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ABSTRACT

Development of a Microscopic Activity-Based Framework for Analyzing the Potential Impacts of Transportation Control Measures on Vehicle Emissions

by

W. W. Recker and A. Parimi

The 1990 Clean Air Act Amendments (CAAA) and the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) have defined a set of transportation control measures to counter the increase in the vehicle emissions and energy consumption due to increased travel. The value of these TCM strategies is unknown as there is limited data available to measure the travel effects of individual TCM strategies and the models are inadequate in forecasting changes in travel behavior resulting from these strategies. The work described in this report begins to provide an operational methodology to overcome these difficulties so that the impacts of the policy mandates of both CAAA and ISTEA can be assessed. This research demonstrates the benefits in vehicle emissions reduction based on optimal scheduling and linking of the activities performed by the individuals in a household. The potential of transportation policy options to alleviate vehicle emissions is determined in a comprehensive activity-based approach. The model formulated is tested under different policy scenarios, including an evaluation of potential benefits achieved by replacing all the vehicles in the fleet by vehicles conforming to present day emissions technology.

1. INTRODUCTION

1.1 Problem Description and Relevance

Transportation has played a major, even legendary role in shaping the United States, influencing the location of economic activity, the form and size of cities, and the style and pace of life in the nation. Its central role in shaping development, however, is not unique to this country. The mobility and access provided by transportation have been instrumental to economic and social development worldwide and throughout history. Transportation systems foster economic growth by facilitating trade, permitting access to resources, and enabling greater economies of scale and specialization. They also expand cultural and social connections, increase employment and educational opportunities, and offer more options for where to live (TRB Special Report, 1997).

The motor vehicle has become an integral part of the daily lives and activities of individuals, influencing their decisions on where and how they reside, work, shop and socialize. The exceptional aspect of the U.S. transportation system is the unmatched scale and the extent of use of one mode of travel, the motor vehicle.

Depending on the method of calculation, it is estimated that the United States allocates between 25 and 45 percent of its energy production to motor vehicles and the infrastructure necessary to support them. Recent estimates are that the automobile is responsible for almost 90 percent of the energy consumed for travel in the U.S., 80 percent in Western Europe and 60 percent in Japan (Schipper *et al*, 1992). Transportation energy consumption and environmental health are interrelated issues. It is estimated by U.S. EPA (1991) that in a typical U.S. city, the motor vehicle emissions account for between 30 to 50 percent of hydrocarbon, 80 to 90 percent of carbon monoxide, and 40 to 60 percent of nitrogen oxides emissions.

Advances in technology have played and will continue to play a role in the Nation's ability to better manage both energy consumption and harmful emissions associated with vehicular transport. However, it is estimated that it is probably technologically possible to achieve an energy efficiency of only 30 percent (compared to today's 15 percent) using conventional powertrains. Electric vehicle technologies have the potential to save between 10 to 30 percent in primary energy, and fuel cell technology may ultimately produce a vehicle with three times the efficiency of today's vehicles, if their enormous economical and technical challenges can be overcome. Catalytic converters and other emissions control devices have achieved highly positive results in the reduction of vehicle emissions. Since the passage of the first Clean Air Act in 1970, tailpipe HC emissions have been reduced by 91 percent (compared to a 1971 model car). The corresponding reductions for CO and NO_x have been 96 and 85 percent respectively. However, during the period 1981-1992, the total vehicle miles traveled (VMT) for the Nation rose by more than 33 percent and the number of trips increased by about 25 percent (U.S. EPA, 1991; Hu and Young, 1992). The increase in the VMT and number of trips substantially offset the emission reductions; the net reduction in CO and NO_x, for example, was only 45 and 25 percent, respectively.

1.2 Emissions Regulated by Federal Laws

Mobile source emissions are significant sources of the air pollutants, ozone and CO. The EPA estimates national emissions of several primary pollutants (including CO, lead, NO_x, particulate matter, sulfur dioxide and VOCs) yearly. Mobile and stationary source emission trends indicate a reduction in recent years; area source emissions have demonstrated little change over time.
Ozone is not emitted directly by mobile sources. It is formed in a complex chemical process that occurs when precursor emissions of VOCs and NO_x react in the presence of sunlight and heat. The EPA has set National Ambient Air Quality Standards (NAAQS) for ozone and CO. CO is a pollutant with localized effects. Typically, more than 90 percent of CO emissions are derived from mobile sources. CO is a by-product of incomplete combustion. The adverse health effects of ozone and CO are possible as the lung functions are affected. EPA requirements have focused on reducing VOCs as the most effective strategy to achieve the ozone standard.

The 1990 Clean Air Act Amendments (CAAA) and the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) place an emphasis on modeling to provide an accurate accounting of progress toward meeting air quality goals and deadlines. This is important because non-attainment can lead to highway funds being withheld if the goals are not met.

The CAAA has established rules for gasoline volatility, evaporative and running losses, tailpipe emissions standards, alternative fuel programs, reformulated and oxygenated fuels, and inspection and maintenance programs. The technological advances that conform to these rules could produce almost half of the CAAA - required reductions in emissions by 2010 (Pechan, 1992). However, expected VMT growth (forecast to be about 2 percent annually) will offset much of this reduction (Kessler and Schroeer, 1995).

The CAAA and the ISTEA have, in combination, defined a broad range of transportation control measures (TCMs) to combat the deleterious impact of increased travel on attainment of energy and emissions reductions. TCMs include telecommuting, flexible work hours, congestion and parking charges, ridesharing, no-drive days, signal prioritization and expansion of public transport. However, both because of the limited data available to measure the travel effects of combined (or even individual) TCM strategies and the inadequacy of models to forecast changes in travel behavior resulting from these strategies, the value of these TCMs is currently unknown and the subject of controversy (Lyons, 1995).

1.2.1 Clean Air Act Amendments

These amendments established a new process for relating one of the most significant air quality problems, ground-level ozone, to the transportation system. The CAAA has established a process that requires non-attainment areas to reduce emissions in order to attain the National Ambient Air Quality Standards (NAAQS). These emissions are divided into three categories - mobile, stationary and area sources. The SIPs establish emission limits (emission budgets) for the non-attainment areas.

The non-attainment areas with similar pollution levels for each criteria pollutant were classified as moderate, serious, severe and extreme. This system was designed to address non-attainment problems by imposing a combination of prescribed measures that address the severity of the air quality problems while giving the states ultimate responsibility for and flexibility in solving the problems.

The CAAA provide the momentum for many federal and local initiatives to improve ambient air quality standards. The amendments also required the development of methods for improved determination and forecasting of mobile source emissions. The requirements of the CAAA establish significant new challenges to transportation and air quality modelers to improve estimates of traffic and emissions from mobile sources. The modelers must project mobile source emission inventories for the state implementation plan (SIP) process and calculate the differences in emissions between the Build and No-Build conditions of transportation plans, programs and projects.

The conformity requirements have established critical tests for comparing the Build and No-Build conditions of plans, programs and projects. These tests require a demonstration that the Build emissions are less than the No-Build emissions. The No-Build scenario represents the current transportation system, including future projects that have received environmental approvals under the National Environmental Policy Act (NEPA) process. The Build scenario comprises the No-Build scenario together with all of the new projects being proposed.

It is difficult to meet the conformity criteria for volatile organic compounds (VOCs) and particularly difficult to meet for oxides of nitrogen (NO_x). The NO_x criteria are difficult to meet because the NO_x emission rates increase with increased speeds, (this is not the case with VOC and CO emission rates) and increased speeds are typically the objective in implementing highway system improvements.

1.2.2 Intermodal Surface Transportation Efficiency Act

In December 1991, ISTEA was signed by the President to provide authorizations for highway construction, highway safety, and mass transportation expenditures through fiscal year 1997. The important features of ISTEA are as follows :

- The National Highway System was established.
- State and local governments were given far greater flexibility in modeling solutions to their individual transportation problems.
- Congestion Mitigation and Air Quality (CMAQ) program was provided for transportation assistance in non-attainment areas to help achieve the NAAQS.

- Expanded funding was proposed for new technologies.
- Highway traffic safety received more funds
- Truck regulation uniformity was enhanced
- Private entities were permitted to own toll facilities

1.3 Transportation Control Measures

Transportation Control Measures (TCMs) are an important part of an overall strategy for reducing mobile source emissions. The CAAA established procedures for integrating TCMs into transportation and environmental planning. TCMs are often focused on the commuting trip because work trips typically have lower vehicle occupancies, occur daily, and tend to be concentrated during the congested peak hours. In many cases, TCMs are implemented through employer-based commuter programs. Specific TCM activities implemented by employers include : tele-commuting programs; the distribution of commuting marketing materials; flexible, staggered work hours; transit pass and rideshare subsidies; rideshare matching information and services; and bicycle amenities. ISTEA and CAAA requirements for conformity necessitate that transportation programs be consistent with the mobile source emission reduction strategies of the SIP. This regulatory requirement promotes the integration of TCMs into the mix of such air quality control strategies, as new technologies, growth management, expanded transportation service alternatives, and improved management of the existing transportation system. TCMs should not be seen as an independent solution to air quality and congestion problems but as a component of a comprehensive strategy.

1.4 Research Objective

The nature of the interactions among the collection of individual and household travel decisions in response to TCMs lay at the heart of the failings of conventional models and data to provide adequate measures of their potential impact. Vehicle energy use and emissions depend not only on distance and the speed it is driven at, but also on the number of trips, the time between them, and whether the vehicle was warmed up or not when started; i.e., on the spatio-temporal linkages between the collection of activities that individuals and households perform as part of their daily schedule.

The work described in this study begins to provide an operational methodology to overcome these difficulties so that the impacts of the policy mandates of both CAAA and ISTEA can be assessed. This research will demonstrate the benefits in vehicle emissions reduction based on optimal scheduling and linking of the activities performed by the individuals in a household. The potential of transportation policy options to alleviate vehicle emissions is determined in a comprehensive activity-based approach. The model formulation is tested under different policy scenarios, including an evaluation of the potential benefits achieved by replacing all of the vehicles in the fleet by vehicles conforming to present-day emissions technology.

1.5 Overview of Research Methodology

The work is based on previous research in which a network-based activity assignment protocol (Household Activity Pattern Problem, or HAPP) was developed for complex travel activity decisions within a household (Recker, 1995). This research incorporates routing, scheduling, and activity assignment into a hybrid model that includes the interactions between household members and integrates mode availability, and temporal constraints that result in the household individuals' joint path through time and space. The aggregation of individual travel decisions of each member of a household reflect the complete range of travel characteristics affecting both energy consumption and vehicle emissions. The network-based activity assignment protocol is extended in this study to incorporate emissions based on the Mobile 5 vehicle emissions model, and the resulting modeling system applied to a sample of households drawn from an existing activity/travel survey conducted in the greater Portland area of Oregon. Conclusions are drawn relative to the potential emissions savings that can be expected from efficient trip chaining behavior, ride-sharing among household members, as well as from technological advances in vehicle emissions control devices.

1.6 Report Outline

The organization of the remainder of this report is as follows:

- Section 2 gives a description of the MOBILE 5 emissions model.
- Section 3 formulates the HAPP behavioral model framework used in optimization.

- Section 4 gives details of the data used for the analysis.
- Section 5 gives a description of the GAMS/CPLEX solver used in the optimization.
- Section 6 discusses the characteristics of the household sample used for the analysis.
- Section 7 presents and evaluates the model results under different scenarios.
- Section 8 presents conclusions and provides directions for future research.

