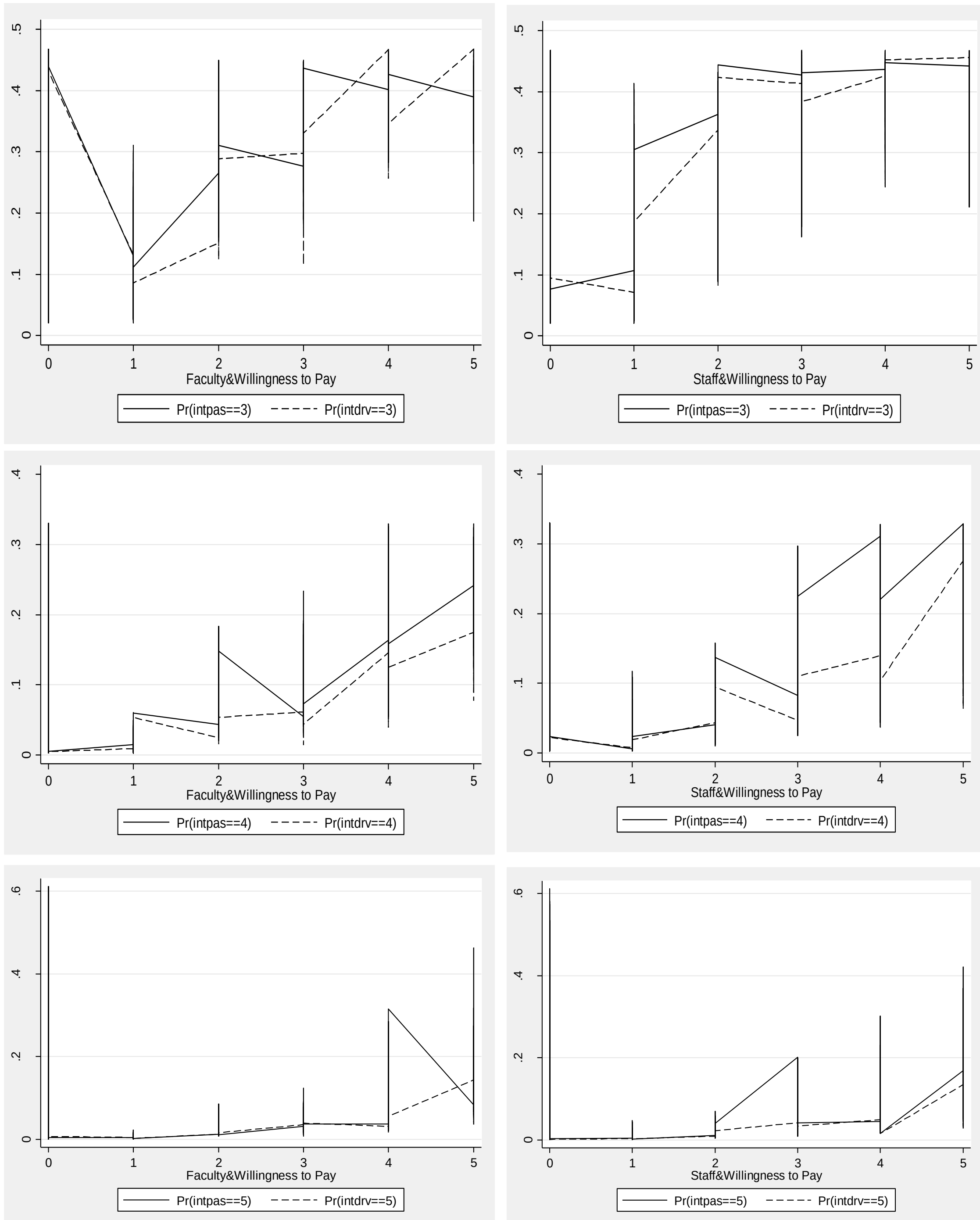


Figure 4-2 Probability profiles for interaction variables: faculty& willingness to pay and staff & willingness to pay

Faculty and staff member profiles are slightly different from student profiles; however, the probability of interest in being a passenger is higher in general (Figure 4-3). Staff members show higher interest in the service in almost all outcome levels except for five. At the moderate interest level, the interest to serve as passenger and driver is very close.

Figure 4-4 presents probability profiles with respect to the distance variable (distance>15 miles). For the moderately interested outcome, (outcome 3), probability of interest as passenger and as driver decreases as the distance increases. However, interest to serve as driver has a steeper slope. For the very interested outcome (outcome 4), both interest as passenger and driver probabilities increase as distance increases. Also, the probability profile of interest in the role of passenger is significantly higher than serving as driver. The profile for extremely interested does not show a significant level of interest.

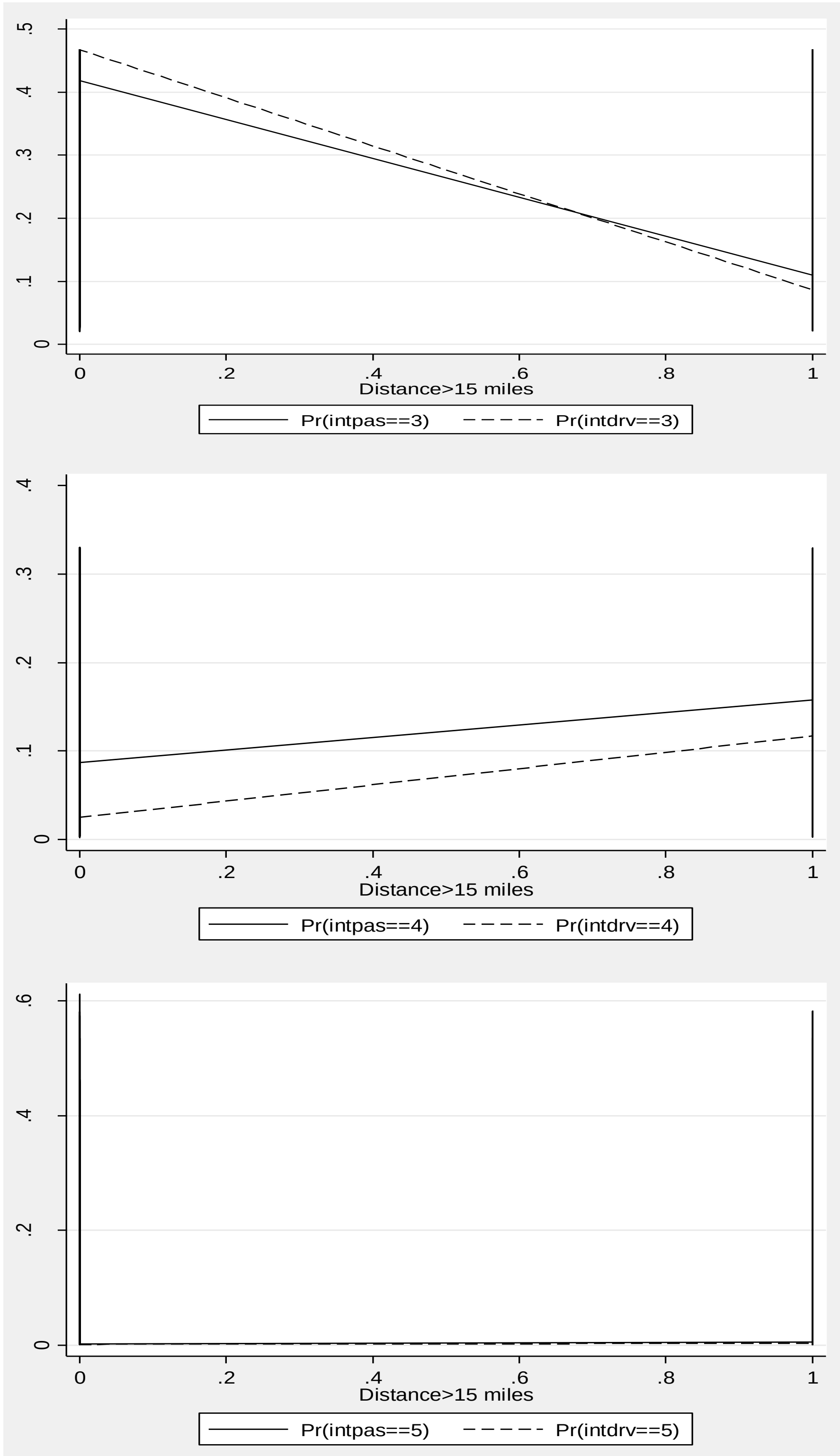


Figure 4-3 Probability profiles for (distance>15) variable

4.6.4. Marginal Effects (Elasticities)

Table 4-16 presents marginal effects according to logit model estimations for both passenger and driver models. The marginal effects measure the effect of a unit change (change from zero to one in the case of dummy variables) in the predicted probabilities while holding all other dependent variables constant at their mean values. Therefore, the effect of this change depends on all parameters in the model, the data as well as the probability outcome categories (i.e. 1 to 5, or interest from not at all to extreme). The probabilities given for each outcome category (P(1) through P(5)) are computed based on variable means.

Looking into marginal effects is important in analyzing ordered-response model results, because these models do not have a conditional mean function (E[$y|\boldsymbol{x}$]) to analyze. Therefore, to evaluate impacts of parameters, the effects of parameters on the probabilities are computed. The partial effects in ordered response models are:

$$\delta_j(\boldsymbol{x}_i) = \frac{\partial \Pr(y_i = j|\boldsymbol{x}_i)}{\partial \boldsymbol{x}_i} = \left[f\left(\mu_j - \boldsymbol{\beta}'\boldsymbol{x}_i\right) - f\left(\mu_{j-1} - \boldsymbol{\beta}'\boldsymbol{x}_i\right)\right].\beta. \quad (5\text{-}7)$$

In equation 5-7, β represents the coefficient of the parameter for which the marginal effect is calculated. The marginal effects for dummy variables measure the effect of a change in the variable's value (x_i) from zero to one while holding all other variables at their mean values (Equation 5-8). In equation 5-8, γ represents the coefficient of the dummy variable.

$$\Delta_j(\boldsymbol{x}_i) = \left[F\left(\mu_j - \boldsymbol{\beta}'\boldsymbol{x}_i + \gamma\right) - F\left(\mu_{j-1} - \boldsymbol{\beta}'\boldsymbol{x}_i + \gamma\right)\right] - \left[F\left(\mu_j - \boldsymbol{\beta}'\boldsymbol{x}_i\right) - F\left(\mu_{j-1} - \boldsymbol{\beta}'\boldsymbol{x}_i\right)\right] \quad (5\text{-}8)$$

The marginal effect of a change in status and willingness to pay interaction variables for all status groups are significant for the probability of being in moderately interested both in the role of passenger and driver. The effects are also significant but lower for the driver model. For example, if we look at the effects of the interaction variable faculty & willingness-to-pay in the passenger model, faculty are 14% less likely to be not interested at all in being a passenger, 4.7% less likely to be not very interested, 12.2% more likely to be moderately interested, 4.6% more likely to be very interested and 1.9% more likely to be extremely interested. These effects are 13%, 1.1%, 10.3%, 2.6% and 1.2%, respectively, in the driver model. Similar patterns are observed for other status groups, as well. For instance, undergraduate and graduate students are 12.2% and 13% likely to be moderately interested in being passenger and 9.2% and 10.1% in being a driver, respectively.

When looking at the distance factor (distance>15 miles), an average person is 6.4% more likely not to be interested at all in being a passenger and 12.1% not interested at all in being a driver.

Most of the factors related to reasons that would make campus members more inclined to carpool/vanpool have significant and positive effect. For example, web application (9.6%), convenient parking (7.3%), cost of gas (8.4%), cheaper parking options (7.2%), and convenient ride home service (7.6%) make average campus members more likely to be moderately interested to be a passenger. Similar are the effects on the likelihood to be interested in being a driver (web application (9.5%), convenient parking (6.6%), cost of gas (11.1%), good company (7.1%), and cheaper parking options (8.5%)). The probability of being very or extremely interested for these factors are positive but low, less than 5% in most cases. A web application that would provide carpool/vanpool matching service would increase the likelihood of being very interested to be a passenger at 4.4% and of being extremely interested at just 1.9%.