2. "MOBILE" EMISSION MODELS

2.1 MOBILE Model Components

The primary components of the MOBILE emission factor models include : the base emission factors, the effect of local conditions (e.g., temperature and vehicle speed), characterization of the vehicle fleet, the impact of fuel characteristics, and the effect of inspection and maintenance programs. None of these factors is static; technology is continually evolving, leading to changing in-use emission performance, while changes in economic conditions can lead to changes in vehicle sales and travel patterns. The EPA expends considerable effort to quantify and stay current with the influence of all of these factors on motor vehicle emission levels. The key factors in the MOBILE models are discussed below.

Emission Factors : These factors are also known as base emission rates. These factors are developed from test measurements of in-use vehicles at various odometer readings. The emission factors are represented by two components, namely, a zero-mile level (or intercept) and a deterioration rate (or slope). The zero-mile level represents the new-vehicle emission rate, while the deterioration rate depicts emission control system deterioration that takes place as the vehicle ages.

Test Conditions : Standardized test procedures have been developed (e.g., the Federal Test Procedure, or FTP) to measure emission rates from motor vehicles. These procedures include specific driving cycles (i.e., speed versus time profiles), temperatures, vehicle load, and starting conditions. Although the test procedures were developed from data intended to represent average urban driving conditions, they do not necessarily match those that vehicles experience in each community. Therefore, EPA has developed correction factors to account for differences between the test procedures and actual operating conditions.

Fleet Characteristics : The base emission rates represent the average emission level of each model year in the vehicle fleet for each vehicle class (e.g., light-duty vehicles versus heavy-duty vehicles). A fleet average emission rate incorporating the contribution of all model years and vehicle classes is the output from the MOBILE model. The age distribution, the rate of mileage accumulation, and the mix of travel experienced by the vehicle classes considered in MOBILE can all influence the contribution of each vehicle class to the fleet average emission rate. Although the MOBILE models utilize national average data as default values for these parameters, local data can be input by the user to tailor a run for a specific community and provide a more accurate estimate of emissions.

Fuel Characteristics : Emission test measurements are normally conducted on a standardized test fuel known as Indolene. The characteristics of this fuel are well defined and ensure that test results are repeatable. However, in-use fuels are generally much different than Indolene, and differences in fuel volatility and other fuel parameters (e.g., oxygenate content) influence both evaporative and exhaust emission rates. All MOBILE versions reviewed in this work require fuel volatility as an input. Additionally, MOBILE4.1 provided an option to model the effects of oxygenated fuels on carbon monoxide estimates, and MOBILE5 includes the ability to model the impact of reformulated and oxygenated gasoline on hydrocarbon and oxides of nitrogen emissions as well.

Emission Control Programs : The model-year-specific emission factor equations are based on test data that do not include the effects of local emission control program (i.e., inspection and maintenance (I/M) and anti-tampering programs). These programs are intended to reduce emissions from in-use vehicles, and differences in program design (e.g., annual versus biennial testing) can have a significant impact on their effectiveness. Thus, MOBILE contains provisions for identifying the specific parameters applicable to the program being modeled.

2.2 MOBILE Model Input Data

There are a number of required and optional user inputs to the MOBILE models that allow the user to account for regional differences in travel parameters, ambient conditions, enforcement programs, etc. These are listed in Table 1, and briefly described in the following discussion.

Required Inputs :

To run the MOBILE models, a number of local conditions are required that describe the travel parameters, ambient conditions, and fuel parameters. These include the following :

- Volatility class : Although not required in MOBILE4.1, this parameter is required in the MOBILE4 and MOBILE5 versions. It was used in MOBILE4 as a surrogate for fuel volatility in some calculations; MOBILE5 requires it for modeling the effects of reformulated gasoline.
- Temperature : The minimum, maximum, and average daily temperatures are required because the emissions are a strong function of ambient temperature.
- Reid Vapor Pressure (RVP) : The fuel volatility (measured as RVP in pounds per square inch) also is an important parameter in emissions calculations. The RVP has a significant influence on evaporative emissions (higher fuel volatility translates into higher evaporative emissions), and it also impacts exhaust emission estimates.
- Region : The region (i.e., low or high altitude) must also be input by the user. The hydrocarbon and carbon monoxide emissions are magnified because vehicles (particularly older vehicles with mechanically based fuel delivery systems) generally run rich at high altitudes (i.e., more fuel is introduced into the combustion chamber than can be completely burned by the available oxygen).
- Calendar year : The calendar year of evaluation must be specified by the user. The fleet-average emission rate generally decreases as future years are specified because of increasingly stringent motor vehicle emission standards.
- Average speed : Speed also plays an important role in estimating vehicle emissions. The lower speeds (i.e., below 20 mph) of vehicles result in higher emissions (i.e., it takes a longer time to cover the same distance) because emissions are reported in grams/mile. At high speeds (above 48 mph in MOBILE4.1; above 55 mph in MOBILE5), emissions are also predicted to increase.
- Operating mode - As will be described in the next section, the condition (i.e., cold start, hot start, or stabilized) under which the vehicle is operating has a significant impact on vehicle exhaust emissions. For example, exhaust hydrocarbon emissions can be several times higher while the vehicle is warming up compared to those under stabilized operation.

Optional Inputs :

In addition to the above required inputs, the MOBILE models allow for a number of optional inputs that better describe the locality being modeled; these are also shown in Table 2.1 and Table 2.2.

Table 2.1: Required Inputs for the MOBILE models

Required Inputs		
Parameter	Comments	Version
Volatility Class	Used in conjunction with reformulated gasoline effects	M4, M5
Min and Max Daily Temperature	Used to estimate TCF temp, evap temps, diurnal emissions	All
"Period 1" RVP	RVP before volatility control	All
"Period 2" RVP	RVP with volatility control	All
"Period 2" Start Year	Implementation date for volatility control	All
Region	Low/High Altitude	All
Calendar Year	Range: 1960 to 2020	All
Average Speed	Single speed for all veh types or separate speed for each	All
Ambient Temperature	Utilized for TCFs, etc., if user specifies	All
Operating Mode Percentages	Percent VMT in cold start, hot start, and stabilize modes	All

- M5: MOBILE5/MOBILE5a
- M4.1: MOBILE4.1
- M4: MOBILE4

Table 2.2: Optional Inputs for the MOBILE models

Optional Inputs/Features		
Parameter	Comments	Version
Month of evaluation	Jan or Jul – choice based on winter or summer evaluation	M5
Tampering Rates	User may input locally derived tampering rates	All
Trip Length Dist (Trip Duration)	Used in estimating running loss emissions	M4.1, M5
VMT mix by veh type	User may input locally derived VMT mix	All
Mileage Accumulation	User may input locally derived mileage accumulation	All
Registration Distribution	User may input locally derived registration distribution	All
Basic Emission Rates	User may input alternate basic emission rate equations	All
Reporting HC Results	HC may be reported as THC, NMHC, VOC, TOG, NMOG	M4.1, M5
New Evaporative Test Procedures[1]	Differing phase-in for evap procedures can be modeled	M5
Disable CAAA Requirements	Cold CO, Tier I exhaust, and evap benefits can be disabled	M5
I/M Program	Transient (IM240) test included in MOBILE 5 and MOBILE 4.1	M4.1, M5
A/C-Towing-Humidity Corrections	These corrections can be included, but accuracy uncertain.	All
Anti-Tampering Program	Effects of an anti-tampering program can be included.	All
Functional Pressure/Purge	Effects of a functional evap system check can be included.	M4.1, M5
Refueling Emissions	Uncontrolled with stage II, with on-board, or zeroed.	All
Oxygenated Fuels	Ether/alcohol market share and oxygen content required.	M4.1, M5
Alternate Diesel Sales Fraction	User may input locally derived LDV Diesel registration Info.	M4.1, M5
Reformulated Gasoline	Effects of reformulated gasoline can be included.	M5
California LEV Program	LEV program can be modeled with choice of start date.	M5

[1] MOBILE5a was updated to include the correct implementation schedule for the enhanced evaporative test procedures. Thus, this option is not needed for routine analyses.

Among the more important optional inputs are the following:

- Registration distribution : Many local-level analyses make use of the registration distribution option because the age of the vehicle fleet is an important parameter in determining the fleet-average emission rate. Generally, these data are readily available from state Departments of Motor Vehicles.
- Inspection and maintenance (I/M) programs : If an area has an operating I/M program, the effects of this can, and should, be modeled. The impact can be quite significant, particularly for transient, loaded mode programs which can be modeled by MOBILE5.
- Anti-tampering programs : I/M programs often include a visual check of emission control system components to assure the vehicle owner has not disabled or otherwise tampered with the system. The MOBILE models allow for the impact of these programs to be modeled.
- Refueling emissions : Although many air pollution control districts consider refueling emissions (i.e., emissions that occur when a fuel tank is filled) to be stationary source emissions, the MOBILE models are capable of modeling this process. Oxygenated and reformulated fuels - fuels containing oxygenates (e.g., ethanol) result in significant reductions in exhaust hydrocarbon and carbon monoxide levels. Additionally, the reformulated gasoline requirements contained in the 1990 CAAA result in decreased hydrocarbon emissions. MOBILE4.1 is capable of modeling the impact of oxygenated fuels on carbon monoxide emissions, while MOBILE5 has the capability of modeling the effects of oxygenated fuels and reformulated gasoline on hydrocarbon, carbon monoxide, and oxides of nitrogen emissions.

2.3 MOBILE Model Output

The MOBILE output consists of exhaust hydrocarbon (HC), carbon monoxide (CO), and oxides of nitrogen (NOx) emission rates (in grams/mile [g/mi]) for eight separate vehicle categories :

- LDGV light-duty gasoline vehicles (i.e., passenger cars),
- LDGTL light-duty gasoline trucks (under 6000 lbs. gross vehicle weight),

- LDGT2 - light-duty gasoline trucks (6000 to 8500 lbs. gross vehicle weight),
- HDGV - heavy-duty gasoline vehicles (over 8500 lbs. gross vehicle weight),
- LDDV - light-duty Diesel vehicles (i.e., passenger cars),
- LDDT - light-duty Diesel trucks (under 8500 lbs. gross vehicle weight),
- HDDV - heavy-duty Diesel vehicles (over 8500 lbs. gross vehicle weight), and
- MC - motorcycles.

In addition, evaporative HC emissions are reported as g/mi or grams/event (e.g., grams per hot soak).

2.4 Motor Vehicle Emission Modes

Motor vehicle emissions consist of a large number of chemical species that primarily result from combustion within the engine and from fuel evaporation at various locations throughout the fuel delivery and storage system. Three particular emission components are modeled by the MOBILE models: hydrocarbons (HC), carbon monoxide (CO), and oxides of nitrogen (NOx). These are the emission components that result in the two major non-attainment pollutants related to mobile sources: ozone and carbon monoxide.

The quantification of emissions involves determining emission rates for two fundamentally different types of emission-producing processes: emittance from the vehicle's exhaust system, and evaporation from the fuel storage and delivery system. Emissions from each of these basic types of emission-producing processes, exhaust and evaporative, can be further categorized, as discussed below.

2.4.1 Exhaust Emissions

Cold Start - Under cold start conditions, the vehicle engine has been turned off for some time and the catalytic converter (if the vehicle is so equipped) is cold. HC and CO emissions are higher when a cold engine is first started than after the vehicle is warmed up. This is because catalytic emission control systems do not provide full control until they reach operating temperature (i.e., light-off), and a richer fuel air mixture must be provided to the cylinders under cold operating conditions to achieve satisfactory engine performance (e.g., startability and driveability). EPA considers a cold start for a catalyst-equipped vehicle to occur after the engine has been turned off for one hour. For non-catalyst vehicles, a four-hour engine-off period distinguishes a cold start.

Rich mixtures are necessary to achieve smooth combustion during warm-up because gasoline does not fully vaporize and mix with the air in a cold engine. Extra fuel is added to ensure that an adequate amount of fuel is vaporized to achieve a combustible mixture. Complete vaporization eventually occurs in the engine cylinder as a result of the high temperatures created by combustion. However, the excess fuel that was needed to ensure adequate vaporization to start the combustion process cannot be completely burned due to a lack of sufficient oxygen in the cylinder. The result is that partially burned fuel and unburned fuel are emitted in relatively high concentrations from a cold engine. Elevated emissions of these pollutants in this cold transient phase occur from the time a cold engine starts until it is fully warm. While engine-out NOx emissions tend to be low during rich operation of a cold engine, the lack of catalyst activity to control this pollutant results in elevated cold start NOx emissions as well.

Hot Start - Under hot start conditions, the vehicle engine has been turned off for such a short time that the catalyst has not had time to cool to ambient temperature. Thus, the warm-up period is shorter (if present at all) than that required under cold start conditions. For that reason, HC and CO hot start emissions are significantly lower than under cold start operation. Under the standard test procedure used by EPA, a hot start test begins exactly 10 minutes after a fully warmed up engine has been shut off. After only 10 minutes, no mixture enrichment is required to achieve a reliable re-start and the catalyst is usually still above its light-off temperature.

Hot Stabilized - After warm-up has occurred, and the engine and emission control systems have reached full operating temperatures, the vehicle is considered to be in the hot stabilized mode. Generally, emissions are relatively low (compared to cold start emission rates) under hot stabilized conditions. However, emissions are also highly dependent on vehicle speed and engine load. It has been revealed recently that varying off-cycle load conditions (i.e., under conditions not tested on the standard automotive driving cycle used for vehicle certification purposes) can have a dramatic impact on emissions.

Idle Emissions - Although not generally considered for inventory purposes, idle emissions may need to be considered for certain transportation-related analyses. The MOBILE models report idle emissions in terms of grams/hour, and emissions are a function of operating mode (i.e., stabilized or cold start) and temperature. Because many of the changes incorporated into the MOBILE5 model (e.g., incorporation of Tier I emission standards, reformulated gasoline, low emission vehicles) resulted in unreliable estimates of idle emissions, the idle subroutines have been temporarily disabled in MOBILE5. When MOBILE5 was released, EPA recommended continued use of MOBILE4.1 to estimate idle emission rates. However, EPA has recently developed a methodology to convert MOBILE5a gram/mile running exhaust emission rates to gram/hour idle rates.

2.4.2 Evaporative Emissions

Evaporative emissions consist entirely of hydrocarbon emissions. These emissions can be categorized into the six groups discussed below.

Hot Soak - When a hot engine is turned off, fuel exposed to the engine (e.g., in carburetor float bowls or in fuel injectors) may evaporate and escape to the atmosphere. These so-called "hot soak" emissions are modeled by MOBILE as grams/event, which are then converted within the model to a g/mi basis.

Diurnal - Diurnal temperature fluctuations occurring over a 24-hour period cause *breathing* to occur at the gasoline tank vent. To prevent the escape of fuel vapor, the vent is routed to a charcoal canister where the vapor can be adsorbed and later purged into the running engine. These emissions are calculated by the MOBILE models in terms of grams/event, and, as with hot soak emissions, are then converted to a g/mi basis.

Running Losses - Running loss emissions are those resulting from vapor generated in gasoline fuel tanks during engine operation. Running losses are especially a problem on vehicles that have exhaust systems in close proximity to the gasoline tank. Running loss emissions occur when the vapors emitted from the tank vent exceed the rate at which they are being purged from the canister by the engine. This HC emission category had long been assumed to be insignificant, but research over the past several years has shown this assumption to be incorrect, and running losses have been included in EPA's emission factors models since the MOBILE4 version (published in 1989). These emissions are calculated by the MOBILE models in terms of g/mi.

Resting Losses - Resting losses have only recently been included in the MOBILE models, with the MOBILE4.1 version (published in 1991) including resting losses for the first time. EPA considers resting losses to be those emissions resulting from vapors, permeating parts of the evaporative emission control system, migrating out of the carbon canister, or evaporating liquid fuel leaks. EPA also states that a portion of what are now considered resting losses was previously included in the hot soak and diurnal categories. Resting losses are dependent upon temperature and the type of carbon canister that is used in the evaporative emission control system (i.e., open-bottom versus closed-bottom). These emissions are calculated as grams/hour and are then converted to g/mi.

Refueling Losses - There are two components of refueling emissions : vapor space displacement and spillage. As a fuel tank is being refueled, the incoming liquid fuel displaces gasoline vapor that has established a pseudo-equilibrium with the fuel in the tank, effectively pushing the vapor out of the tank. Spillage simply refers to a small amount of fuel that is assumed to drip on the ground and subsequently evaporate into the ambient air. Refueling emissions are calculated in terms of grams/gallon of dispensed fuel and are converted to a g/mi basis.

Crankcase Emissions - Although not a true evaporative source, crankcase emissions are generally considered in the evaporative emissions category. They are the result of defective positive crankcase ventilation (PCV) systems that allow blow-by from the combustion process (which is normally routed to the vehicle's intake manifold) to escape to the atmosphere. These emissions are modeled as g/mi.

3. REVIEW OF ACTIVITY-BASED ANALYSIS AND A MATHEMATICAL PROGRAMMING APPROACH

3.1 Review of the Trip-Based, Four-Step Model of Travel Demand

The travel demand model systems developed in the 50's and the 60's involved: aggregation of data to make the database tractable and to reduce computational requirements; simple models that do not require lengthy computation for the estimation of their parameters and preparation of forecasts; and models that include only the most salient variables. The cost and speed of computation and the software available for statistical analysis and database management are some of the factors to be considered during the early stages of development of the four-step modeling process. The simplifying assumptions adopted in the four-step procedure facilitated quantitative analysis of urban passenger travel demand, using home-interview survey results, land use inventory data, and computational capabilities that were available decades ago.

The development of the four-step procedure was motivated by the planning needs of the 50's and 60's when the expansion of transportation infrastructure was in effect. The period of the suburban boom had four main foundations: new road, zoning of land uses, government-guaranteed mortgages and a baby boom. It was required that the road networks be effectively connected to the central city as the place of employment and the suburbs as the place of residence with the rapid suburbanization. Commute trips to and from work were the primary trips considered for developing plans for road networks. Thus the trip-based, four-step model system is a streamlined procedure that just served the planning needs of that time given the planning contexts in which the model was developed.

The procedure, however, contains limitations, some of which were discussed extensively when disaggregate choice models were proposed in the 70's. There were significant changes in the demographic and socio-economic characteristics of households (single parents, small households and more working women), urban forms (commercial developments in suburbs), industrial composition, distribution systems (shopping malls) and consequently in travel patterns. The emphasis of planning has shifted from infrastructure development to transportation systems management to travel demand management. The trip-based, four-step planning process does not serve well in the current scenario.

Drawbacks of the trip-based, four-step planning process in the current transportation planning contexts include:

<u>Lack of Behavioral Emphasis:</u>

The model's attempt to represent demand by the four components linked together presents certain problems. The four-step procedure does not represent the decision mechanisms underlying travel behavior. The case of a change in the trip attraction due to the implementation of parking pricing in a downtown area would not be accounted for by the four-step procedure because trip attraction is determined in the trip generation phase which is not sensitive to the parking cost. Similarly, the impact of new highway segments on trip distribution would be under-estimated while mode shift could be overestimated. The issues of induced trips and suppressed demand are difficult to address in the four-step procedure. People do not decide on how many trips to make before deciding what to do, where to go, and how to get there.

<u>Lack of Time Dimension:</u>

That the four-step procedure does not incorporate the time-of-day dimension is important because the main concern of transportation planning has been congestion, which occurs with the concentration of demand in the same geographical area in the same period. Thus the absence of the time dimension requires the use of empirical procedures to determine hourly demand volumes.

<u>Trip Independence:</u>

The four-step procedure treats each trip as an independent entity for analysis. This assumption leads to a number of serious limitations which arise from the fact that trips made by an individual are linked to each other and the decisions underlying the trips are all inter-related. The result of this procedure may violate the modal continuity condition; mode choice for a trip with non-home origin is conditioned on the mode selected for the first home-based trip. Consider a home-based trip chain with a series of linked trips. The result also ignores the fact that people plan ahead and choose a mode while considering the entire trip chain, not each individual trip separately. This problem is further added by the fact that the modal split phase of the four-step procedure tends to be most sensitive to changes in the network level of service. This is the step where the disaggregate choice models are often incorporated. Thus this limitation may lead to an over-prediction of mode shift as the travel mode maybe the last thing individuals change in response to the travel demand management measures.

A change in the travel environment may not be captured fully by the four-step modeling procedure. The procedure is also insensitive to the effects of traffic congestion. Thus the process of developing efficient tools for the travel demand management is not possible within the framework of the four-step procedure.

3.2 Activity-Based Travel Demand Forecasting

There is general consensus that the demand for travel is derived from a need or desire to participate in activities that are spatially distributed over the geographical landscape. As described in the previous section, the conventional travel demand approach examines each trip in isolation and at best provide only limited information regarding the particular trip (since they generally ignore both the history that precedes the trip as well as the future that follows); the approach provides virtually no information on the impact of decisions regarding the particular trip on other travel decisions (both prior and subsequent). This deficiency has been the primary concern among a group of transportation researchers to develop and operationalize "activity-based" travel demand analyses.

Jones et al. (1990) provide a comprehensive definition of activity analysis as: *a framework in which travel is analyzed as daily or multi-day patterns of behavior, related to and derived from differences in life styles and activity participation among the population.* The emerging features of activity analysis are identified in Jones et al. (1990) as:

- Explicit treatment of travel as a derived demand, derived from the desire to participate in other non-travel activities.

- Focus on sequences or patterns of behavior rather than an analysis of discrete trips.
- Analysis of households as the decision-making units.
- Examination of detailed timing and duration of activities and travel.
- Incorporation of spatial, temporal and inter-personal constraints.
- Recognition of the interdependencies among events which occur at different times, involve different people and occur in different places.
- Use of household and person classification schemes based on differences in activity needs, commitments and constraints.

The motivation for the development of activity-based approaches has derived from discontentment with the established procedures, on both theoretical and operational grounds. The forecast of some trip-based models has proved to be inaccurate due to inappropriate representation of travel behavior. Kitamura (1996) has given an overview of the roles and advantages of activity-based approach in travel demand forecasting and discussed requirements for forecasting models in current transportation planning contexts.

The activity-based approach to travel demand analysis is founded on the concept that travel is a derived demand with the demand arising due to the desire to participate in an activity at a location that is separated from one's current location. The conventional travel demand models do not conform to this concept and they segment trips by trip purpose and model the trips for different purposes separately.

The activity-based approach to travel demand analysis and modeling traces its roots to the seminal work on urban travel demand analysis undertaken in the mid to late 1970's at the Transport Studies Unit (TSU) at Oxford University under the leadership of Ian Heggie, working under a grant from the Social Sciences Research Council (Jones et al. (1983)). The activity-based approach was founded on the work undertaken by the sociologist and planner, F. Stuart Chapin Jr. at the University of North Carolina at Chapel Hill (Chapin, (1974)), and by the geographer Torsten Hagerstrand at Lund University in Sweden (Hagerstrand(1970)). Kurani and Lee-Gosselin(1996) note that Chapin's work contributed by identifying patterns of behavior across time and space, while Hagerstrand's work delineated systems of constraints on activity participation in time and space. It is important to note the clear influence of fields other than economics in the development of activity-based approach to travel demand analysis.

The development of activity-based approach to travel demand analysis is characterized by a desire to understand the phenomenon of urban travel, not merely to develop models that appear to produce acceptable forecasts. The early work on the activity-based approach to travel demand analysis used travel surveys on small samples in order to gain a good understanding of urban travel behavior. The HATS methodology (Jones et al. (1979)) which is a gaming solution was used very successfully at the TSU, Oxford, in the study of household level travel decisions and the constraints within which those decisions are made.