Members who do not have a car are 8.7% more likely to be moderately interested, 4% more likely to be very interested and 1.8% more likely to be extremely interested in carpooling/vanpooling as a passenger.

Table 4-6 Marginal effects (Logit)

	Passenger		Driver		Passenger		Driver		Passenger		Driver		Passenger		Driver		Passenger		Driver	
	P(1)=0.239		**P(1)=0.301**		**P(2)=0.343**		**P(2)=0.348**		**P(3)=0.323**		**P(3)=0.285**		**P(4)=0.068**		**P(4)=0.046**		**P(5)=0.025**		**P(5)=0.020**	
	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z	dy/dx	z
Undergraduate& Willingness-to- pay	-0.141	-13.2	-0.117	-10	-0.047	-6.6	-0.009	-2.2	0.122	11.3	0.092	9.3	0.046	10.2	0.023	7.7	0.019	8	0.011	6.2
Graduate& Willingness-to-pay	-0.15	-15.6	-0.128	-12.2	-0.05	-6.9	-0.01	-2.2	0.13	12.8	0.101	11	0.049	11.2	0.025	8.6	0.02	8.6	0.012	6.6
Faculty& Willingness-to-pay	-0.141	-11.8	-0.13	-9.5	-0.047	-6.5	-0.011	-2.2	0.122	10.6	0.103	8.9	0.046	9.6	0.026	7.4	0.019	7.7	0.012	6
Staff& Willingness- to-pay	-0.139	-13.7	-0.123	-10.9	-0.046	-6.8	-0.01	-2.2	0.121	11.8	0.097	10.1	0.046	10.5	0.025	8.1	0.019	8.2	0.011	6.4
Distance 5-to-15 miles*	0.033	1.3	0.018	0.6	0.01	1.4	0.001	0.7	-0.028	-1.3	-0.014	-0.6	-0.01	-1.4	-0.004	-0.7	-0.004	-1.4	-0.002	-0.7
Distance>15 miles*	0.064	2.1	0.121	3.5	0.018	2.5	0.002	0.4	-0.054	-2.2	-0.091	-3.6	-0.02	-2.3	-0.022	-3.6	-0.008	-2.3	-0.01	-3.4
Washington Area*	0.048	2.1	0.032	1.2	0.017	2	0.003	1	-0.042	-2.1	-0.025	-1.2	-0.016	-2	-0.006	-1.2	-0.007	-2	-0.003	-1.1
Baltimore Area*	-0.004	-0.1	-0.085	-2.7	-0.001	-0.1	-0.015	-1.6	0.004	0.1	0.071	2.5	0.001	0.1	0.02	2.2	0.001	0.1	0.01	2.1
SOV>4 times per week*	0.032	1.6	-0.056	-2.5	0.01	1.6	-0.005	-1.7	-0.027	-1.6	0.044	2.4	-0.01	-1.6	0.011	2.4	-0.004	-1.6	0.005	2.3
Rarely or never carpool/vanpool*	0.133	7.1	0.109	4.6	0.067	4.8	0.02	2.5	-0.118	-6.9	-0.091	-4.3	-0.056	-5.2	-0.026	-3.6	-0.025	-4.7	-0.012	-3.4
Removal of vanpool fee*	-0.044	-2.1	-0.117	-5.2	-0.018	-1.7	-0.027	-2.7	0.039	2	0.099	4.8	0.016	1.8	0.03	3.8	0.007	1.8	0.015	3.5
Web application*	-0.108	-5.9	-0.114	-5.2	-0.051	-4.3	-0.021	-2.8	0.096	5.7	0.095	4.9	0.044	4.7	0.027	4.1	0.019	4.2	0.013	3.7
Convenient parking*	-0.083	-4.4	-0.081	-3.6	-0.034	-3.6	-0.011	-2.2	0.073	4.4	0.066	3.5	0.031	3.9	0.018	3.2	0.013	3.6	0.008	3
Cost of parking*	-0.049	-2.5	-0.073	-3.2	-0.019	-2.1	-0.01	-2	0.043	2.4	0.06	3.1	0.017	2.3	0.016	2.8	0.007	2.2	0.008	2.7
Cost of gas*	-0.094	-5	-0.135	-6.2	-0.04	-3.9	-0.023	-3.2	0.084	4.9	0.111	5.9	0.035	4.3	0.032	4.9	0.015	3.9	0.015	4.3
Good company*	-0.048	-2.5	-0.086	-4	-0.018	-2.2	-0.013	-2.3	0.042	2.4	0.071	3.8	0.017	2.3	0.019	3.4	0.007	2.2	0.009	3.2
Cheap parking*	-0.08	-4.3	-0.102	-4.7	-0.035	-3.3	-0.018	-2.6	0.072	4.2	0.085	4.5	0.031	3.6	0.024	3.8	0.013	3.4	0.011	3.5
Convenient ride home service*	-0.086	-4.4	-0.032	-1.3	-0.036	-3.5	-0.003	-1	0.076	4.4	0.026	1.3	0.032	3.8	0.007	1.3	0.014	3.6	0.003	1.3
Frequent	-0.058	-2.9	-0.046	-2	-0.018	-3	-0.003	-1.6	0.05	2.9	0.036	2	0.018	2.9	0.009	2	0.008	2.9	0.004	2

pickup/drop off service*																				
Do not have a car*	-0.097	-4.7	-0.018	-0.6	-0.048	-3.3	-0.002	-0.5	0.087	4.5	0.015	0.6	0.04	3.6	0.004	0.6	0.018	3.4	0.002	0.6
Need to pick up children*	0.101	3.1	-0.003	-0.1	0.017	4.2	0	-0.1	-0.081	-3.3	0.002	0.1	-0.026	-3.7	0.001	0.1	-0.011	-3.7	0	0.1
Like independency*	0.048	2.8	0.049	2.4	0.017	2.5	0.005	1.6	-0.042	-2.7	-0.039	-2.4	-0.016	-2.6	-0.01	-2.3	-0.007	-2.6	-0.005	-2.2
Gender (Male)*	0.034	1.9	-0.016	-0.8	0.011	1.9	-0.001	-0.7	-0.029	-1.9	0.013	0.8	-0.011	-1.9	0.003	0.8	-0.004	-1.9	0.001	0.8
Age 36-to-45 *	0.059	1.6	0.099	2.4	0.013	2.6	-0.004	-0.6	-0.049	-1.7	-0.071	-2.6	-0.017	-1.8	-0.016	-2.8	-0.007	-1.8	-0.007	-2.7
Age > 45 *	0.079	2.5	0.116	3.3	0.017	3.7	-0.004	-0.7	-0.065	-2.7	-0.084	-3.6	-0.022	-2.9	-0.019	-3.7	-0.009	-2.9	-0.009	-3.5
Licensed to drive*	0.035	1	0.001	0	0.015	0.8	0	0	-0.031	-1	-0.001	0	-0.013	-0.9	0	0	-0.005	-0.9	0	0

(*) dy/dx is for discrete change of dummy variable from 0 to 1

4.7. Model Validation

The models (passenger and driver) are validated by using approximately 80% of the data for estimation and the remaining 20% for prediction. The coefficient estimates obtained from the driver and passenger models are then applied to the out of sample data. Predicted values for each interest outcome group are presented in Table 5-17. These predicted values are compared with the probabilities that are obtained from the observed data.

Table 4-7 Model Validation, predicted vs. observed probabilities of the outcomes

Probability	**Passenger Model**		**Driver Model**	
	Predicted	**Observed**	**Predicted**	**Observed**
P(NAI)	0.275	0.308	0.358	0.327
P(NVI)	0.343	0.255	0.325	0.306
P(MI)	0.300	0.278	0.261	0.262
P(VI)	0.062	0.100	0.037	0.082
P(EI)	0.021	0.059	0.019	0.024

The differences between the predicted and observed probabilities for each of the outcomes (NVI to EI) are evaluated. It is noted that probabilities for outcome groups NAI, NVI and MI are very close to the observed values in both driver and passenger models. The probability predictions for outcome groups VI and EI are, however, slightly underestimated in both driver and passenger models. These results indicate that there may be some factors that may not be captured by these models. As it is discussed in the next section, a more focused survey may reveal that additional factors.

Despite these differences, one can conclude that these differences are acceptable and that the models are able to predict the probabilities of each of the ordered response categories.

4.8. Summary and Conclusions

Companies, agencies and institutions need to consider a portfolio of alternative transportation options to meet their GHG emissions reduction goals, which are set either by voluntarily or regulatory requirements. Vanpooling can be a significant part of such an alternative transportation program as it is capable of targeting commuters without access to transit and commuters who are willing to share rides. This research adds to existing literature on commute trip reduction strategies in general and attitudes towards carpooling/vanpooling in particular. It introduces an econometric modeling approach that investigates potential for carpooling/vanpooling, distinguishing roles of passenger and driver. This approach can be adopted by large-scale employers to provide better focused transportation services to their employees.

Two ordered-response models, a passenger and a driver model, were estimated to understand factors affecting decision to carpool/vanpool. These models were estimated with ordered logit and probit model specifications to investigate if assumptions on error terms have a significant impact on the estimation. The models were applied on data obtained from the commuter survey conducted at UMD. The results showed that logit and probit model specifications did not show a significant difference and that logit formulation performs slightly better for the passenger model based on log-likelihood value at convergence (within 95% confidence interval). Moreover, results showed that the common determinants thought to be affecting carpooling/vanpooling behavior are not necessarily valid in a University setting, which may be explained by the high level of education, environmental consciousness and other factors.

The analysis revealed various important findings about anticipated carpooling/vanpooling behavior of the UMD College Park campus members. First, the assumption that two models should be calibrated to study the interest in being a passenger or a driver is found to be a valid approach, as the results indicated that the factors affecting them and their impacts are different. On the contrary, research in the literature, does not make this distinction. Also, while many of the findings regarding factors affecting vanpooling were parallel to the findings in the literature, some factors were found to have different impacts. For example, results from earlier studies indicate that long distance residents are more likely to vanpool. In contrast, this study found that longer residential distance negatively impacts the propensity to vanpool, from both passenger and driver perspectives. However, with the additional information provided by the probability profiles, it is found that as the residential distance increases, the probability of being very interested in the passenger and driver roles increases while probability of being moderately interested decreases. Proximity to transit also appears to have a significant impact. Although there was no direct factor available to measure the effect of the proximity to transit, by looking into residential area factors, e.g. residing in Baltimore and Washington areas enabled us to reach the conclusion that transit availability is a significant factor.

An interesting finding is that the people who drive most days of the week to campus (factor, SOV>4 times per week) have a higher propensity to fill the role of driver, which can be explained by the perception of high commuting cost by SOV. People who never or rarely carpool as expected, are not likely to be interested in a vanpool program, neither in the passenger nor driver role; the negative impact being higher for the passenger model. This shows that the university should disincentivize SOV commuter trips in addition to incentivizing shared ride trips. It is seen that removal of a vanpool participation fee increased the interest in being a driver. Thus, a highly subsidized service or a flat-rate low fee service may help people get accustomed to the service, especially in the early stages of the carpooling/vanpooling program.

Web application is found to be one of the most important factors that increase the demand for vanpooling in both the passenger and driver roles. Cost of parking is significant, but not as effective, which may be due to the low parking rates of the University (compared to campuses in city settings). Cost of gas, however, has a high impact. Good company factor is found to have high impact in the driver model. This factor has a lower impact in the passenger model, which may be explained by other activities, such as sleeping and reading, which can be done during the trip as a passenger. Not having a car is a significant determinant for interest in vanpooling in the passenger role, but not in the driver role. This result also points the importance of modeling driver and passenger interest separately, as most studies in the literature state that not having a car or having fewer cars in a household increases propensity to vanpool. Other factors that are found to affect passenger and driver models include: convenient ride home service, and need of picking up/dropping of children. Respondents aged between 35 and 45 are less likely to wish to serve as driver. From the analysis of marginal effects, it was found that the marginal effects of most of the factors are higher in the passenger model than in the driver model.