Heggie (1978) presented in his paper that urban travel behavior is a complex phenomenon that could not be easily represented in the discrete choice models (especially logit models) that were gaining popularity at the same time as the foundations of activity-based approach were being laid. Heggie argued that the behavior being modeled - the mode choice for the work trip, as part of the discrete choice modeling framework, was not the correct behavioral phenomenon. In other words, a good tool was being used to address the wrong problem. The discrete choice models that were being developed at that time were designed to take into account neither the dependencies among trips and between people, nor the constraints on activity participation and travel behavior.

The activity-based approach to travel demand forecasting can be considered the only real scientific resolution or paradigm shift, in Kuhnian (1970) terms, in the history of the development of travel demand forecasting models. The shift from aggregate to disaggregate models was a shift in statistical technique rather than a shift in the paradigm and thus can be considered as an incremental change in the approach to travel demand modeling.

The activity-based approach to travel demand analysis includes many theoretical concepts and methodologies. The themes of the approach can be clearly understood from the research done on this topic. Pas (1985) described these themes as:

- analysis of demand for activity participation (and the analysis of travel as a derived demand)
- the scheduling of activities in time and space
- the constraints (interpersonal and spatio-temporal) on activity and travel choice
- the interactions between activity and travel choices over the day, as well as interactions between individuals
- the structure of the household and the roles played by the household members.

A focus of the present activity-based research is on time use. A recent review by Pas (1996) gives an introduction to time-use studies and their relationship to travel demand modeling. The activity-based approach provides a coherent structure for travel behavior analysis and demand forecasting. The understanding of the scheduling of activities over a span of time gives a better foundation for the understanding of travel demand. The trips made are not analyzed independently as the activities are linked to each other and thus the trips made to pursue these activities are also inter-related.

The activity-based modeling approach can eliminate most of the limitations of the four-step procedure. The activity-based models are thus more applicable than the trip-based four-step procedure. There are several factors that have made activity-based models amenable tools for travel demand forecasting (Kitamura et al. (1995)). They include accumulation of activity-based research results, advances in survey methods and statistical estimation methods, and advances in computational capabilities and other available software. These models of travel behavior can be developed based on the principles of activity-based approach. The activity-based microsimulation of travel behavior has become a practical tool for transportation planning and policy analysis.

The advantages of the activity-based approach are summarized in Kitamura et al. (1995). They are:

- daily behavior: treats a daily activity-pattern as a whole, thus avoiding the shortcomings of the conventional trip-based methods.

- realism: incorporates various constraints governing trip making, facilitating realistic prediction and scenario analyses;
- induced demand: by representing activity engagement behavior; the activity-based approach can rigorously address the issue of induced or suppressed demand.

The activity-based microsimulation of activity engagement and travel offer the following advantages:

- time of day: predicts travel behavior along a continuous time axis.
- TDM evaluation: is capable of realistically assessing the impact of TDM measures on the entire daily demand.
- versatility : can address various policy scenarios.
- flexibility : can be modified for specific study objectives.
- accuracy control : using synthetic household samples, can produce results with desired levels of spatial and temporal resolutions.
- comprehensive evaluation tool : activity-based approach simulates the entire daily activities and travel. The policy implementation can be done on the entire daily activity leading to better benefit measures.

The activity-based approach requires increased levels of data requirements and there are analytical complexities involved in the model. The advantages offered by this approach are the ability of the approach to overcome the limitations of the conventional trip-based methods and to address policy sensitive measures.

3.3 Applicability of the Activity-Based Approach in Modeling Emissions

There is a need for transportation planning analysis to incorporate emissions analysis. This has changed the requirements for travel demand forecasting models. Weiner (1993) lists as emissions modeling requirements the following:

- VMT by hour of day by grid square

- Average speed by hour by grid location
- Vehicle mix by hour of the day by grid square
- Proportion of cold starts by the hour of the day
- Seasonal variation in VMT, vehicle mix, etc.
- Annual growth in VMT

Thus, appropriate methodologies should address the following issues:

- trip starting time and ending time can be determined in a logically coherent manner.
- elapsed time between successive trips by the same vehicle can be estimated such that the involvement of a cold start in the latter trip can be determined.
- vehicle type is explicitly treated.
- day-to-day variations and seasonal variations in travel demand are appropriately captured.

The first two issues can be addressed by including the time-of-day dimension into the model framework. The models of household vehicle type choice and utilization developed in the past have not been adopted by the MPO's. These models forecast the total annual VMT for each household vehicle, but do not match vehicles and trips. They do not determine the assignment of the vehicles in a household fleet to the trips made by the respective household members. Thus the results do not support the emissions analysis with the spatial dimension. The vehicle allocation to the trips can be modeled so that the above problem is addressed.

There is an increasing recognition that predicting travel demand for a typical weekday does not adequately support decision making in transportation planning. The distribution of travel demand over a year cannot be obtained using the typical weekday approach if we use average travel demand. As the traffic congestion is not limited to the traditional peak periods of commute traffic, the weekend days should not be ignored in the process. The traditional trip-based demand approach is also not capable of supporting the prediction of air quality standard violations.

Activity-based models meet many of these requirements imposed on travel demand models by the current emissions planning needs. In addition to these requirements, there are several desirable features of activity-based forecasting models. The requirements for short-term forecasting can be given as:

- mechanisms of activity engagement
- internal consistency
- comprehensive activity itinerary
- activity scheduling
- inter-personal linkages
- temporal variations
- trip attributes

3.4 Review of Existing Operational Activity-Based Models

A review of recent work in activity-based travel modeling shows that a wide variety of methodologies are being advanced and employed in modeling a variety of aspects of activity-travel behavior, including participation in in-home and out-of-home activities, and dependencies among household members and daily activity-travel patterns. Existing operational activity-based models can be categorized as follows:

- Computational Process Models
- Structural Equations Models
- Microsimulation-based Models
- Mathematical Programming Models

The following sections provide a review of models falling into the first three of these model types; because it is used in this analysis, a more detailed description of the mathematical programming approach is provided in a separate section.

3.4.1 Computational Process Models

The development and application of computational process models (CPM's) has given a new direction to activity-based travel modeling. These models attempt to represent explicitly the process used by the individual to make a decision. Computational process models allow for a variety of decision-making strategies that are different depending on the circumstances. CARLA and STARCHILD are two early examples of such CPM-type models. CPM's have been applied primarily to the scheduling and rescheduling problems.

<u>CARLA:</u>

Combinatorial Algorithm for Rescheduling the List of Activities (CARLA) (Jones et al. (1983)) enumerates the feasible alternative schedules. One way of conceptualizing scheduling is to assume that the decision-maker first generates all possible activity schedules for a given time horizon and then chooses one of these to execute on the basis of their evaluation. This assumption is unrealistic if the number of possible alternatives is more than a few. The spatio-temporal constraints may reduce the number of constraints to a few.

Fundamental constraints of this sort are various capability limits related to the activities with respect to space and time and other joint activities. CARLA is a combinatorial algorithm that was developed as a means of identifying the feasible alternative schedules. It is comparable to Lenntrop's PESASP model (1976). It identifies the feasible alternative schedules through the implementation of the branch-and-bound algorithm, which reorganizes the given activity program. It is not known if CARLA can identify the same constraints as people do and it does that in the same way as people do. These constraints are not accurately perceived and few constraints are absolute. The availability of the complete set of feasible schedules allows the use of alternative criteria to establish the best schedule. It is assumed that the time horizon is a day or shorter, whereas this may differ for different activities or activity types.

<u>STARCHILD:</u>

Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions (STARCHILD), a comprehensive activity-based modeling system, has been developed by

Recker, McNally and Root (1986). This modeling system offers one possible direction for the implementation of such approaches in transformation planning and analysis.

The STARCHILD model utilizes a simulation approach comprised of six stages:

- Specification of individual activity programs from an examination of household activity programs and constraints, and the interactions between household members given the existing supply environment.
- Generation of the set of feasible, individual travel/activity patterns through a constrained, combinatorial scheduling algorithm.
- Identification of distinct members of the set of feasible travel/activity patterns by means of pattern recognition techniques.
- Identification of a non-inferior (perceived) pattern set for individual choice utilizing a multi-objective programming approach.
- Specification of a representative activity pattern set, forming the choice set for each household member, utilizing pattern recognition and classification theory.
- Formulation of a pattern choice model which specifies individual travel/activity pattern choice probabilities.

The daily scheduling process in this framework is divided into two stages. In the pre-travel stage, the individuals schedule activities that satisfy their needs and desires. The evolution of the schedule is continuously monitored during the travel stage. The changes made in the schedule are due to unforeseen consequences of the schedule, new demands or unexpected incidents. It is assumed that the individuals attempt to select an optimal sequence of activities, in terms of their duration, locations and modes, in order to maximize the total utility of the activities, while maximizing the flexibility of the schedule, minimizing the time spent away from home and minimizing the coordination effort involved in the scheduling. The individuals are assumed to first filter out a subset of all feasible activity schedules in the conceptual framework, then choose the alternative schedule in this subset with the highest utility. The assumption is also made that the utilities of the activity schedules are computed as the sum of utilities assigned to the different time components making them up. In the calibration of STARCHILD, in-home activities presented a problem because no information was available from the travel diary data obtained. Thus such activities are considered as discretionary. Their utilities are assumed to depend on duration at home and the number of other household members being at home. STARCHILD provides a means of generating alternative activity schedules and an estimated model for the choice between these alternatives. A utility maximization framework is employed in the model. An attempt has been made to identify and retain alternatives that dominate others. The reasoning is that people may use a non-compensatory decision rule to screen out alternatives. The process of reducing the number of alternatives in STARCHILD still seems to require that all feasible alternatives are generated. It does not in general guarantee that a realistically small number of alternatives remain in the final choice set.

3.4.2 Structural Equations Models

Structural equations model has been applied in a number of areas. This methodology has been used to capture relationships among macroscopic indicators of activity and travel. Golob and his collaborators pioneered the use of this methodology in travel demand modeling. The recent applications of structural equation models to develop activity-based travel demand models have been undertaken by Fujii et al. (1996), Golob (1996), Golob et al. (1996) and Golob et al. (1995).

The current applications of structural equation models to travel demand make use of the methodology to capture some of the complex relationships considered important in the activity-based approach to travel demand. Fujii et al. (1996) use the methodology of structural equation models to model commuters' time use and travel after work hours using data collected in the Osaka-Kobe metropolitan area. This model showed that with 10-minute savings for the commute trip, slightly more than 7 minutes will be used for in-home activities, thus bringing into focus the idea of a constant travel time budget.

Golob et al. (1996) presented the most elaborate model in this group of studies. The endogenous variables in the model system are work/school activity duration, work/school journey time, maintenance activity duration, maintenance journey, discretionary activity duration and discretionary journey time. Maintenance activities include weekly grocery shopping, pick up and drop off passengers, personal business and other activities. Discretionary activities include other types of shopping, meals out-of-home and other social activities. Model coefficients are estimated by segment while constraining selected coefficients to be common among subsets (or the entire set) of the segments. This is equivalent to incorporating interaction terms that consist of combinations of an exogenous variable and one of the segmentation variables. These structural equation models have looked into the relationship among activity engagement (time allocation) and travel.

Golob and McNally (1995) developed a joint model of the out-of-home activity participation and travel of opposite sex couples who are heads of households. The research aimed at identifying the interactions between activity participation and travel and between the two individuals being modeled. This research, using the data collected in the Portland area during the Oregon-Southwest Washington Household Activity Diary Survey, provides quantitative estimates of the effects of out-of-home activity participation on travel behavior and the interdependencies between the male and female household heads in their activity participation and travel.

3.4.3 Microsimulation-Based Models

The microsimulation-based models are dynamic systems where the behavior is modeled over time. The system's behavior is also complex. The complexity can be due to:

- complex decision rules for the individual actors within the system
- many different types of actors interacting in complex ways
- system processes which are path dependent
- the system is am open one in which exogenous forces operate on the system over time, thus changing the internal behavior of the system
- uncertainties involved in the system

Thus, it is a very complex case where there is difficulty in dealing with estimation of a future state given the inherently complex nature of the system's behavioral process. The future state of the system can be estimated by explicitly tracing the evolutionary path of the system over time given the existing conditions. These numerical models which are modeled over time are called simulation models. The conventional four-step travel demand models are not simulation models.

They are static equilibrium models that predict a path-independent future year-end state without concern for either the current state or the path traveled by the system from the current to the future state. The simulation model is formulated at the disaggregate level or micro-level of individual decision making units such as individual persons, households and vehicles. The strength of the disaggregate modeling approach is in being able to fix decision makers within explicit choice contexts with respect to:

- the salient characteristics of the individuals involved
- the salient features of the choice context (the options set and the constraint set)
- any context-specific rules of behavior which may apply.

This inherent strength of the microsimulation model is compromised if one cannot provide detailed inputs to the model. The micro-level outputs required from the activity / travel behavior models provide the necessary importance for these models. Despite the large computational requirements of a microsimulation model, it might turn out that microsimulation is a computationally efficient method for dealing with large-scale forecasting problems.

PCATS:

PCATS simulates the individual's activity engagement and travel within Hagerstrand's prisms. It is assumed that the simulation period can be divided into periods of two types when defining prisms for each individual, namely, open periods and blocked periods. Open periods are ones in which the individual has the option of traveling and engaging in activities. Blocked periods are ones in which the individual has committed to engage in certain activities at certain locations. Thus the activities participated within a open period are called flexible activities and those participated in a block period are called fixed activities. The time-space prism in which the individual's activity and travel are contained is defined by the ending time and location of a blocked period and the beginning time and location of the subsequent block period given the speed of travel. The individual is assumed to make activity engagement and travel decisions at the beginning of each open period and also when an activity is completed within an open period. The distribution of duration of flexible activities is determined by activity type by assuming that the parameters of the distribution are a function of personal attributes and other explanatory variables. The explanatory variables used are person and household attributes, past activity engagement, time of day, time availability, and location type indicator. The duration models are then estimated by the maximum likelihood method. The activity type choice model developed has a two level hierarchy and is formulated as a nested-logit model. The destination and mode choice model is also formulated as a nested-logit model. The first level includes the choice of destination and the second level includes the conditional choice of travel mode, given the destination. The duration of the activity is then determined given its type, location and the mode used to reach the activity location. The maximum possible activity duration is first determined based on the size of the prism. The destination-mode choice model is not differentiated by trip purpose. The model system does not have the capability to endogenously generate fixed activities. There are many areas requiring further research.

AMOS:

Activity-Mobility Simulator (AMOS) is a change model that predicts changes in travel behavior that will follow a change in the travel environment. Its development has been motivated by the recognition that the traditional trip-based, four-step procedure is incapable of incorporating TDM and policy sensitive measures.

The baseline activity-travel pattern analyzer inspects daily travel diary data and determines for completeness of the data. It also checks whether the sample trip maker or the travel pattern is a category intended for analysis. The response option generator requires the following input: household and person attributes, network and land use characteristics, TDM attributes, and the indicators of the baseline activity-travel pattern characteristics prepared by the analyzer. The generator simulates the sample individual response to the TDM measure. This is neural-network based and the probability of each possible response option is computed, given the input variables.

The activity-travel pattern modifier examines the baseline pattern and performs activity re-sequencing, activity re-linking, mode and destination assignment and trip timing adjustment wherever necessary. This is required when the baseline pattern is infeasible. A rule-base is used to examine the feasibility of the modified activity-travel pattern. The evaluation routine assigns a utility measure to the modified activity-travel pattern using time-use utility functions. The attractiveness of the modified pattern is determined by the utility produced by engaging in in-home and out-of-home activities included in the pattern.

The acceptance routine evaluates the set of time-utilities associated with the activity-travel patterns generated and determines whether the search for a better pattern should continue or one of the patterns generated should be adopted. The routine is based on the assumption that the individual forms a subjective distribution of utilities associated with alternative patterns; assesses the likelihood of obtaining a better activity-travel pattern and terminates the search when the cost of search exceeds the expected gain of searching further.

The statistics accumulator produces two files. One of the files contains the information about the alternative activity-travel patterns generated for a sample individual in the simulation. The other file contains the attributes of the pattern adopted by each sample individual.

An AMOS prototype has been developed and implemented in Washington D.C. metropolitan area with the intent of predicting traveler response to selected TDM measures. The TDM measures considered for evaluation are parking surcharge, parking pricing with employer-paid voucher, pedestrian / bicycle facility improvements, congestion pricing and the combinations of these measures. The results are given in RDC (1995). AMOS is capable of producing travel forecasts by simulating daily travel patterns. It has also demonstrated that the TDM measures considered have certain impacts on travel demand. This has also shown that a microsimulation model of daily travel behavior, which adheres to the principles of activity-based approach, is not only feasible but is also capable of providing a practical tool for policy analysis.

TRANSIMS:

The TRansportation ANalysis and SIMulation System (TRANSIMS) is a set of integrated analytical and simulation models and supporting data bases which are being developed by the Los Alamos National Laboratory (LANL). The project to develop TRANSIMS is one part of the multi-track Travel Model Improvement Program sponsored by the U.S. Department of Transportation and the Environmental Protection Agency. The TRANSIMS project has been identified as a major effort to develop new, integrated transportation and air quality forecasting procedures necessary to satisfy ISTEA and the Clean Air Act Amendment.

TRANSIMS software framework is a decision-making aid that integrates transportation planning and traffic engineering. It provides an environment that allows detailed simulations to support evaluation of alternative transport solutions. It is a simulation of the travel of individuals on a regional scale. A connection of travel activity to air quality and other global consequences of the system that supports that activity are established. The requirements of the Clean Air Act (CAA) and its amendments (CAAA) and the Intermodal Surface Transportation Efficiency Act (ISTEA) as well as emerging technologies available to transportation systems give the motivation for the improvements or changes to existing planning and forecasting methods. The TMIP review panel recommends that new methods relate travel behavior to air quality and provide the ability to study the impact of alternative transport availability on air quality. This approach has been taken by TRANSIMS. It treats the entire transport system of an urban area as a large, multiple time-scale, dynamic system that provides for and produces individual traveler activity.

The time scales used are a long time scale associated with land use and demographic distribution as they pertain to characterization of travelers, and intermediate time scale associated with intermodal trip chain route planning and a very short time scale associated with driving and other modal execution of trip plans in the transport system. A traveler activity is simulated at each time scale. The TRANSIMS approach resolves to individual travelers and passes traveler-referenced information between simulations across all the scales. The primary differences from the four-step process are derived from the disaggregate representation of travelers and the computation of individual behavior and observation of the aggregate behavior in the system. The TRANSIMS architectural framework is composed of several modules that interact with each other and with a variety of databases. The TRANSIMS intermodal route planner produces its trip chains based on traveler-by-traveler transportation demand and knowledge of the road network that includes average vehicle flow for all roads in the network. The environmental simulation predicts the air pollution and fuel use produces by the transportation system and the environmental conditions that affect trip planning and driving conditions. This model is intended to support the requirements imposed by legislation and by necessity to include consideration of environmental and other effects of these decisions, policies, and designs.

The TRANSIMS procedures deal with individual travelers and freight shipments and progresses through several steps to estimate travel. TRANSIMS forecasts travel for individual households, residents and vehicles rather than for zonal aggregations of households. TRANSIMS also forecasts the movement of individual loads of freight. The TRANSIMS process forecasts information related to trip generation and trip distribution in an "activity planner" and for mode and route assignment in a "trip planner." The trip planner is then iterated to modify trip destinations and/or mode choice in response to congestion on chosen modes or routes. In this way TRANSIMS performs the functions of the traditional four-step travel forecasting process, but it does so in a different manner and exceeds the capabilities of the existing process.

The forecast trips are then loaded on the transportation network with a microsimulation procedure to determine the performance of individual vehicles and the transportation system, Motor vehicle emissions are then estimated using traffic information produced by TRANSIMS. A major advantage of TRANSIMS for air quality analysis is the amount of detail it provides regarding motor vehicle operation. Vehicle emissions are calculated for each vehicle, for its operating state, at the point where it is located, at every second it is operating and for a limited time when the vehicle is parked following a trip. The emissions are then used with other models in the air quality analysis to estimate air pollution.

Microsimulation at the level of detail performed by TRANSIMS is currently possible only with very fast, high capacity computers. It is expected, however, that by the time TRANSIMS has been completed, technical capabilities will have advanced sufficiently for comparable computing capacity to be more readily available.

3.5 The HAPP Mathematical Programming Model

Both Kitamura (1988) and Stopher (1993) point to the STARCHILD MODEL (Recker et al., 1986a, 1986b) as the only known operationalized model that predicts a set of activity patterns from household decision-making information. Although based loosely on mathematical programming principles, the STARCHILD model is severely limited in that it:

- provides no mechanism for household interaction, modeling the activity/travel patterns of each household member separately,
- relies on a heuristic solution procedure based on exhaustive enumeration and evaluation of feasible solutions,
- discretizes the temporal dimension and relies on pattern recognition algorithms to distinguish simple temporal displacements of similar solutions, and
- has no provision for addressing either activity or vehicle allocation decisions or for consideration of complex modal choice decisions, such as carpooling.

The mathematical programming approach offered by Recker (1995) removes these restrictions by developing a theoretical framework to operationalize activity-based travel demand methodologies. Specifically, the household activity pattern problem (HAPP) is posed as a variant of the pick up and delivery problem with time windows (PDPTW). In the most general case considered, the model addresses the optimization (relative to the household's utility function) of the interrelated paths through the time/space continuum of a series of household members with a prescribed activity agenda and a stable of vehicles and ridesharing options available.

3.6 Model Formulation

The formulation of the model that is presented here follows closely that of Recker (1995). In the development of the model that follows, a deliberate attempt has been made to maintain, to the extent possible, both the notation and structure of the well-known PDPTW. In order to take advantage of previous work involving the PDPTW, the formulation of the general HAPP involving ridesharing options is developed from the base case in which the travel mode is restricted to solo driving.

Solo Driving Case:

Following Solomon and Desrosiers (1988) the following notation is adopted:

$A = \{1, 2, \ldots, i, \ldots, n\}$	the set of out-of-home activities scheduled to be completed by travelers in the household.
$\eta = \{1, 2, K, \lvert\eta\rvert\}$	the set of household members.
$V = \{1, 2, \ldots, \upsilon, \ldots, \lvert V\rvert\}$	the set of vehicles used by travelers in the household to complete their scheduled activities.
$P^{+} = \{1, 2, \ldots, i \ldots, n\}$	the set designating location at which each activity is performed.
$P^{-} = \{n+1, n+2, \ldots, n+i, \ldots, 2n\}$	the set designating the ultimate destination of the "return to home" trip for each activity. (It is noted that the physical location of each element of P^{-} is "home".)
$\Omega_{V}^{\upsilon} \in A$	the subset of activities that cannot be performed by vehicle υ.
Ω_{H}^{α}	the set of activities that cannot be performed by household member α.
$[a_i, b_i]$	the time window of available start times for activity i. (Note: b_i must precede the closing of the availability of activity i by an amount equal to or greater than the duration of the activity.)
$[a_{n+i}, b_{n+i}]$	the time windows for the "return home" arrival from activity i.
$[a_0, b_0]$	the departure window for the beginning of the travel day.
$\bar{a}_0^{\alpha}$	the earliest possible departure time for household member α.
$\bar{b}_{2n+1}^{\alpha}$	the latest return home time for household member α.