Several policy implications can be made based on these results. Considering that there is significant difference in the behavior of passengers and drivers, the University should carefully consider vanpool service characteristics and investigate feasibility of a third-party vanpooling program or a program that allows multiple drivers. A more flexible service that would allow the use of the service part of the month/year may also be attractive. Also, the findings indicate that the provision of a web application that gives matching service significantly increases the propensity to use the service. The university already provides a web page for carpooling purposes. This service could be extended for vanpool services. Other important actions that could be taken into consideration involve parking policies. Literature indicates that parking shortage encourages carpooling/vanpooling. Providing parking incentives, such as priority parking and cheaper parking options to carpool/vanpool members, while using disincentives for SOV users, will help increase interest in vanpooling and discourage SOVs. These policies should be developed in conjunction with the regional transportation services and opportunities. For example, the Washington D.C. area has a high rate of HOV lanes, regional commuter services and transit availability, which are known to encourage carpool/vanpool behavior.

To conclude, the econometric analysis presented in this study can be used by employers when developing alternative transportation options for commute trips. The reductions of SOV resulting from the application of these programs can significantly contribute to GHG reduction efforts at institutional, local and regional levels. The analysis method can be adopted by other higher education institutions, as well as by large-scale employers, cities or metropolitan areas. The results provide insight about the potential user characteristics of the service; thus, providing information on the type of service that would yield higher participation. In addition, to help in service design, the method presented in this research helps identify the target groups for marketing purposes.

Chapter 5: Network Extraction and OD Demand Estimation for Subarea Analysis

5.1. Introduction

Recognizing the significant role of transportation in climate change, U.S. agencies, including those at the federal (e.g. U.S. DOT, U.S. EPA, U.S. DOE) and local levels, have been developing policies and regulations targeting GHG emissions reduction using their existing legal authorities (WRI, 2010; ICF, 2010). Many state DOTs (e.g. Washington, California and Oregon) and MPOs (e.g. Southern California, Chicago, and Baltimore) are required to demonstrate progress in stabilizing and reducing GHG emissions in their transportation plans. As such, these DOTs and MPOs are working on incorporating climate change into their Long-Range Transportation Planning (LRTP) processes. They are developing strategies to mitigate GHG emissions and adapt to climate change. These requirements introduce many challenges, one of which is estimating the potential impact of emissions reduction strategies from a particular region or sub-region.

Agencies need to evaluate alternative GHG emissions reduction scenarios in order to decide which strategies best meet their environmental goals. State DOTs and MPOs often need to analyze the impacts of proposed traffic management strategies for reducing congestion and emissions in only a subarea of a larger region. However, OD matrices are typically developed for large regions, and may be forecasted at a state-, national- or even international-level. To study a subarea, demand data must be aggregated in areas external to the area of study so as to be consistent with a network representation of the subarea that will have been extracted from the large region.

A two-stage demand estimation procedure is developed with a focus on providing up-to-date time-dependent origin-destination (OD) demand matrix for a subarea traffic network. The first stage generates an induced OD demand matrix for the subarea network using path-based traffic assignment results from the larger regional network. The second stage seeks a consistent network flow pattern using the induced OD demand information from the first stage and archived traffic measurements in the subarea network.

Currently two primary measures are considered in practice: GHG emissions (in tons of CO_2 emitted or tons of CO_2 equivalent, incorporating other GHGs), and vehicle-mile traveled (VMT, as a proxy for tailpipe emissions) (NCHRP, 2010). The major models available for GHG emissions measurement are EPA's latest MOBILE/MOBILE6, MOVES2010 and California Air Resource Board's (CARB) emission models motor vehicle emission factor (EMFAC) (NCHRP, 2010). These models, although improved to include e.g. vehicle speed and operating conditions, are not appropriate for detailed analysis of project- or subarea-level GHG emissions reduction strategies as they cannot capture the emission impacts of vehicle interactions and congestion effects. These models typically use VMT data that come from either traffic counts or static four-step travel demand models, which do not account for congestion effects. The proposed methodology permits micro-, macro- and meso-scopic simulation-based analyses that can capture such effects.

In this chapter, a subarea analysis capability is developed. The proposed technique has wide applicability, but is described herein in the context of a meso-scopic simulation tool to be used in conjunction with dynamic network analysis models.

Tools to estimate impacts of TDM strategies typically use spreadsheet-based applications (e.g. EPA's COMMUTER Model; California Air Resources Board's Cost-Effective Model; Trip Reduction Impacts for Mobility Management Strategies (TRIMMS), developed by CUTR under the National Center for Transit Research), or special software that use VMT and/or trip-based emission factors (e.g. Federal Highway Administration's Travel Demand Management Evaluation Model) (ICF, 2008). Models for evaluating operational strategies, such as incident management, information systems, and work zone management, include sketch planning tools (e.g. ITS Deployment Analysis System (IDAS), Screening for ITS (SCRITS), and STEAM), deterministic tools (e.g. Traffix and Highway Capacity Software (HCS)) and traffic simulation tools (e.g. macroscopic simulation models such as FREQ, PASSER, and TRANSYT-7F, mesoscopic models such as DYNASMART-P and TRANSIMS, and microscopic models such as CORSIM/TSIS, Paramics, and VISSIM). This research applies the developed sub-area analysis tools within a meso-scopic simulation approach. In contrast with micro- and macro-level tools, such meso-scopic models can balance computational efficiency and accuracy.

Such an approach will allow consideration and rapid evaluation of a large number of scenarios and will support transportation network planning, operations decisions, and GHG emission reduction efforts. The capability is suitable for applications that may not require analysis on a complete network representation, but captures the network impacts. The essential input for such a capability is time dependent origin-destination (OD) demand and this research specially focuses on providing this essential input.

5.2 Examples of Applications Where Subarea Analysis is Needed

There are numerous applications in which subarea analyses associated with traffic management with a goal of reducing emissions must be undertaken and subarea demand forecasts are required. Cordon pricing, pricing by VMT, and other applications in which travel by car is taxed or offered at a price have received significant attention in recent years. Such strategies are promising because they not only aid in reducing emissions, but they aim to tackle congestion woes. Additionally, revenue obtained through such strategy implementations can be used for transit improvements and other alternative transportation modes. Cordon pricing has had success in such locations as Singapore, Stockholm, London and Milan (AASHTO-TRB, 2010; Rotaris et al., 2009). Tokyo is currently considering cordon pricing for emissions reduction (Sato and Hino, 2005), as well. Comprehensive network analysis is essential for predicting performance of these strategies before adoption. Current cordon pricing applications use ad-hoc approaches for strategy design. Observations after implementation or simulation models combined with surveys before the implementation are employed for evaluating performance and impacts of pricing strategies. In these studies, evaluation is limited to the subarea where pricing is applied. Subarea analysis with the OD demand that preserves the OD information from the complete network related to the subarea is needed to evaluate network effects of the pricing strategies.

Another application where subarea OD demand is essential as input to design of transit-oriented impact analysis. For example, Dock and Swenson (2003) presented a methodology for aggregating individual transit-oriented development sites into a subregional growth scenario. They used a subarea model to compare impacts of a transit-oriented growth scenario with a conventional growth scenario for a subregion of suburban communities. Likewise, freight and passenger modal shifts, and resulting impact on emissions, can also be analyzed in response to various strategies for given locations (e.g. Park et al., 2004; Lee et al., 2009).

Various TDM and congestion management strategies, such as those involving HOV/HOT lanes, bus rapid transit (BRT), corridor management, and information provision, have been implemented or considered by many states and MPOs. Environmental impact analyses of these projects are required prior to implementation.

Another area of application is network resilience and vulnerability analyses for climate adaptation studies**.** For instance, Chang and Nojima (2001) developed a measure of subarea transport accessibility to analyze long-term impacts of earthquakes on system performance. They argue that measuring system performance aids in understanding effects of past disasters and preparation and adaptation to future ones.

The proposed subarea analysis technique can be useful in such applications by creating a subarea network with associated demand for the particular study location.

5.3. Background of Dynamic Traffic Assignment and Subarea Analysis

There is a need to evaluate effectiveness of GHG emissions reduction strategies in a dynamic network platform, to track emissions, and to identify areas for improvement. Dynamic traffic assignment (DTA) methods address many of the limitations of static planning tools, and provide planning agencies with modern approaches to tackle emerging challenges. Simulation-based DTA models (Mahmassani, 2001; Ben-Akiva et al., 2001; Mahmasani et al., 2004) systematically combine (1) dynamic network assignment models, used primarily in conjunction with demand forecasting procedures for planning applications, and (2) traffic simulation models, used primarily for traffic operational studies to capture the evolution of traffic flows in a traffic network, which result from the decisions of individual travelers making path choice decisions. By considering the time-varying nature of traffic flows, DTA can produce practically useful estimates of state variables such as speeds, queue lengths, delays, and congestion effects to better assess the functional and environmental impacts of a variety of traditional and emerging transportation planning measures. However, DTA models require high-level representation of the transportation system components, leading to a more challenging planning process. The preparation of networks with the required level of detail is one of the most cumbersome steps for DTA planning applications. Because original traffic networks utilized by metropolitan planning organizations are generally developed for conventional static planning applications, they lack several essential features such as time-dependent OD demand input, highway interchange modeling, and signal control information for an operational planning tool. Therefore, development of a transportation network for any DTA modeling tool calls for careful integration, and in some cases reconciliation of different data sources.

Subarea analysis is an essential capability for integrating DTA-based operational planning tools into regional planning applications for several reasons. First, analyses of operational decisions and Intelligent Transportation System (ITS) deployment alternatives generally require a high level of detail in only a portion of the regional or metropolitan area network rather than in the entire network. In many cases, greater level of detail in network and operational strategy representation is necessary only for directly affected areas, not for outer reaches of the network. In other cases, large-scale regional networks entail minimal secondary and tertiary impacts outside a given subarea due to weak structural interactions, in which case a subarea analysis would be satisfactory. Another case where subarea analysis is of great use is that when the analysis is of special concern of a local organization, jurisdiction or an authority and the analysis boundaries are determined by their specific needs. The computational advantages of using a subarea network instead of a large regional network are also evident for cases where consideration and rapid evaluation of large number of policy scenarios are needed.

Several modeling challenges must be addressed in the subarea analysis problem in the DTA modeling framework. These challenges are due to complex interaction between demand and supply sides of the original network and the subarea network. For example, it is desirable for the network model at the subarea level to retain the capability to capture changes in overall demand in the original network (specifically, for demand with at least one trip end outside the subarea) in response to changes in supply in the subarea. Of particular importance is the need to estimate up-to-date time-dependent OD trip desires for the subarea analysis. Essentially, the subarea OD demand information could be obtained by two different approaches: (1) calculating subarea OD demand using the traffic assignment result in the original network; and (2) estimating OD demand based on real-world traffic measurements in the subarea. The first approach is referred as the induced OD matrix construction problem in Larson et al. (2001) and the term is adopted in this study to define the reduced or aggregated OD matrix which is obtained by considering only subarea related demand in the overall network.

Several aggregation techniques have been proposed to construct the induced OD demand matrix. For example, the Drive Project (1989) described a two-step procedure.

The first step performs an equilibrium assignment in the complete network to obtain path flow information, which is used in the second step to calculate an induced OD matrix for the subarea. Given the static equilibrium link flow solution in a subarea network, Larson et al. (2001) proposed an entropy maximization model to construct the most likely route flow pattern (among route flow patterns that are consistent with the given link flow solution pattern in the extracted network). Xie et al (2009) proposed a link based method for practical reasons such as availability of input data and complexity.