$[a_{2n+i}, b_{2n+i}]$	the arrival window by which time all members of the household must complete their travel.
s_i	the duration of activity i.
t_{uw}	the travel time from the location of activity u to the location of activity w.
c^{υ}_{uw}	travel cost from location of activity u to the location of activity w by vehicle υ.
B_c	the household travel cost budget.
B^{υ}_t	the travel time budget for the household member using vehicle υ.
$P = P^+ \cup P^-$	the set of nodes comprising completion of the household's scheduled activities.
$N = \{0, P, 2n+1\}$	the set of all nodes, including those associated with the initial departure and final return to home.

As implied above, different elements of P^+ may correspond to the same physical location; all elements of P^- correspond to the same physical location (home) and consequently $t_{n+u,n+w} = c_{n+u,n+w} \equiv 0, \forall\ u,w \in P^+$.

In the analogy to the PDPTW, activities are viewed as being "picked up" by a particular household member (who, in this basic case, is uniquely associated with a particular vehicle) at the location where performed and, once completed (requiring a service time s_i) are "logged in" or "delivered" on the return trip home. Multiple "pickups" are synonymous with multiple sojourns on any given tour. The scheduling and routing protocol relative to some household objective produces the "time-space diagram" commonly referred to in travel/activity analysis.

In the PDPTW, demand functions (d_i) and a vehicle capacity (D) are introduced to ensure that the schedule of pickups and deliveries does not violate the capacity constraint of any particular vehicle. This notion is extended to the HAPP by defining as constraints

$$D = \begin{cases} D^s & = \text{maximum number of sojourns in any tour} \\ \underline{\text{or}} & \\ D^T & = \text{maximum time spent away from home on any tour} \end{cases}$$

with the corresponding demand

$$d_u = \begin{cases} d_u^s = 1 \\ \underline{\text{or}} \\ d_u^T = s_u + t_{w'u};\ w' = \text{stop on tour immediately preceding } i. \end{cases}$$

Decision variables directly analogous to those of the PDPTW are defined as:

X_{uw}^{υ} , $u, w \in N, \upsilon \in V, u \neq w$	binary decision variable equal to unity if vehicle υ travels from activity u to activity w, and zero otherwise.
H_{uw}^{α}, $u, w \in N, \eta, u \neq w$	binary decision variable equal to unity if household member α travels from activity u to activity w, and zero otherwise.
$\overline{T}_0^{\alpha}, \overline{T}_{2n+1}^{\alpha}$, $\alpha \in \eta$	the times at which household member α first departs from home and last returns to home, respectively.
T_u , $u \in P$	the time at which participation in activity u begins.
$T_o^{\upsilon}, T_{2n+1}^{\upsilon}$, $\upsilon \in V$	the times at which vehicle υ first departs from home and last returns to home, respectively.
Y_u , $u \in P$	the total accumulation of either sojourns or time (depending on the selection of D and d_u) on a particular tour immediately following completion of activity u.

With these definitions, the basic HAPP can be represented as:

Minimize Z = Household Travel Disutility (1)

subject to:

$$\sum_{\upsilon \in V} \sum_{w \in N} X_{uw}^{\upsilon} = 1 \quad , \quad u \in P^{+} \tag{2}$$

$$\sum_{w \in N} X_{uw}^{\upsilon} - \sum_{w \in N} X_{wu}^{\upsilon} = 0 \quad u \in P, \ \upsilon \in V \tag{3}$$

$$\sum_{w \in P^{+}} X_{0w}^{\upsilon} \leq 1 \quad , \quad \upsilon \in V \tag{4}$$

$$\sum_{u \in P^{-}} X_{u,2n+1}^{\upsilon} \leq 1 \quad , \quad \upsilon \in V \tag{5}$$

$$\sum_{w \in N} X_{wu}^{\upsilon} - \sum_{w \in N} X_{w,n+u}^{\upsilon} = 0 \quad u \in P^{+}, \ \upsilon \in V \tag{6}$$

$$T_u + s_u + t_{u,n+u} \leq T_{n+u} \quad u \in P^{+} \tag{7}$$

$$X_{uw}^{\upsilon} = 1 \Rightarrow T_u + s_u + t_{uw} \leq T_w \quad , \quad u, w \in P, \ \upsilon \in V \tag{8}$$

$$X_{0w}^{\upsilon} = 1 \Rightarrow T_0^{\upsilon} + t_{0w} \leq T_w \quad , \quad w \in P^{+}, \ \upsilon \in V \tag{9}$$

$$X_{u,2n+1}^{\upsilon} = 1 \Rightarrow T_u + s_u + t_{u,2n+1} \leq T_{2n+1}^{\upsilon} \quad , \quad u \in P^{-}, \ \upsilon \in V \tag{10}$$

$$a_u \leq T_u \leq b_u \quad , \quad u \in P \tag{11}$$

$$a_0 \leq T_0^{\upsilon} \leq b_0 \quad , \quad \upsilon \in V \tag{12}$$

$$a_{2n+1} \leq T_{2n+1}^{\upsilon} \leq b_{2n+1} \ , \quad \upsilon \in V \tag{13}$$

$$X_{uw}^{\upsilon}=1 \Rightarrow Y_u+d_w=Y_w \quad u \in P,\ w \in P^{+}\ \upsilon \in V \tag{14}$$

$$X_{uw}^{\upsilon}=1 \Rightarrow Y_u-d_{w-n}=Y_w \quad u \in P,\ w \in P^{-}\ \upsilon \in V \tag{15}$$

$$X_{0w}^{\upsilon}=1 \Rightarrow Y_0+d_w=Y_w \quad ,\ w \in P^{+},\ \upsilon \in V \tag{16}$$

$$Y_0=0 \ ,\ 0 \le Y_u \le D \ ,\ u \in P^{+} \tag{17}$$

$$X_{uw}^{\upsilon}=\begin{cases}0\\1\end{cases} \ ;\ u,w \in N \ ,\ \upsilon \in V \tag{18}$$

$$\sum_{\upsilon \in V}\sum_{u \in N}\sum_{w \in N} c_{uw}^{\upsilon} X_{uw}^{\upsilon} \le B_c \tag{19}$$

$$\sum_{u \in N}\sum_{w \in N} t_{uw} X_{uw}^{\upsilon} \le B_t^{\upsilon} \ ,\ \upsilon \in V \tag{20}$$

$$\sum_{w \in P^{-}} X_{0,w}^{\upsilon}=0 \ ,\ \upsilon \in V \tag{21}$$

$$\sum_{u \in N} X_{u,0}^{\upsilon}=0 \ ,\ \upsilon \in V \tag{22}$$

$$\sum_{u \in P^{+}} X_{u,2n+1}^{\upsilon}=0 \ ,\ \upsilon \in V \tag{23}$$

$$\sum_{w \in N} X_{2n+1,w}^{\upsilon}=0 \ ,\ \upsilon \in V \tag{24}$$

$$\sum_{w \in \Omega_v^{\upsilon}}\sum_{u \in P} X_{uw}^{\upsilon}=0 \ ,\ \upsilon \in V \tag{25}$$

$$\sum_{\alpha\in\eta}\sum_{w\in N} H_{uw}^{\alpha} = 1 \quad , \quad u \in P^{+} \tag{26}$$

$$\sum_{w\in N} H_{uw}^{\alpha} - \sum_{w\in N} H_{wu}^{\alpha} = 0, \quad u \in P \quad , \quad \alpha \in \eta \tag{27}$$

$$\sum_{w\in P^{+}} H_{0w}^{\alpha} \leq 1, \quad \alpha \in \eta \tag{28}$$

$$\sum_{u\in P^{-}} H_{u,2n+1}^{\alpha} \leq 1, \quad \alpha \in \eta \tag{29}$$

$$\sum_{w\in N} H_{wu}^{\alpha} - \sum_{w\in N} H_{w,n+u}^{\alpha} = 0, \quad u \in P^{+} \quad , \quad \alpha \in \eta \tag{30}$$

$$T_u + s_u + t_{uw} - T_w \leq (1 - H_{uw}^{\alpha})M, \quad u, w \in P \quad , \quad \alpha \in \eta \tag{31}$$

$$\overline{T}_0^{\alpha} + t_{0w} - T_w \leq (1 - H_{0w}^{\alpha})M, \quad w \in P^{+} \quad , \quad \alpha \in \eta \tag{32}$$

$$T_u + s_u + t_{u,2n+1} - \overline{T}_{2n+1}^{\alpha} \leq (1 - H_{u,2n+1}^{\alpha})M, \quad u \in P^{-} \quad , \quad \alpha \in \eta \tag{33}$$

$$\overline{T}_0^{\alpha} \geq \overline{a}_0^{\alpha}, \quad \alpha \in \eta \tag{34}$$

$$\overline{T}_{2n+1}^{\alpha} \leq \overline{b}_{2n+1}^{\alpha} \quad \alpha \in \eta \tag{35}$$

$$\sum_{w\in \overline{P}} H_{0,w}^{\alpha} = 0 \quad \alpha \in \eta \tag{36}$$

$$\sum_{u\in N} H_{u,0}^{\alpha} = 0 \quad \alpha \in \eta \tag{37}$$

$$\sum_{u\in P^{+}} H_{u,2n+1}^{\alpha} = 0 \quad \alpha \in \eta \tag{38}$$

$$\sum_{w \in \Omega_H^\alpha} \sum_{u \in P} H_{uw}^\alpha = 0 \quad , \quad \alpha \in \eta \tag{39}$$

$$\sum_{\alpha \in \eta} H_{uw}^\alpha = \sum_{\upsilon \in V} X_{uw}^\upsilon \quad , \quad u \in P^+, w \in P \tag{40a}$$

$$\sum_{\alpha \in \eta} H_{0w}^\alpha = \sum_{\upsilon \in V} X_{0w}^\upsilon \quad , \quad w \in P \tag{40b}$$

Note that Equations (8), (9), and (10) may be rewritten:

$$T_u + s_u + t_{uw} - T_w \leq (1 - X_{uw}^\upsilon)M, \quad u, w \in P, \ \upsilon \in V \tag{8'}$$

$$T_0^\upsilon + t_{0w} - T_w \leq (1 - X_{0w}^\upsilon)M, \quad w \in P^+, \ \upsilon \in V \tag{9'}$$

$$T_u + s_u + t_{u,2n+1} - T_{2n+1}^\upsilon \leq (1 - X_{u,2n+1}^\upsilon)M, \quad u \in P^-, \ \upsilon \in V \tag{10'}$$

where M is a large positive number.

Equations (2) through (20) are virtually identical to those specified by Solomon and Desrosiers (1988) for the PDPTW, with the addition of the budget constraints (i.e., Equations (19) and (20)) and subject to the redefinition of terms, and have an analogous interpretation in the HAPP. Equations (21) through (24) explicitly state conditions implicit in the PDPTW.

Examples of potential components of the disutility function of the household that may be easily specified in the objective function of Equation (1) include:

$$\sum_{\upsilon \in V} \sum_{u \in N} \sum_{w \in N} c_{uw}^\upsilon X_{uw}^\upsilon \qquad \text{total household travel cost.} \tag{1a}$$

$$\sum_{\upsilon \in V} \sum_{u \in N} \sum_{w \in N} t_{uw} X_{uw}^\upsilon \qquad \text{total travel time.} \tag{1b}$$

$\sum_{u \in P^+}(T_u - b_u)$ a measure of the risk of the inability to complete activities because of stochastic variations in travel times and/or activity durations. (1c)

$\sum_{u \in P^-}(T_u - b_u)$ a measure of the risk of not returning home in time due to stochastic variations in travel time or activity participation. (1d)

$\sum_{u \in P^+}(T_{u+n} - T_u)$ a measure of the delay in returning home incurred by trip chaining. (1e)

$(T^{\upsilon}_{2n+1} - T^{u}_{0})\ ,\ \upsilon \in V$ the extent of the travel day for each household member. (1f)

$\sum_{\upsilon \in V}\sum_{w \in P^+} K X^{\upsilon}_{0w}\ ,\ w \in P^+$ the base disutility of performing any discretionary activities outside the home on a given day. (1g)

Equations (1) - (40) constitute the HAPP formulation for the general case in which the only practical restriction is that of solo driving (i.e., excludes the potential to carpool). The HAPP mixed-integer model specified by the above is in a form that can be solved using the CPLEX algorithm in the GAMS software package developed by the World Bank; properties of this solver are described in a separate section..

Ridesharing Case:

The inclusion of a ridesharing option significantly alters the basic formulation of the previous cases. While maintaining a similar structure to previous cases, the set of nodes is expanded to include "drop-off passenger" and "pick-up passenger" activities at the locations of the prescribed household activities; the former being discretionary, however, while the latter remain compulsory. The elements of the set defining the vehicles available to the household is also expanded by designating "driver seat" and "passenger seat(s)" for each vehicle in the stable. Defining these new sets as:

P^{+}_{DO}	set of serve passenger "drop off" activity locations.
P^{+}_{PU}	set of serve passenger "pick-up" activity locations.
$\overline{P}^{+}$	$P^{+} + P^{+}_{DO} + P^{+}_{PU}$
$P^{-}_{DO}, P^{-}_{PU}, \overline{P}^{-}$	respective eventual home trips to "unload".
$\tilde{V}$	passenger "seats".
$\overline{V}$	$V + \tilde{V}$,

with the corresponding elements:

$A = \{1, 2,\ldots, i,\ldots, n\}$

$V = \{1, 2,\ldots, |V|\}$

$\tilde{V} = \{|V|+1, |V|+2,\ldots, 2|V|\}$

$\overline{V} = \{1,\ldots, |V|, |V|+1,\ldots, 2|V|\}$

$P^{+} = \{1, 2,\ldots, i,\ldots, n\}$

$P^{+}_{DO} = \{n+1, n+2,\ldots, n+i,\ldots, 2n\}$

$P^{+}_{PU} = \{2n+1, 2n+2,\ldots, 2n+i,\ldots, \overline{n}\}$, $\overline{n} = 3n$

$P^{-} = \{\overline{n}+1, \overline{n}+2,\ldots, \overline{n}+i,\ldots, \overline{n}+n\}$

$P^{-}_{DO} = \{\overline{n}+n+1, \overline{n}+n+2,\ldots, \overline{n}+n+i,\ldots,\overline{n}+2n\}$

$P^{-}_{PU} = \{\overline{n}+2n+1, \overline{n}+2n+2,\ldots, \overline{n}+2n+i,\ldots,2\overline{n}\}$

$\overline{P}^{+} = P^{+} \cup P^{+}_{DO} \cup P^{+}_{PU} = \{1, 2,\ldots, \overline{n}\}$

$\overline{P}^{-} = P^{-} \cup P^{-}_{DO} \cup P^{-}_{PU} = \{\overline{n}+1, \overline{n}+2,\ldots, 2\overline{n}\}$

$\overline{P} = \overline{P}^{+} \cup \overline{P}^{-} = \{1, 2,\ldots, 2\overline{n}\}$

$\overline{N} = \{0, \overline{P}, 2\overline{n}+1\}$,

the constraints defining the HAPP with ridesharing options can be grouped into six broad categories: (1) temporal constraints on the vehicles, (2) temporal constraints on the household members performing the activities, (3) spatial connectivity constraints on the vehicles, (4) spatial connectivity constraints on the household members, (5) capacity, budget and participation constraints, and (6) vehicle and household member coupling constraints. These constraints are presented in detail below:

(1) Vehicle Temporal Constraints:

$$T_u + s_u + t_{u,\bar{n}+u} - T_{\bar{n}+u} \le \left(1 - \sum_{w\in\bar{P}}\sum_{\upsilon\in\bar{V}} X_{uw}^{\upsilon}\right)M, \quad u \in \bar{P}^+,\ \upsilon \in \bar{V} \tag{41}$$

$$T_u + s_u + t_{uw} - T_w \le (1 - X_{uw}^{\upsilon})M, \quad u, w \in \bar{P}^+,\ \upsilon \in \bar{V} \tag{42}$$

$$T_0^{\upsilon} + t_{0w} - T_w \le (1 - X_{0w}^{\upsilon})M, \quad w \in \bar{P}^+,\ \upsilon \in \bar{V} \tag{43}$$

$$T_u + s_u + T_{u,2\bar{n}+1} - T_{2\bar{n}+1}^{\upsilon} \le (1 - X_{u,2\bar{n}+1}^{\upsilon})M, \quad u \in \bar{P}^-,\ \upsilon \in \bar{V} \tag{44}$$

$$T_{u+n} - T_u - s_{u+n} \le (1 - X_{w,u+n}^{\upsilon})M, \quad u \in P^+,\ w \in 0, \bar{P},\ \upsilon \in V \tag{45}$$

$$T_u + s_u - T_{u+2n} \le (1 - X_{w,u+2n}^{\upsilon})M, \quad u \in P^+,\ w \in 0, \bar{P},\ \upsilon \in V \tag{46}$$

$$T_u - b_u \le \left(1 - \sum_{w\in\bar{P}}\sum_{\upsilon\in\bar{V}} X_{wu}^{\upsilon}\right)M \ge -T_u + a_u, \quad u \in \bar{P} \tag{47}$$

$$a_0 \le T_0^{\upsilon} \le b_0, \quad \upsilon \in V \tag{48}$$

$$a_{2\bar{n}+1} \le T_{2\bar{n}+1}^{\upsilon} \le b_{2\bar{n}+1}, \quad \upsilon \in V \tag{49}$$

$$T_0^{\upsilon} - T_0^{\upsilon+|V|} = 0, \quad \upsilon \in V \tag{50}$$

$$T_{2\bar{n}+1}^{\upsilon} - T_{2\bar{n}+1}^{\upsilon+|V|} = 0, \quad \upsilon \in V \tag{51}$$

The constraints embodied in Equations (41) - (47) are roughly equivalent to the corresponding constraints for Case 4 of the HAPP and the associated PDPTW, the principal exceptions being the expansion of the activity and vehicle sets, and the introduction of discretionary "serve passenger" activities. For example, Equation (41) ensures that the constraint that the "return home" be subsequent to activity participation is enforced on only those "serve passenger" trips that are actually made; for $u \in P^+$ the right side of Equation (41) is identically zero. Similarly for Equation (45), which ensures that activities take place within their allotted time windows. Equations (42)- (44) ensure that travel between any two activity locations can occur if and only if there is sufficient time to reach the destination prior to commencing the associated activity.

Equations (45) and (46) constrain activities that are accessed as a passenger to occur after the passenger is dropped off at the destination and be completed prior to being picked up for the return home. Equations (47) and (48) ensure that the initial vehicle departure times and final return home times fall within the allotted time windows. Equations (49) and (50) require that these times be identical for the vehicle and its passenger seat.

(2) Household Member Temporal Constraints:

$$T_u + s_u + t_{uw} - T_w \le (1 - H_{uw}^{\alpha})M, \quad u, w \in \overline{P}, \ \alpha \in \eta \tag{52}$$

$$\overline{T}_0^{\alpha} + t_{0w} - T_w \le (1 - H_{0w}^{\alpha})M, \quad w \in \overline{P}^{+}, \ \alpha \in \eta \tag{53}$$

$$-(1 - H_{u,2\overline{n}+1}^{\alpha})M \le T_u - \overline{T}_{2n+1}^{\alpha} \le (1 - H_{u,2\overline{n}+1}^{\alpha})M, \quad u \in \overline{P}^{-}, \ \alpha \in \eta \tag{54}$$

$$\overline{a}_0^{\alpha} \le \overline{T}_0^{\alpha} \le \overline{b}_0^{\alpha} \ , \ \alpha \in \eta \tag{55}$$

$$\overline{a}_{2\overline{n}+1}^{\alpha} \le \overline{T}_{2\overline{n}+1}^{\alpha} \le \overline{b}_{2\overline{n}+1}^{\alpha} \ , \ \alpha \in \eta \tag{56}$$

With the exception of the expansion of the activity and vehicle sets, Equations (52) - (56) are equivalent to Equations (31) - (35).

(3) Spatial Connectivity Constraints on the Vehicles:

$$\sum_{\upsilon \in \overline{V}} \sum_{w \in \overline{N}} X_{uw}^{\upsilon} = 1 \ , \quad u \in P^{+} \tag{57}$$

$$\sum_{\upsilon \in V} \sum_{w \in \overline{N}} X_{uw}^{\upsilon} \le 1 \ , \quad u \in P_{DO}^{+} \cup P_{PU}^{+} \tag{58}$$

$$\sum_{w \in \overline{P}} X_{uw}^{\upsilon+|V|} \le \sum_{w \in \overline{P}} X_{u+jn,w}^{\upsilon} \ , \quad u \in P^{+}, \ \upsilon \in V, \ j = 1,2 \tag{59}$$

$$X_{0u}^{\upsilon+|V|} \le X_{0,u+n}^{\upsilon} + \sum_{w \in \overline{P}^{-}} X_{w,u+n}^{\upsilon} \ , \quad u \in P^{+}, \ \upsilon \in V \tag{60}$$

$$X_{uw}^{\upsilon} = 0 \ , \ u \in \overline{N}, \ w \in P_{DO}^{+} \cup P_{PU}^{+} \ , \ \upsilon \in V \tag{61}$$

$$\sum_{w \in \overline{N}} X_{uw}^{\upsilon} - \sum_{w \in \overline{N}} X_{wu}^{\upsilon} = 0 \ , \quad u \in \overline{P}, \ \upsilon \in \overline{V} \tag{62}$$

$$\sum_{w \in \overline{P}^{+}} X_{0w}^{\upsilon} \le 1 \ , \ \upsilon \in \overline{V} \tag{63}$$

$$X^{\upsilon}_{uw} \le \sum_{r \in \overline{P}^{+}} X^{\upsilon}_{0r} \quad , \ \upsilon \in V \ , \ u,w \in \overline{P} \tag{64}$$

$$\sum_{u \in \overline{P}^{-}} X^{\upsilon}_{u,2\bar{n}+1} \le 1 \quad , \ \upsilon \in \overline{V} \tag{65}$$

$$\sum_{w \in \overline{N}} X^{\upsilon}_{wu} - \sum_{w \in \overline{N}} X^{\upsilon}_{w,\bar{n}+u} = 0 \ , \quad u \in \overline{P}^{+}, \ \upsilon \in \overline{V} \tag{66}$$

$$\sum_{w \in \overline{P}^{-}} X^{\upsilon}_{0,w} = 0 \quad , \ \upsilon \in \overline{V} \tag{67}$$

$$\sum_{u \in \overline{N}} X^{\upsilon}_{u0} = 0 \quad , \ \upsilon \in \overline{V} \tag{68}$$

$$\sum_{u \in \overline{P}^{+}} X^{\upsilon}_{u,2\bar{n}+1} = 0 \quad , \ \upsilon \in \overline{V} \tag{69}$$

$$\sum_{w \in \overline{P}} X^{\upsilon}_{2\bar{n}+1,w} = 0 \quad , \ \upsilon \in \overline{V} \tag{70}$$

Equation (57) requires that all compulsory activities must be accessed either by a vehicle driver or as a carpool passenger; Equation (58) is the stipulation that "serve passenger" activities, if performed, must be by one and only one vehicle driver. Equations (59) and (60) ensure that activities accesses as a passenger are coupled to a corresponding "serve passenger" trip. Equation (61) precludes passengers from "serve passenger" activities. Equation (62) ensures that there is a connected path for each vehicle and no activity location is revisited. Equations (63) - (65) state that not all vehicles may be used in completing the household activity agenda, but if one is, its initial tour must begin at home. Equation (66) requires the "eventual return to home" from an activity be assigned to the vehicle that was used to accessed the activity. Equations (67) - (70) prohibit linkages among illogical activities, regardless of the specification of the objective function.