Growing interest in the application of simulation-based DTA models has been accompanied by several studies on the estimation of dynamic OD trip desires. Substantial research has been devoted to the dynamic demand estimation problem using time-varying link counts. Early models (Cremer and Keller, 1981;1987) were proposed to estimate time-dependent OD flows on individual components, such as a single intersection or a freeway facility; these models aim to estimate unknown dynamic OD split fractions based on the entry and exit flow measurements, under the simplifying assumption of constant link travel time. Extending the concepts and solution methodologies of the static OD estimation problem, Cascetta et al. (1993) proposed a generalized least-squares (GLS) estimator for dynamic OD demand based on a simplified assignment model for a general network. A bi-level generalized least-squares optimization model and an iterative solution framework have been proposed by Tavana and Mahmassani (2001) to estimate dynamic OD demand and to maintain internal consistency between the upper-level demand estimation problem and the lower-level DTA problem. Tavana (2001) also provided an extensive literature review of the dynamic OD demand estimation problem and its inherent connection to the dynamic traffic assignment problem. Zhou et al. (2003)

and Mahmassani and Zhou (2005) presented several dynamic demand estimation and updating methods for planning and operational applications using multi-day traffic measurements.

Providing time-dependent OD demand for subarea analysis represents a new class of demand estimation problems that are of growing importance in deploying DTA for planning applications including GHG emission reduction efforts. It differs considerably from the conventional OD demand estimation problem with a target demand table, because the traffic assignment solution obtained for the complete network does not directly provide a compatible reference for the time-dependent OD matrix in the subarea. As the historical OD demand data, which are typically the basis of induced OD demand construction, cannot provide up-to-date demand inputs, it is necessary to utilize other archived traffic measurements to capture network system dynamics. A sound demand updating procedure for subarea analysis, moreover, needs to maintain elaborate linkages between the subarea and surrounding area and to maintain essential structural information on OD, path and link flow patterns in the reduced subarea network.

This dissertation describes a two-stage subarea demand estimation procedure to provide time-dependent OD trip information for subarea analysis. Following the problem definition and process overview in the next section, a detailed description of the induced demand calculation procedure is given in section 5.4. An excess-demand traffic assignment formulation is then applied to accommodate possible changes in external trips, which is consistent with an entropy maximization derivation. Finally, a case study based on a large-scale regional planning network is presented in Section 5.5 to illustrate the proposed procedure.

5.4. Problem Statement and Process Overview

Consider a large-scale regional traffic network with a set of nodes connected by a set of directed links. The zonal structure of the entire network is defined by multiple origin zones $u \in U$ and destination zones $v \in V$, and the static OD trip desires in the complete network are expressed as the number of vehicle trips $d_{u,v}$ traveling from origin zone u to destination zone v during the analysis period of interest. As a subset of the regional traffic network, the subarea network is defined by a set of nodes N and a set of links L, with $L' \subseteq L$ denoting the subset of links with observations in the subarea. The subarea boundary is assumed to be prespecified by traffic planners, the subarea zonal structure is specified as a set of origin zones I and a set of destination zones J, and the analysis period of interest is discretized into departure time intervals τ=1, 2, …, T_d. Accordingly, the time-dependent OD trip desires in the subarea are expressed as the number of vehicle trips $d_{i,j,\tau}$, traveling from origin zone i to destination zone j in departure time interval τ , $\forall\ i \in I, j \in J$ and τ=1, 2, …T_d. Given a historical OD demand matrix in the complete network, the predefined subarea boundary, time-dependent traffic measurements for a subset of links in the subarea, that is, measured link flow $c_{l,t}$ on link $l \in L'$ during observation interval t=1, 2, …., T_c, the objective of the subarea demand estimation problem is to find a consistent subarea time-dependent OD demand matrix.

The proposed procedure includes two stages where the output from one stage is input to the next. In the first stage, path flow patterns in the complete network are generated to calculate the induced OD demand in the subarea network. To consider all trip desires that might use the transportation facilities in the subarea, the induced OD demand table should not only include the demand originating and/or terminating in the subarea network, but also include vehicular flows passing through the subarea network. The induced OD demand information is then combined with available real-world traffic observations in the second stage to update the subarea OD demand matrix. Figure 5-1 depicts a detailed flow chart of the procedure.

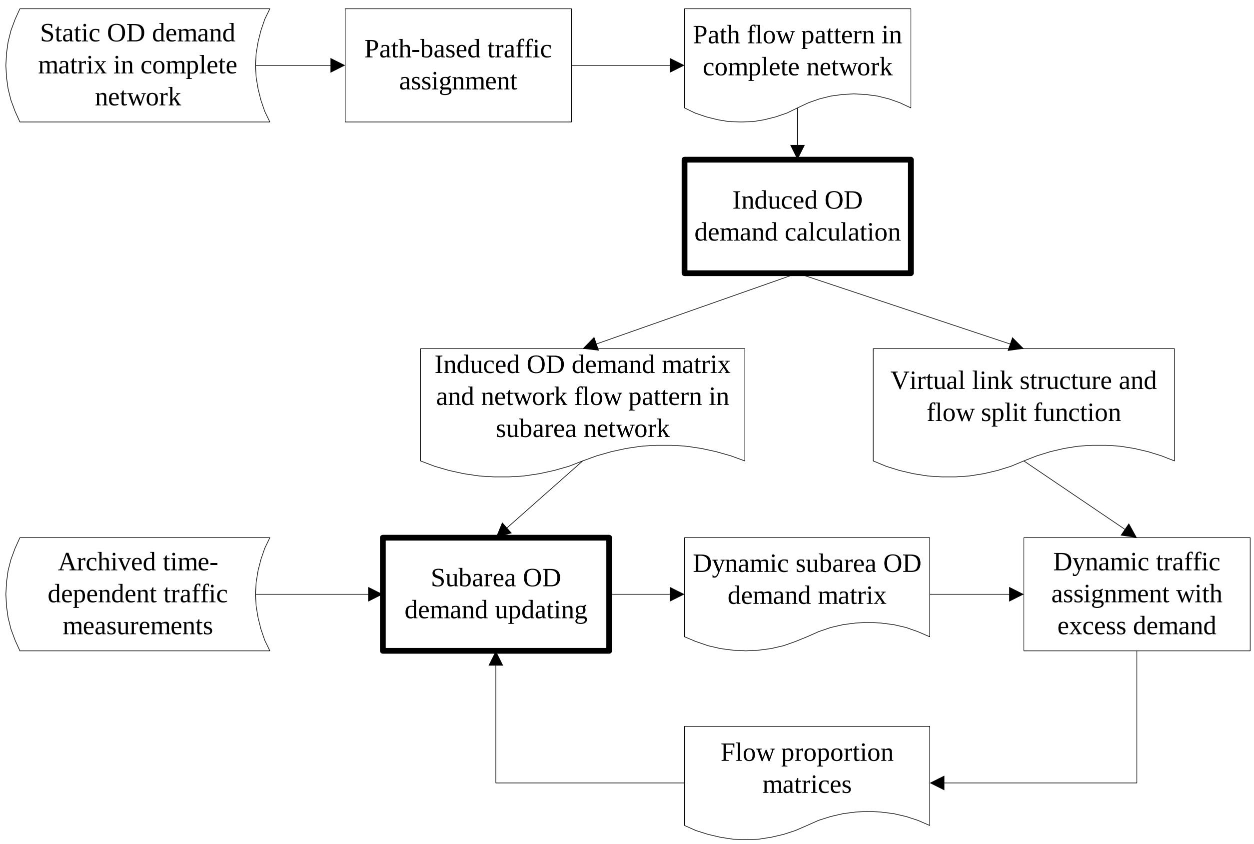


Figure 5-1 Flow chart for subarea demand estimation procedure

Stage I: Induced Demand Calculation

In order to obtain the best estimate of time-dependent travel time on virtual links (explained later in *Excess-Demand Traffic Assignment Formulation* section), this study first converts the given historical static OD matrix to a time-dependent OD table with a time-of-day profile, and then a path-based dynamic traffic assignment program, namely DYNASMART-P (Mahmassani at al., 2004), is used to load the OD demand onto the complete network to generate the path flow pattern in the entire network. The network path flow pattern can be expressed in terms of the number of vehicles $f_{u,v,h,\tau'}$ from origin u to destination v using path h departing at time τ' . Conceptually, the traffic assignment process can be written as

$$\overline{F} = TAP(D) \tag{5-1}$$

where

$\overline{F}$ = simulated/induced path flow vector, with elements [$\overline{f}_{u,v,h,\tau'}$]

D = OD demand vector with elements [$d_{u,v,\tau'}$]

TAP = traffic assignment process function

The traffic assignment process maintains the flow conservation equations between OD flows and path flows on the complete network, that is,

$$\sum_h \overline{f}_{u,v,h,\tau'} = d_{u,v,\tau'}, \quad \forall u,v,\tau' \tag{5-2}$$

where the sum in Eq. (5-2) is taken over all paths h between u and v at each departure time interval τ'.

The induced OD demand can be obtained by identifying all path flows that use the subarea network. To clearly visualize the mapping between path flows in the complete network and aggregate OD flows related to the subarea network, one can partition all the OD zones in the complete network as either internal or external zones with respect to the subarea, and accordingly categorize all the OD pairs in the complete network into the following four groups: (a) Internal–Internal (I-I), (b) External-Internal (E-I), (c) Internal-External (I-E), (d) External-External (E-E), as shown in Figure 5-2.

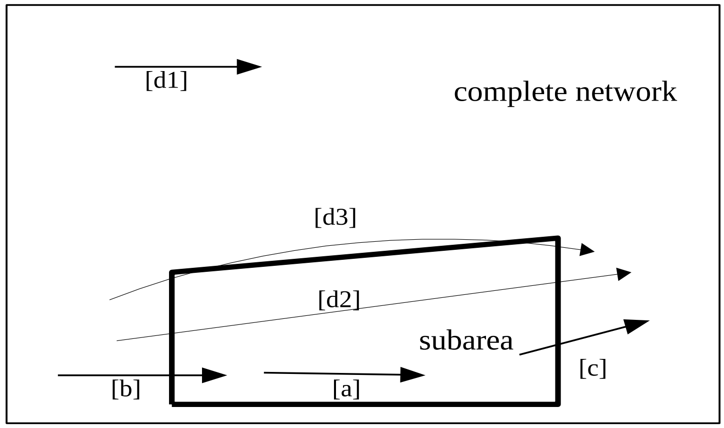


Figure 5-2 Four types of paths with respect to subarea network

In the E-E path group, we can further consider three subgroups: (d1) only using the complement network, (d2) traversing the subarea network and (d3) bypassing the subarea network. Clearly, all the nodes along a path in group (d1) are located in the complement network. It should be noted that, an E-E path that passes through the subarea network can enter and exit the subarea network multiple times. In this study, we can define a subpath as the portion of the original path that starts from the first entering zone to the last exit zone in the subarea. If more than half of the path trajectory along a subpath is located inside the subarea network, we classify the path in group (d2). Similarly, a subpath in group (d3) has more than half of its trajectory located in the compliment network. Another simple rule is that a subpath with more than 50% of its travel time spent in the subarea network is considered as a traversing path, otherwise it is specified as a bypassing path. As both types of flows in subgroups (d2) and (d3) can respond to possible transportation policy changes in the subarea, the trip rates in the induced OD demand matrix should include path flows in both (d2) and (d3). The flow equation for induced OD can be written as

$$\bar{d}_{i,j,\tau} = \sum_{u,v,h,\tau'} \bar{f}_{u,v,h,\tau'} \sigma^{i,j,\tau}_{u,v,h,\tau'} \quad (5\text{-}3)$$

where $\sigma^{i,j,\tau}_{u,v,h,\tau'}$ is the time-dependent path flow indicator, $\sigma^{i,j,\tau}_{u,v,h,\tau'}$=1 if zones i and j are the first entering zone and last exit zone for path flow (u,v,h,τ') traveling into the subarea at entering time τ, $\sigma^{i,j,\tau}_{u,v,h,\tau'}$=0 otherwise.

The following describes the algorithmic implementation of equation (5-3).

Initialize $\bar{d}_{i,j,\tau}$ = 0 for $i \in I$ and $j \in J$, $\tau \in T_d$

For the h^{th} path from zone u to zone v at time τ' on the original network,

Scan the path node sequence,

Identify the first entering zone and the last exit zone in the subarea network as origin zone i and destination zone j.

If zones i and j can be found, and the h^{th} path trajectory enters the subarea at time τ, then $\bar{d}_{i,j,\tau} = \bar{d}_{i,j,\tau} + \bar{f}_{u,v,h,\tau'}$.

EndFor

Excess-Demand Traffic Assignment Formulation

After calculating trip desires using the subarea network, the next question is how to model the response of traversing and bypassing E-E trips to traffic condition and operational policy changes in the subarea. Because the demand structure of the subarea network is not independent from the rest of the network, a realistic subarea analysis model needs to maintain a connection between the extracted subarea network and the original network. For example, if the level of service in the subarea degrades, the vehicle flows originally traversing the subarea could shift to the surrounding area and become bypassing flows. Note that, for I-I, E-I, and I-E OD pairs some subpath flows might also use the complement network. For simplicity, we only focus on E-E OD pairs in this research.

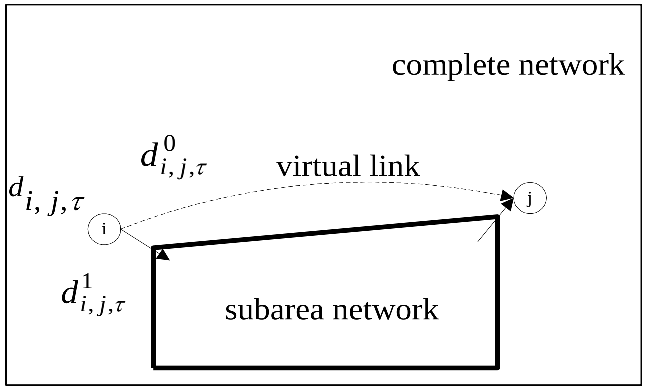


Figure 5-3 Virtual link for OD pair (i,j,τ)

As shown in Figure 5-3, the virtual links between each boundary OD pair (i,j,τ) in the subarea network are introduced to accommodate bypassing E-E flows that originally use the surrounding area. The mathematical model for determining the flow split between traversing and bypassing E-E trips is given as follows. Total OD demand for subarea OD pair (i,j,τ) is expressed as:

$$d_{i,j,\tau} = \sum_m d^m_{i,j,\tau} = d^0_{i,j,\tau} + d^1_{i,j,\tau} \qquad (5\text{-}4)$$

where

m = 0-1 indicator for bypassing or traversing flows (complementary/subarea network indicator)

$d^0_{i,j,\tau}$ = E-E OD flows from zone i to zone j departing at τ that are carried by the virtual link in the complementary network (bypassing trips)

$d^1_{i,j,\tau}$ = E-E OD flows from zone i to zone j departing at τ that are accommodated in the subarea network (traversing trips).

In the following, an excess-demand formulation is adopted to capture the existing split of E-E OD flows between the subarea network and the complement network. For each boundary OD pair, we consider a simple flow split function:

$$d^m_{i,j,\tau} = d_{i,j,\tau} \frac{e^{\theta_{i,j} T^m_{i,j,\tau}}}{e^{\theta_{i,j} T^0_{i,j,\tau}} + e^{\theta_{i,j} T^1_{i,j,\tau}}} \tag{5-5}$$

where $T^0_{i,j,\tau}$ and $T^1_{i,j,\tau}$ are average path travel times for (i,j,τ) bypassing and traversing the subarea network respectively, and $\theta_{i,j}$ is a dispersion parameter to be estimated.

The above formula can be interpreted as estimating the most likely route flow pattern based on the maximum entropy principle. Because the complement network is not physically modeled, we need to re-construct the E-E path flow pattern in the subarea network. There exist many possible combinations (or states) of traversing and bypassing flows in the subarea network. The entropy maximization principle provides a criterion for choosing the distribution that maximizes path flow entropy subject to two constraints, namely the total flow constraint and the total travel time constraint. The number of combinations for $d^m_{i,j,\tau}$ is

$$Z(d^m_{i,j,\tau}) = \frac{d_{i,j,\tau}!}{\prod_m d^m_{i,j,\tau}!} = \frac{d_{i,j,\tau}!}{d^0_{i,j,\tau}!\, d^1_{i,j,\tau}!}. \tag{5-6}$$

Let $TT_{i,j,\tau}$ denote the total travel time incurred by all traversing and bypassing trips related to OD pair (i,j,τ) for departure time interval τ. That is, $TT_{i,j,\tau}$ is the sum of travel time for all the subpath flows along OD pair (i,j,τ) at time τ obtained from the traffic assignment result on the complete network. The total travel time constraint (5-7) aims to ensure that the new set of traversing and bypassing flows in the subarea network should produce the same total travel time as $TT_{i,j,\tau}$, and $T^0_{i,j,\tau}$ and $T^1_{i,j,\tau}$ are unchanged.

$$\sum_m \left(d^m_{i,j,\tau} \times T^m_{i,j,\tau}\right) = TT_{i,j,\tau}. \tag{5-7}$$

The set of path flow patterns, that is most likely to occur, can be obtained by solving an optimization model that maximizes $Z(d^m_{i,j,\tau})$ subject to constraints (5-4) and (5-7). Rather than maximizing $Z(d^m_{i,j,\tau})$ directly, we can take its logarithm and approximate it by Stirling's formula, leading to an equivalent entropy maximization model for each individual OD pair:

$$\max \quad \ln Z(d^m_{i,j,\tau}) \approx \sum_m \left(d^m_{i,j,\tau} \ln d^m_{i,j,\tau} - d^m_{i,j,\tau}\right) \tag{5-8}$$

subject to constrains (5-4) and (5-7).

The corresponding Lagrangian function is (subscripts (i,j,τ) are omitted for simplicity).

$$L = \sum_m \left(d^m \ln d^m - d^m\right) + \lambda(d - \sum_m d^m) + \theta(TT - \sum_m d^m \times TT^m),$$

where λ and θ are Lagrangian multipliers for constraints (5-4) and (5-7), respectively. Its first order necessary optimality condition is

$$\frac{\partial L}{\partial d^m} = \ln d^m - \lambda - \theta \times TT^m = 0 \text{ with solution } \ln d^m = \lambda + \theta \times TT^m .$$

Substituting $d^m = e^{\lambda + \theta \times TT^m}$ back into constraint (4), we obtain $\sum_m e^{\lambda + \theta \times TT^m} = d$, leading to $e^{\lambda} = \frac{d}{\sum_m e^{\theta \times TT^m}}$ and $d^m = d \times \frac{e^{\theta \times TT^m}}{e^{\theta \times TT^0} + e^{\theta \times TT^1}}$.

Essentially, the optimization problem produces an analytical optimal solution in the same Logit-type form as (5-5). Similar derivations that map equilibrium link flows to the most likely route flow pattern can be found in Larson et al. (2001) and Rossi et al. (1989). Detailed mathematical treatment of the entropy optimization theory can be found in (Fang et al., 1997). After calculating the bypassing and traversing flow proportions and the corresponding travel times based on the traffic assignment result on the complete network, we can further calibrate the coefficient $\theta_{i,j}$ for each OD pair.

The traffic assignment model with elastic demand can be solved by the standard fixed demand traffic assignment program through network representation. In our implementation, virtual links are not physically modeled in the subarea network for the dynamic traffic assignment program, and the elastic demand is assigned to the subarea network according to the following three steps.

(1) Calculate $T^1_{i,j,\tau}$ based on the traffic flow pattern in the subarea network, and determine $T^0_{i,j,\tau}$ from the traffic assignment result in the complete network,

(2) Estimate the flow split for each OD pair and determine OD demand $D^1 = [d^1_{i,j,\tau}]$,

(3) Perform dynamic traffic assignment using OD demand D^1 in the subarea network.

Note that $T^1_{i,j,\tau}$ are time-varying as the result of dynamic traffic assignment. If a static traffic assignment model is used to generate the path flow pattern, then $T^1_{i,j,\tau}$ would be time-invariant. In this case, the flow split function (5-5) might lead to large modeling errors as the travel time measurements of the subarea network and related virtual link would be inconsistent.

Stage II: Dynamic OD Demand Updating Procedure Using Archived Traffic Measurements

Given induced OD demand information from the first stage and time-dependent link measurements, the dynamic OD demand estimation procedure aims to find a consistent time-dependent OD demand table that minimizes (1) the deviation between estimated link flows and observed link counts (2) the deviation between the estimated network flow pattern and the induced network flow pattern in the subarea. The induced network flow pattern can be expressed in terms of OD flows, path flows and link flows in the subarea.

In the context of dynamic traffic assignment, especially in congested networks, the mapping matrix between OD demand and link flows are not constant and are, themselves, a function of the unknown OD demand values. A bi-level dynamic OD estimation formulation (Zhou et al., 2003) is adapted here. Specifically, the upper-level problem aims to estimate the dynamic OD trip desires based on given link counts and flow proportions, subject to non-negativity constraints for demand variables. The flow proportions are in turn generated from the dynamic traffic network loading problem at the lower level, which is solved by a DTA simulation program, with a dynamic OD trip table calculated from the upper level. The weights w_1, w_2, and w_3 associated with the combined deviations could be interpreted as the decision maker's relative preference or importance belief for the different objectives or different information sources. They could also be considered as the dispersion scales for the error terms in the ordinary least-squares estimation procedure. Several interactive multi-objective programming methods can be applied in this context to determine appropriate weights that lead to best compromise solutions for inconsistent information sources, for example, sensed traffic counts vs. simulated traffic counts on the same link. Essentially, a representative subset of non-dominated solutions is first generated by varying the weights, and then the decision maker (i.e. planner) can determine the weights based on the following three criteria: minimum combined deviation, best trade-off and minimum distance from the ideal point. Because the temporal patterns in the induced OD demand and simulated time-dependent link counts are generated from an external time-of-day profile (rather than being observed directly), the following estimator only considers total induced demand and total simulated link counts over the planning horizon in order to avoid possible estimation biases. In other words, the actual measured time-dependent link counts $c_{l,t}$ will play a major role in inferring the temporal characteristics of the subarea OD demand matrix. Detailed assessment along this line can be found in Zhou et al.(2003).

Upper level: Constrained ordinary least-squares problem

$$w_1 \sum_{l,t} [\sum_{i,j,\tau} p_{l,t,i,j,\tau} \times d_{i,j,\tau} - c_{l,t}]^2 + w_2 \sum_{i,j} [\sum_{\tau} d_{i,j,\tau} - \bar{d}_{i,j}]^2 + w_3 \sum_{l} [\sum_{i,j,\tau} p_{l,i,j,\tau} \times d_{i,j,\tau} - \bar{f}_l]^2 \tag{5-9}$$

s.t. nonnegativity constraints $d_{i,j,\tau} \geq 0 \quad \forall i, j, \tau$

where

$d_{i,j,\tau}$ = estimated traffic demand from zone i to zone j at departure interval τ

$c_{l,t}$ = measured traffic flows on link l at observation interval t

$\bar{d}_{i,j}$ = induced traffic demand from zone i to zone j

$\bar{f}_l$ = simulated traffic counts on link l, obtained from the traffic assignment result in the complete network

$p_{l,t,i,j,\tau}$ = time-dependent link-flow proportions, i.e. fraction of vehicular flows from origin i to destination j, starting their trips during departure interval τ, contributing to the flow on link l during observation interval t

$p_{l,i,j,\tau}$ = link-flow proportions, i.e. fraction of vehicular flows from origin i to destination j, starting their trips during departure interval τ, contributing to the flow on link l

w_1, w_2, w_3 = weighting factors for different objective functions.

Lower level: Elastic demand dynamic traffic assignment problem

$$P = EDTA(\mathrm{D}) \tag{5-10}$$

where

P = link-flow proportion matrix

D = time-dependent OD demand matrix containing elements $[d_{i,j,\tau}]$ for the subarea network.

$EDTA$ = function of elastic demand traffic assignment process.

The following details the iterative bi-level dynamic OD demand updating procedure. The final output is a time-dependent OD demand matrix ready for the subarea analysis. Let k be the iteration number.

Step 1: (Initialization) k = 0. Using [$\bar{d}_{i,j}$], the induced OD demand matrix, as an initial demand matrix D_0 , generate link-flow proportions P_0 from the DTA simulator.

Step 2: (Optimization) Substituting link-flow proportions P_k, solve the upper level OD estimation problem to obtain demand D_k.

Step 3: (Simulation) Using demand D_k, run the DTA simulator to generate new link-flow proportions P_{k+1}.

Step 4: (Evaluation) Calculate the combined deviation according to objective function (9).

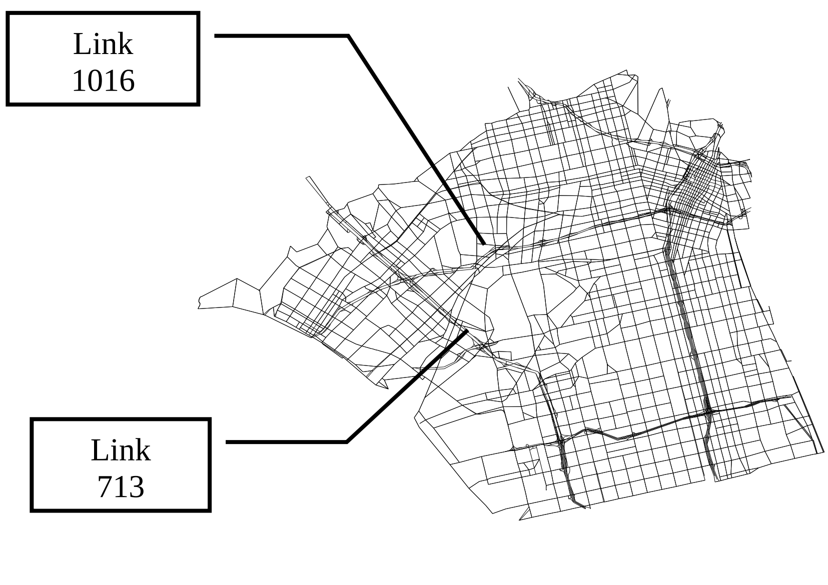
Step 5: (Convergence test) If the convergence criterion is satisfied (estimated demand is stable or no significant improvement in the overall objective), stop; otherwise k = k + 1 and go to Step 2.

To obtain a unique solution to the above ordinary least-squares formulation, one needs to ensure that the number of unknown variables (time-dependent OD demand flows) is not greater than the sum of the number of independent link observations $c_{l,t}$, the number of OD pairs in the demand matrix $\bar{d}_{i,j}$ and the number of induced link flow counts $\bar{f}_l$. In fact, in the above OD demand updating problem, the system identification condition is relatively easer to satisfy than in the standard OD demand estimation problem, since a large number of simulated link counts obtained from assignment in the complete network are available in the subarea network. If the system is still underdetermined when including all the links in the subarea, the simulated path counts can be introduced to increase the number of constraints. Accordingly, path-flow proportion matrices should be generated from the lower-level DTA program to map subarea OD flows to path flows. On the other hand, to reduce the computational effort associated with the nonlinear optimization program, one can select a set of critical links and critical paths to construct the "target" network flow pattern, as opposed to including all links and paths in the subarea.

5.5. Case Study: Illustration of the Procedure on Los Angeles Subarea Network

The test network used for illustrating the procedure is the regional transportation planning network of the Southern California Association of Governments (SCAG). The network includes four California Department of Transportation (CALTRANS) districts covering Los Angeles and Ventura counties, San Bernardino and Riverside Counties, Imperial County (not included in the Year 2000 planning process) and Orange County. The network and the historical OD demand data are obtained from the Year 2000 Regional Transportation Plan (SCAG, 2000). In year 2000, the region population was 16.12 million served by a 14,504 route-mile (or an equivalent 51,827 lane-mile) highway network. The total vehicle traffic in the region was 17.2 million in peak periods and approximately 34 million in all time periods. Los Angeles County, where the study area is located, has the highest share in the regional vehicular traffic with 9.6 million vehicle trips in the peak periods and 19 million trips in all time periods. In Figure 5-4(a), the rectangle shown in the complete network plot marks an approximate boundary of the subarea. The subarea network for which the OD estimation procedure is applied is shown in Figure 5-4(b).

(a)



(b)

Figure 5-4 (a) SCAG regional planning network and (b) Los Angeles subarea network representation

The network characteristics for both complete and subarea networks are given in Table 5-1.

Table 5-1 SCAG Original and Subarea Network Size Comparison

	Complete network	Subarea network	%
Number of links (excluding connectors)	68,535	8,530	12.45
Number of nodes (excluding zone centroids)	27,187	3,197	11.76
Number of TAZ's	3,191	60	1.88

The input data was obtained from the SCAG regional planning model. In this static transportation planning model, the OD demand matrix for the complete network covers the AM peak period (6:00 am to 9:00 am), corresponding to a 3191 by 3191 matrix. The matrix was converted to a time-dependent OD table with a time-of-day profile, and the signal control data were generated using an approximation approach because the detailed signal timing data was not available at the time of this study.

After compiling the necessary input data for the complete network, DYNASMART-P was run with an initial OD demand to obtain the simulated path flows. As shown in the procedure in Figure 5-1, the first stage outputs an induced OD matrix for the subarea. At the second stage, the induced dynamic OD demand is updated by utilizing both archived traffic measurements and the induced OD matrix. The archived traffic measurements are obtained from the California Freeway Performance Measurement System (PeMS) (2005). In the PeMS database, traffic measurements such as occupancy, volume, and speed are available either as raw data (30 second intervals) or as aggregated data (5 minute intervals). 244 detectors from the PeMS database related to the subarea are selected and mapped to the subnetwork links in DYNASMART-P. In this study, 5-min aggregated measurements were collected from these 244 links on August 2, 2004 (Monday) and input to the bi-level dynamic OD estimation procedure.

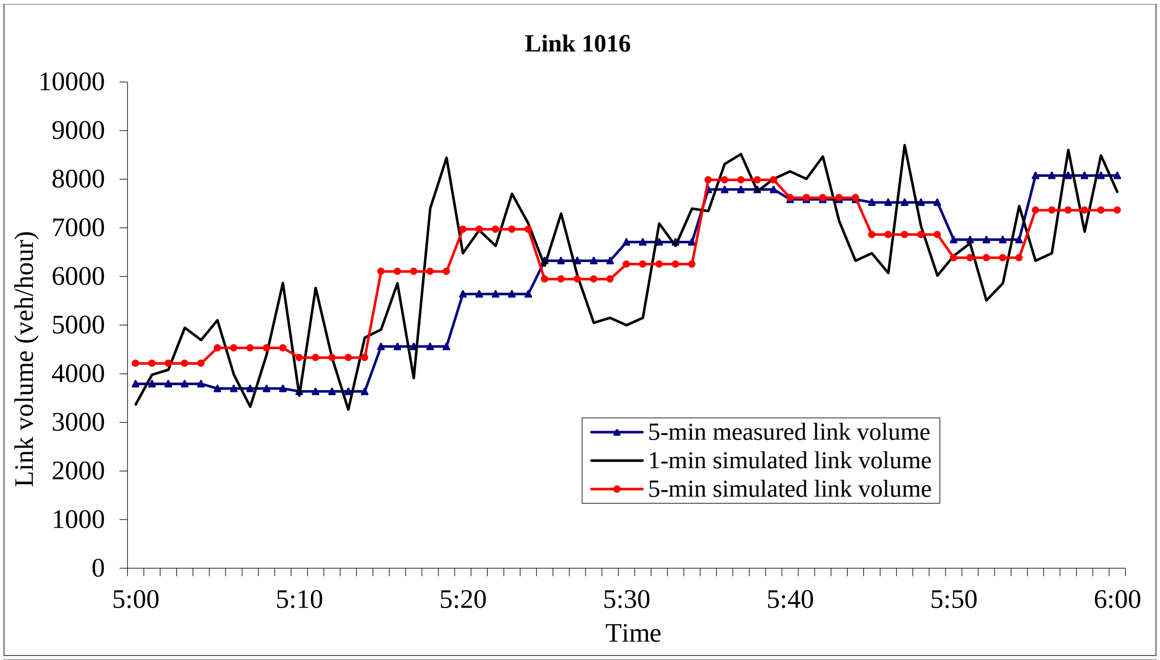
In order to evaluate the performance of the procedure, the Root Mean Squared Error (RMSE) between observed link volumes $c_{l,t}$ and simulated link volumes $c'_{l,t}$ are used as the measure of effectiveness.

$$RMSE = \sqrt{\frac{\sum_{l}\sum_{t}(c'_{l,t} - c_{l,t})^2}{|\,l\,|.|\,t\,|}} \tag{5-11}$$

Table 5-2 RMSE Values of Estimation Results with and without Traffic Measurements

	Induced OD demand only	Induced OD demand + archived traffic measurements	% Improvement
Density (veh/lane/mile)	15.7	13.1	16.5
Volume (veh/hour/lane)	340.5	257.9	24.2
Speed (mile/hour)	18.6	14.7	20.0

Table 5-2 lists average estimation errors under two scenarios: (1) induced OD demand only, and (2) induced OD demand with archived traffic measurements. Clearly, additional up-to-date traffic measurements can capture the time-varying traffic patterns in the subarea network and significantly reduce the estimation errors for three major traffic measures. Figure 5-5 details the time-varying measured and simulated volume on two links from 5:00 am to 6:00 am. It should be noted that, the simulated link volume profile under a 5-min aggregation interval shows a more slowly changing pattern than the counterpart under a 1-min aggregation interval, while simulated 1-min link volume data are able to reveal the underlying dynamic nature of traffic flow patterns. It should be noted that, this preliminary case study is performed to illustrate the procedure on a real world network with limited information. Further work is needed in both network specification and model calibration to improve the overall system estimation performance. Especially, because no real-world path flow data are currently available to calibrate the proposed excess-demand assignment model, in this dissertation, the important split fractions between bypassing and traversing E-E trips are estimated only from the simulation results, and they remain unchanged in the subarea OD demand estimation process. A more systematical and sound estimation procedure should integrate the unknown split fractions into the current OD demand estimation framework. In other words, link observations in the subarea network should be used to estimate and adjust the split fractions, in addition to average travel times for using the subarea and complement networks.



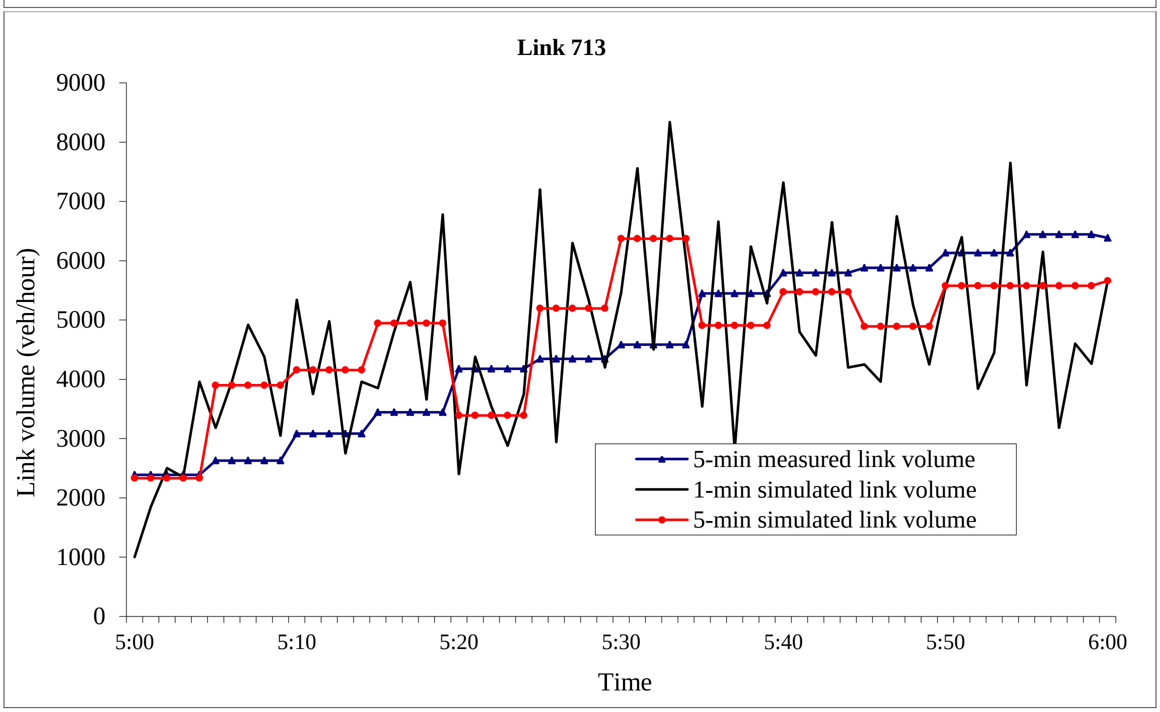


Figure 5-5 Illustration of performance of OD estimation procedure on selected links

5.6. Conclusions

The dynamic traffic assignment methodology overcomes many of the known limitations of static tools used in practice. The computational intensiveness of simulation-based DTA methodologies places limitations on the application of such tools to large-scale networks limiting the opportunities for assessing the impacts of GHG emissions reduction strategies. To allow the consideration and rapid evaluation of a large number of scenarios, this dissertation has described a two-stage subarea OD demand estimation procedure to construct and update important time-dependent OD demand input for subarea analysis. The first stage effectively utilizes path-based traffic assignment information to calculate the path flow pattern in the complete network and then to construct a comparable target demand matrix for the OD demand estimation problem in the subarea. The proposed elastic demand traffic assignment formulation allows external-external trips to respond to traffic conditions resulting from network and operational changes in the subarea, and it can be interpreted by an entropy maximization framework. In the second stage, archived time-dependent traffic measurements are utilized to update the induced demand matrix, and this OD updating method enables the OD trip matrix used in the subarea analysis to capture current demand and network flow patterns. The case study illustrates a practical and sound procedure for DTA-based subarea analysis applications, and demonstrates effectiveness of combining traffic measurements with conventional planning data in DTA deployment. Essentially, the use of traffic measurements increases the performance of OD estimation procedure, and path-based simulation-assignment systems can provide an evolving platform for integrating operational considerations in planning models for effective decision support for agencies that are considering strategies for GHG emissions reduction.

Chapter 6: Conclusions and Extensions

6.1 Contributions and Benefits

The transportation sector is a significant contributor to our global climate change problem, which is considered to be one of the most prominent problems that today's society faces. The increased awareness of the transportation system's impact on the environment, economic activity and land-use calls for a broader perspective in transportation analysis, planning and policy-making that takes into account sustainability of the system. A multi-faceted approach is followed in this dissertation with the aim of supporting transportation emissions reduction efforts. This dissertation addressed three complementary problems that share the common goal of supporting transportation emissions reduction efforts by providing tools to help reduce demand for fossil fuels through seemingly different, but synergistically related, ways.

The first problem addressed alternative fuel vehicle (AFV) fleet operations considering limited infrastructure availability and vehicle characteristics that contributes to emission reduction efforts by: supporting alternative fuel use and reducing carbon-intensive freight activity. The G-VRP is formulated and techniques were proposed for its solution. Numerical experiments showed that these techniques perform well compared to exact solution methods and that they can be used to solve large problem instances. The G-VRP will aid organizations with AFV fleets in overcoming difficulties that exist as a result of limited refueling infrastructure and will allow companies considering conversion to a fleet of AFVs to understand the potential impact of their decision on daily operations and costs. These techniques can help companies in evaluating possible reductions in the number of customers that can be served or increase in fleet size needed to serve an existing customer base, as well as any increase in required distance traveled as a result of driving range limitations and added fueling stops. The GVRP formulation and solution techniques are applicable for any fuel choice. They can also be used in seeking optimal tours for gasoline or diesel powered fleets that involve special refueling arrangements.

The second problem is aimed at supporting SOV commute trip reduction efforts through alternative transportation options. This problem contributes to emission reduction efforts by supporting reduction of carbon-intensive travel activity. Following a detailed descriptive analysis of the commuter survey data obtained from the University of Maryland, College Park campus, ordered-response models were developed to investigate the market for vanpooling. The models looked into vanpooling demand, distinguishing the passenger and driver roles which has not been done in the literature. The model specifications included a wide variety of factors to explain the interest in vanpooling for the roles of passenger and driver. In addition to ordered logit and probit estimates of the proposed model specifications, marginal effects of factors are also analyzed. The model results showed that demand for vanpooling in the role of passenger and driver show differences and the factors affecting these demands are not necessarily the same. Therefore, it was found that passenger and driver roles should be separated (in the case of employer-provided services that require one of the participants to be driver). Some of the factors that are found to affect passenger and driver models include: status and willingness-to-pay, distance, residential location, commuting to campus most days of the week by SOV, driving alone when commuting to campus, convenient ride home service, not having a car, need of picking up/dropping of children, age, convenient parking options, and cost of gas and parking.

The third problem is aimed at providing essential input data, origin-destination (OD) demand data, for analysis of various emission reduction strategies, contributing to emission reduction efforts by helping to improve system efficiency and reducing carbon-intensive travel activity. The DTA methodology helps overcome limitations of static planning tools used in practice. However, simulation-based DTA methodologies themselves place limitations on the application of such tools to large-scale networks due to the computational intensity. Thus, they are also limited for assessing the impacts of emissions reduction strategies on large-scale networks. This dissertation has described a two-stage subarea OD demand estimation procedure to construct and update important time-dependent OD demand input for subarea analysis in an effort to overcome the computational limits of DTA methodologies. This procedure utilizes path-based traffic assignment information and time-dependent link measurements to calculate path flow patterns in the complete network to construct a comparable target demand matrix for the OD demand estimation problem in the subarea. The proposed elastic demand traffic assignment formulation allows evaluation of network performance in response to traffic conditions resulting from network and operational changes in the subarea without losing the essential flow information. The case study demonstrates effectiveness of combining traffic measurements with conventional planning data in DTA deployment. Essentially, the use of traffic measurements increases the performance of the OD estimation procedure. The proposed method in conjunction with path-based simulation-assignment systems can provide an evolving platform for integrating operational considerations in planning models for effective decision support for agencies that are considering strategies for transportation emissions reduction.

6.2 Extensions

The extensions that can be considered for this dissertation are as follows. The GVRP model could be extended to consider more complex fuel-usage models, consideration of fuel prices and heterogeneous fleets in which vehicles may have different driving range limitations or be powered by different sources of fuel. Determining optimal AFS locations jointly with tour finding is another extension that can be considered for future research. In modeling the propensity to carpooling/vanpooling, a latent class model for the analysis of individual heterogeneity could be more informative in explaining latent heterogeneity that varies with factors that are unobserved by the analyst. Also, a more focused survey, specifically designed for investigating vanpooling behavior, would provide more information. Finally, a case study within the subarea analysis framework can be designed to illustrate the benefits of emission reduction strategies, such as vanpooling and cordon pricing as suggested in this dissertation.

Appendix

UNIVERSITY OF MARYLAND COMMUTER SURVEY

SPRING 2010

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Q1 You are being invited to voluntarily participate in a campus-wide transportation survey. The purpose of this study is to understand the behavior of campus community members in commuting to and from campus. You are eligible to participate because you are a student, faculty, or staff member at the University of Maryland, College Park.If you agree to participate, participation will involve completing a survey, which should take no more than 15 minutes. You may choose not to answer some or all of the questions. Your name will not appear on the completed survey. One survey question asks for your local address by street, cross street and city, which is considered identifiable information. Address information will not be used to contact you, will not be made public, and will be used to design more effective transportation services. Also, upon completing the survey you will be asked if you would like your email to be entered into a prize drawing. E-mail addresses are considered identifiable information; e-mail addresses will not be used for any purpose other than distributing the survey and notifying select individuals they've won the prize drawing. If selected for a prize drawing you will be contacted by email only once and notified of where to pick-up your prize.Any questions you have related to the survey will be answered. You may leave the survey at any time before completing it. There are no known risks from your participation and no direct benefit from your participation. There is no cost to you except for your time and you are not compensated monetarily or otherwise for participation in this survey.Your survey responses will remain confidential with the researchers and University of Maryland entities with which the researchers have partnered including the Department of Transportation Services, the Office of Sustainability, and the Student Affairs Assessment Committee. To protect your confidentiality, the researchers will not share identifiable information, which includes local street address and email address information. If we write a report or article about this research project, your identity will be protected to the maximum extent possible.You can obtain further information about this survey by contacting: Sean Williamson Faculty

Research Assistant Center for Integrative Environmental Research T. 301.405.9436E. srw46@umd.edu By participating in the survey, you are giving permission for the investigator to use your information for research purposes. If you agree to participate in this survey, please check the box below, and click "Next." Thank you.

I have read the Consent Form and agree to participate in the survey. (Go To Page 2)
[Code = 1]
I have read the Consent Form and do not agree to participate in the survey. (Go To End)
[Code = 2]

Required answers: 1 Allowed answers: 1

Part 1 - Commuter Information

A. General Information

Q2 What is your classification?

Undergraduate Student [Code = 1]

Graduate Student [Code = 2]

Faculty [Code = 3]

Staff [Code = 4]

Required answers: 0 Allowed answers: 1

Q3 Which best describes you?

Part Time [Code = 1]

Full Time [Code = 2]

Required answers: 0 Allowed answers: 1

Q4 What time do you usually arrive at campus?

Before 6:00 a.m. [Code = 1]

6:00 - 6:30 a.m. [Code = 2]

6:30 - 7:00 a.m. [Code = 3]

7:00 - 7:30 a.m. [Code = 4]

7:30 - 8:00 a.m. [Code = 5]

8:00 - 8:30 a.m. [Code = 6]

8:30 - 9:00 a.m. [Code = 7]

9:00 - 9:30 a.m. [Code = 8]

9:30 - 10:00 a.m. [Code = 9]

After 10:00 a.m. [Code = 10]

Required answers: 0 Allowed answers: 1

Q5 What time do you usually leave campus?

Before 4:00 p.m. [Code = 1]

4:00 - 4:30 p.m. [Code = 2]

4:30 - 5:00 p.m. [Code = 3]

5:00 - 5:30 p.m. [Code = 4]

5:30 - 6:00 p.m. [Code = 5]

6:00 - 6:30 p.m. [Code = 6]

6:30 - 7:00 p.m. [Code = 7]

7:00 - 7:30 p.m. [Code = 8]

7:30 - 8:00 p.m. [Code = 9]

After 8:00 p.m. [Code = 10]

Required answers: 0 Allowed answers: 1

Q6 How far do you live from campus (in miles)?

I live on campus. [Code = 1]

Less than 1 mile [Code = 2]

1 - 5 miles [Code = 3]

6 - 10 miles [Code = 4]

11 - 15 miles [Code = 5]

16 - 20 miles [Code = 6]

More than 20 miles [Code = 7]

Required answers: 0 Allowed answers: 1

Q7 How many minutes does your commute usually take from door to door?

Less than 15 minutes [Code = 1]

15 - 30 minutes [Code = 2]

30 - 45 minutes [Code = 3]

45 - 60 minutes [Code = 4]

Between 1 and 1.5 hours [Code = 5]

More than 1.5 hours [Code = 6]

Required answers: 0 Allowed answers: 1

Q8 What is your local home ZIP code?

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

Q9 Please list your city, local street, and nearest cross street:

City: [Code = 1] [TextBox]

Street 1: [Code = 2] [TextBox]

Street 2 (INTERSECTS WITH STREET 1): [Code = 3] [TextBox]

Required answers: 0 Allowed answers: 3

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The next question will ask about which modes of transportation you take to campus and how often you take each mode.

Required answers: 0 Allowed answers: 0

On average, how many times per week do you commute to campus? Please select how often you use each mode or combinations of modes to commute.

Q10 By bike

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q11 On foot

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q12 Alone, by car

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q13 With others, by car

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q14 Scooter/motorcycle

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q15 By Shuttle-UM

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q16 By MetroBus/other bus

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q17 MetroRail/MARC and Shuttle-UM/bus

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q18 By car and Shuttle-UM (Park & Ride)

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q19 Shuttle-UM/bus and bike

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q20 Car and bike

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q21 Other

Never or rarely [Code = 1]

Once per week [Code = 2]

2 times per week [Code = 3]

3 times per week [Code = 4]

4 times per week [Code = 5]

5 times per week [Code = 6]

More than 5 times per week [Code = 7]

Required answers: 0 Allowed answers: 1

Q22 Please specify "other" if selected above:

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

When you are on campus, how do you get from one place to another? Please select how often you use each mode on-campus:

Q23 Walk

Never [Code = 1]

Once per month [Code = 2]

1 - 2 days a week [Code = 3]

3 - 4 days a week [Code = 4]

5 or more days a week [Code = 5]

Required answers: 0 Allowed answers: 1

Q24 Bike

Never [Code = 1]

Once per month [Code = 2]

1 - 2 days a week [Code = 3]

3 - 4 days a week [Code = 4]

5 or more days a week [Code = 5]

Required answers: 0 Allowed answers: 1

Q25 Car

Never [Code = 1]

Once per month [Code = 2]

1 - 2 days a week [Code = 3]

3 - 4 days a week [Code = 4]

5 or more days a week [Code = 5]

Required answers: 0 Allowed answers: 1

Q26 Scooter/motorcycle

Never [Code = 1]

Once per month [Code = 2]

1 - 2 days a week [Code = 3]

3 - 4 days a week [Code = 4]

5 or more days a week [Code = 5]

Required answers: 0 Allowed answers: 1

Q27 Shuttle-UM

Never [Code = 1]

Once per month [Code = 2]

1 - 2 days a week [Code = 3]

3 - 4 days a week [Code = 4]

5 or more days a week [Code = 5]

Required answers: 0 Allowed answers: 1

Q28 Other

Never [Code = 1]

Once per month [Code = 2]

1 - 2 days a week [Code = 3]

3 - 4 days a week [Code = 4]

5 or more days a week [Code = 5]

Required answers: 0 Allowed answers: 1

Q29 Please specify "other" if selected above:

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

Q30 Do you have a physical disability that would prevent you from using one or more of the transportation modes listed above?

Yes [Code = 1]

No [Code = 2]

Required answers: 0 Allowed answers: 1

B. Driving Information

Q31 When you come by car to campus, how many people do you usually ride with?

Just myself [Code = 1]

1 other person [Code = 2]

2 other persons [Code = 3]

3 other persons [Code = 4]

4 other persons [Code = 5]

5 or more other people in the vehicle [Code = 6]

Required answers: 0 Allowed answers: 1

Q32 When you come by car to campus, what type of parking pass do you use?

Residential permit [Code = 1]

Commuter permit [Code = 2]

Green permit [Code = 3]

Carpool permit [Code = 4]

Paid hourly parking [Code = 5]

Pre-paid single-day parking (Bundle pack permit) [Code = 6]

Other [Code = 7]

Required answers: 0 Allowed answers: 1

Q12='Once per week' OR Q12='2 times per week' OR Q12='3 times per week' OR

Q12='4 times per week' OR Q12='5 times per week' OR

Q12='More than 5 times per week'

Q33 Please list the year, make, and model of the car you usually commute in:

Year: [Code = 1] [TextBox]

Make: [Code = 2] [TextBox]

Model: [Code = 3] [TextBox]

Required answers: 0 Allowed answers: 3

Q12='Once per week' OR Q12='2 times per week' OR Q12='3 times per week' OR

Q12='4 times per week' OR Q12='5 times per week' OR

Q12='More than 5 times per week'

Part 2 - Attitudes Toward Alternative Transport OptionsA. Attitude Toward Carpooling and Vanpooling

Carpooling is defined as commuting by car with 1 - 4 other people.Vanpooling is defined as commuting by van with 5 or more people.We want to know your opinion of carpooling and vanpooling regardless of how you currently commute to campus. The next set of questions will ask about carpooling and vanpooling as modes of transportation to campus.

Required answers: 0 Allowed answers: 0

Q34 Please select the statement that best describes you:

I carpool or vanpool most every day I come to campus. [Code = 1]

I carpool or vanpool to campus at least once per week. [Code = 2]

I carpool or vanpool to campus at least once per month. [Code = 3]

I rarely or never carpool or vanpool. [Code = 4]

Required answers: 0 Allowed answers: 1

Q35 Assuming you own a car, how interested would you be in carpooling to campus as the driver?

Extremely interested [Code = 5]

Very interested [Code = 4]

Moderately interested [Code = 3]

Not very interested [Code = 2]

Not at all interested [Code = 1]

Required answers: 0 Allowed answers: 1

Q36 How interested would you be in carpooling to campus as the passenger?

Extremely interested [Code = 5]

Very interested [Code = 4]

Moderately interested [Code = 3]

Not very interested [Code = 2]

Not at all interested [Code = 1]

Required answers: 0 Allowed answers: 1

Q37 Considering the cost of vehicle maintenance and fuel, how much would you be willing to pay per month to participate in a daily UMD vanpool (as a passenger, not a driver)?

Less than $10 per month [Code = 1]

Between $10 and $20 per month [Code = 2]

Between $20 and $30 per month [Code = 3]

Between $30 and $40 per month [Code = 4]

I would not be willing to pay to participate in a vanpool program. [Code = 5]

Required answers: 0 Allowed answers: 1

Q38 Some universities provide a vanpooling service where one volunteer member is responsible for driving the van and keeping the van at home in the evenings; other members pay a monthly fee to participate in the vanpool. How would the removal of the monthly fee impact your willingness to be the primary driver?

Much more likely to be driver [Code = 5]

Slightly more likely to be driver [Code = 4]

No change [Code = 3]

Slightly less likely to be driver [Code = 2]

Much less likely to be driver [Code = 1]

Required answers: 0 Allowed answers: 1

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What three reasons would make you most inclined to carpool or vanpool? Please rank with one (1) being the most important reason and three (3) the third most important reason:

Q39 Web application that matched me with potential carpool partners

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q40 More convenient parking options

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q41 Increase in the cost of parking

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q42 Increase in the cost of gasoline

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q43 Finding good company to ride with

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q44 Less expensive parking than the days when I drive alone

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q45 A more convenient Guaranteed Ride Home Program

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q46 Frequent pick-up and drop-off times

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

The next question will ask about barriers to carpooling or vanpooling to campus. Please rate how important the following factors are in preventing you
from carpooling or vanpooling to campus:

Q47 I do not have a car.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q48 I need my car for off-campus trips.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q49 I have a constrained or irregular schedule.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q50 I need a specially equipped vehicle.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q51 I need to pick-up/drop-off my children.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q52 I do not have a way to find a carpool or vanpool group.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q53 I do not have time to wait on others.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q54 I do not like to depend on others I do not know well.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q55 I am concerned about my safety.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q56 I prefer to ride alone.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q57 I am concerned about becoming stranded on campus.

Extremely important [Code = 5]

Very important [Code = 4]

Moderately important [Code = 3]

Not very important [Code = 2]

Not at all important [Code = 1]

Required answers: 0 Allowed answers: 1

Q58 If you have any additional comments or suggestions about carpooling or vanpooling, please enter it into the following box:

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

B. Attitude Towards Bicycling

BikeUMD is a University-wide initiative to support bicycling as a mode of transportation to and on campus. Based on the recommendations of a
recent campus bike study, the University has begun to make improvements to support bicyclists on and around campus.

Required answers: 0 Allowed answers: 0

Q59 Overall, how would you rate the improvements on campus biking?

I have not noticed. [Code = 0]

Poor [Code = 1]

Fair [Code = 2]

Average [Code = 3]

Good [Code = 4]

Excellent [Code = 5]

Required answers: 0 Allowed answers: 1

Q60 Have you begun biking to or on campus since March 2009?

Yes [Code = 1]

No, I do not bike to or on campus [Code = 2]

No, I started biking to or on campus earlier than (date): [Code = 3] [TextBox]

Required answers: 0 Allowed answers: 1

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Q61 What made you start biking to or on campus?

More bicycle parking [Code = 1]

Access to bicycle lockers or cages (secure covered cages) [Code = 2]

Access to using a shared car while I am at work [Code = 3]

The ability to occasionally drive to campus when I need to [Code = 4]

Better/safer routes available [Code = 5]

Advice about selecting routes or other bicycle commuting issues [Code = 6]

Better transit connections [Code = 7]

Ability to shower after I arrive [Code = 8]

Bike Shop location change [Code = 9]

Other (please describe) [Code = 10] [TextBox]

Required answers: 0 Allowed answers: 10

Q60='Yes'

Check the three most important bike improvements you think the campus should pursue. Please rank with one (1) being the most important improvement and three (3) the third most important improvement. If you have no opinion, leave this question blank.

Q62 Bicycle lanes on off-campus roads

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q63 Bicycle lanes on campus roads

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q64 Better signs or pavement markings to warn drivers

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q65 Trails or pathways separated from traffic

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q66 Covered and secure bicycle parking at central locations

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q67 More bike racks

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q68 A bicycle station on campus

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q69 Convenient shower and locker facilities

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q70 A bike shop that sells bicycles and gear

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q71 Better lighting around campus for traveling safely in dark

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Please check the three most important reasons that would make you more inclined to give up your parking permit for a bike? Please rank with one (1) being the most important reason and three (3) the third most important reason. If you have no opinion, leave this question blank.

Q72 Free bike

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q73 Free bike rental

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q74 More convenient bike parking (secured and covered)

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q75 A campus map showing bicycle routes

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q76 Dedicated bike lanes to/from campus

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q77 Share the road pavement markings and signs on campus roads

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q78 Shower and locker facilities

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q79 Educational classes on safe biking in traffic

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q80 More police patrol to ensure safety

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q81 Greater enforcement on traffic laws to protect bicyclists on the road

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q82 Prohibiting car traffic on some or all of the campus roads

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q83 Privileged parking for the days you drive

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q84 Guaranteed Ride Home service in case of emergency

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q85 Zipcar on campus

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q86 Carpool or rideshare options

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q87 I would not give up my parking permit.

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

C. Attitude Towards Shuttle-UM

Check the three most important factors that would make you more inclined to take Shuttle-UM. Please rank with one (1) being the most important factor and three (3) the third most important factor.

Q88 Service closer to my home

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q89 More frequent daily service

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q90 More late night and weekend service

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q91 More frequent service during holidays and recess

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q92 Higher prices for parking permits

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q93 Less crowded buses

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q94 Faster service (shorter travel time)

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q95 Wireless service on the bus

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q96 Other

1 [Code = 1]

2 [Code = 2]

3 [Code = 3]

Required answers: 0 Allowed answers: 1

Q97 Please specify "other" if selected above:

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

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Q98 How many hours do you normally work/study/socialize on campus each week?

Less than 10 [Code = 1]

10 - 20 [Code = 2]

20 - 30 [Code = 3]

30 - 40 [Code = 4]

More than 40 [Code = 5]

Required answers: 0 Allowed answers: 1

Q99 What is your gender?

Male [Code = 1]

Female [Code = 2]

Transgender [Code = 3]

Required answers: 0 Allowed answers: 1

Q100 What is your age?

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

Q101 Is this your first year at the University of Maryland?

Yes [Code = 1]

No [Code = 2]

Required answers: 0 Allowed answers: 1

Q102 Are you licensed to drive in the U.S.?

Yes [Code = 1]

No [Code = 2]

Required answers: 0 Allowed answers: 1

Q103 Please provide your e-mail address:

[Code = 1] [TextBox]

Required answers: 0 Allowed answers: 1

Q2='Faculty' OR Q2='Staff'

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