(4) Spatial Connectivity Constraints on the Household Members:

$$\sum_{\alpha \in \eta} \sum_{w \in \overline{N}} H^{\alpha}_{uw} = 1 \quad , \quad u \in P^{+} \tag{71}$$

$$\sum_{w \in \overline{N}} H^{\alpha}_{uw} - \sum_{w \in \overline{N}} H^{\alpha}_{wu} = 0 \quad , \ u \in \overline{P} \ , \ \alpha \in \eta \tag{72}$$

$$\sum_{w\in\overline{P}^+} H^{\alpha}_{0w} \le 1 \quad , \quad \alpha \in \eta \tag{73}$$

$$\sum_{u\in\overline{P}^-} H^{\alpha}_{u,2\overline{n}+1} \le 1 \quad , \quad \alpha \in \eta \tag{74}$$

$$\sum_{w\in\overline{N}} H^{\alpha}_{wu} - \sum_{w\in\overline{N}} H^{\alpha}_{w,\overline{n}+u} = 0 \quad , \quad u \in \overline{P}^+ \quad , \quad \alpha \in \eta \tag{75}$$

$$\sum_{w\in\overline{P}^-} H^{\alpha}_{0w} = 0 \quad , \quad \alpha \in \eta \tag{76}$$

$$\sum_{u\in\overline{N}} H^{\alpha}_{u0} = 0 \quad , \quad \alpha \in \eta \tag{77}$$

$$\sum_{u\in\overline{P}^+} H^{\alpha}_{u,2\overline{n}+1} = 0 \quad , \quad \alpha \in \eta \tag{78}$$

Equations (71) and (72) require that all compulsory activities must be completed by a member of the household, and that the household members have a connected path, respectively. Equations (73) and (74) state that some members of the household may not travel. Equations (75) - (77) are similar in interpretation to Equations (67) - (70).

(5) Capacity Budget and Participation Constraints:

$$-(1-X^{\upsilon}_{uw})M \le Y_u + d_w - Y_w \le (1-X^{\upsilon}_{uw})M, \;\; u \in \overline{P},\; w \in \overline{P}^+,\; \upsilon \in \overline{V} \tag{79}$$

$$-(1-X^{\upsilon}_{uw})M \le Y_u + d_{w-\overline{n}} - Y_w \le (1-X^{\upsilon}_{uw})M, \;\; u \in \overline{P},\; w \in \overline{P}^-,\; \upsilon \in \overline{V} \tag{80}$$

$$-(1-X^{\upsilon}_{0w})M \le Y_0 + d_w - Y_w \le (1-X^{\upsilon}_{0w})M, \;\; w \in \overline{P}^+,\; \upsilon \in V \tag{81}$$

$$Y_0 = 0 \quad , \quad 0 \le Y_u \le D \quad , \quad u \in \overline{P}^+ \tag{82}$$

$$\sum_{\upsilon\in V}\sum_{u\in\overline{N}}\sum_{w\in\overline{N}} c^{\upsilon}_{uw} X^{\upsilon}_{uw} \le B_c \tag{83}$$

$$\sum_{u\in\overline{N}}\sum_{w\in\overline{N}} t_{uw} H^{\alpha}_{uw} \le B^{\alpha}_t \quad , \quad \alpha \in \eta \tag{84}$$

$$\sum_{w\in\Omega^{\upsilon}}\sum_{u\in\overline{N}} X^{\upsilon}_{uw} = 0 \quad , \quad \upsilon \in V \tag{85}$$

$$\sum_{w\in\Omega^{\alpha}_H}\sum_{u\in\overline{N}} H^{\alpha}_{uw} = 0 \quad , \quad \alpha \in \eta \tag{86}$$

Equations (79) - (81) specify the demand continuity relationships at each stop, while Equation (82) is the corresponding capacity constraint. Equation (83) is the household travel cost budget constraint; Equations (84) are the household member's travel time constraints. Equations (85) and (86) represent the vehicle and member activity participation exclusions.

(6) Vehicle and Household Member Coupling Constraints:

$$\sum_{\alpha\in\eta} H^{\alpha}_{uw} - \sum_{\upsilon\in\overline{V}} X^{\upsilon}_{uw} = 0 \quad , \quad u\in\overline{P}^{+},\ w\in\overline{P} \tag{87}$$

$$\sum_{\alpha\in\eta} H^{\alpha}_{0w} + \sum_{\alpha\in\eta}\sum_{u\in\overline{P}^{-}} H^{\alpha}_{uw} - \sum_{\upsilon\in\overline{V}} X^{\upsilon}_{0w} - \sum_{\upsilon\in\overline{V}}\sum_{u\in\overline{P}^{-}} X^{\upsilon}_{uw} = 0 \quad , \quad w\in\overline{P} \tag{88}$$

$$-(1-H^{\alpha}_{0w})M-(1-X^{\upsilon}_{uw})M \le \overline{T}^{\alpha}_{0} - T_{u} \le (1-H^{\alpha}_{0w})M + \left(1-X^{\upsilon}_{uw}\right)M, \quad w\in\overline{P}^{+},\ u\in\overline{N},\ \upsilon\in\overline{V},\ \alpha\in\eta \tag{89}$$

Equation (87) ensures that only one household member is assigned to travel between any activity location and any other location by any particular vehicle "seat". Equation (88) allows for transference of connectivity between vehicles and household members at the home location. Equation (89) requires that the time of the initial departure from home by any household member coincide with the departure time of the vehicle (initial or otherwise) that transports the individual to the activity. Equations (41) - (89), together with an objective function comprised of a linear combination of activity/travel disutility components (e.g., drawn from Equations (1)), constitute the general case of the HAPP model with the provision of ridesharing options.

It is not practical to solve the complete model simply using the GAMS CPLEX module because of the size of the model for this case with ridesharing options. Rather, a decomposition procedure was devised in which the CPLEX solver first was employed to obtain a solution to the non-ridesharing version of the problem. Then, using this as an initial feasible solution to the general problem with ridesharing, Equations (41) - (89) were decomposed into their integer (largely spatial) and non-integer (largely temporal) components. A heuristic was used to generate feasible ridesharing perturbations (branches) of the non-ridesharing solution while satisfying the integer spatial constraints and the absolute temporal constraints embodied in the input data (e.g., travel time and cost matrices, activity durations, and various time windows); the temporal portion of each branch was optimized using the GAMS LP solver and the overall optimal solution selected.

3.7 Modifications to Reflect Emissions Reduction Strategies

The collection of individual travel decisions of each member of a household can be estimated and aggregated to reflect the complete range of travel characteristics affecting both energy consumption and vehicle emissions within a household under restrictive transportation supply environment. The travel characteristics include vehicle allocation, journey starts and stops, trip chaining, ridesharing, and the spatio-temporal paths taken. The HAPP model formulation is refined to incorporate vehicle emissions and energy consumption calculations. The vehicle emissions and energy consumption depend on a number of factors. The factors are the distance and speed driven on the spatio-temporal linkages between the collection of activities that individuals and households perform as part of their daily routine, the number of trips, the time between them, and whether the vehicle was warmed up or not when started. The parameters related to vehicle emissions and energy consumption are included in the model formulation. These parameters recognize emissions and energy by vehicle type used for each trip. The estimates of emissions are based on cold and hot starts which depend on the time interval lapsed between successive trips and correction factors for temperature, speed, and operating mode.

3.7.1 Objective Function

The decision variables corresponding to the above parameters and the changes in the objective function to reflect energy and emissions objectives are also specified in the refined model. The term in the objective function to reflect CO emissions can be given as

$$\sum_{\upsilon \in V} \sum_{u \in N} \sum_{w \in N} X^{\upsilon}_{uw} \left(CCO^{\upsilon}_{uw} + HCO^{\upsilon}_{uw}\right) \qquad (90)$$

where CCO and HCO represent cold- and hot-start emissions, respectively. (Corresponding elements of these two matrices have only one non-zero value depending on whether the travel from u to w involves either a cold start or a hot start, determined by the length of time between the start of activity u and that of the travel to activity w.) Similarly, terms in the objective function to include HC and NO_x emissions are given as

$$\sum_{\upsilon \in V} \sum_{u \in \bar{N}} \sum_{w \in \bar{N}} X_{uw}^{\upsilon} (CHC_{uw}^{\upsilon} + HHC_{uw}^{\upsilon}) \tag{91}$$

$$\sum_{\upsilon \in V} \sum_{u \in \bar{N}} \sum_{w \in \bar{N}} X_{uw}^{\upsilon} (CNO_{x\,uw}^{\;\upsilon} + HNO_{x\,uw}^{\;\upsilon}) \tag{92}$$

3.7.2 Emissions Matrices

The emissions matrices for CO, HC and NO_x emissions are determined between all the activity locations in the household. The calculation of the emissions matrices was based on the MOBILE5 emissions model. The fuel consumption matrix is also determined for the household.

Basic Emission Rates:

The basic emission rates (BERs) in MOBILE5 are expressed in the form of linear equations, consisting of a zero-mile level (ZML), or y-intercept, and one or two deterioration rates, or slopes (increase in emissions per 10000 miles accumulated mileage). The deterioration rate used for a particular vehicle will depend on the mileage of the vehicle. The first deterioration rate is used to calculate emissions deterioration through 50000 accumulated miles, and the second (higher) rate is applied to accumulated mileage beyond 50000 miles. The basic emission rates are expressed in units of grams per mile for the ZMLs and g / mile per 10000 miles for the DRs. The BER equations in MOBILE5 are based on the applicable Federal emission standards and the emission control technologies characterizing the fleet in various model years. These equations are applicable for all non-California areas, both low- and high-altitude. The information in the BER record includes the model year, the zero mile level, and the deterioration rates for HC, CO and NO_x emissions. Only non-tampered exhaust emission rates are considered in the analysis.

The BER equations are given below:

BER = ZML + (DR1 * M), for mileage up to 50K miles (M <= 5)

BER = ZML + DR1*5.0 + DR2*(M - 5.0), for mileage greater then 50K miles (M >5)

Where: BER = Non-tampered basic exhaust emission rates in grams/mile, ZML = Zero mile level in grams/mile,

DR1 = Deterioration rate for <= 50K miles, in grams/mile/10K miles,

DR2 = Deterioration rate for > 50K miles, in grams/mile/10K miles,

M = Cumulative mileage / 10,000 miles.

Low-altitude emission factors are based on conditions representative of approximately 500 feet above mean sea level (+500 ft MSL), and high altitude factors are based on conditions representative of approximately +5500 ft MSL. The emission factors are calculated based on the year in which the vehicle was bought. The individuals in the household reported the mileage of the vehicle.

Speed Correction Factors:

Emission factors vary considerably with the average speed. The speed refers to the average speed of vehicles over trips. The average speed for any trip is given by the total distance traveled divided by the network travel time for that trip. This value will have a significant impact on the resulting emission factors for exhaust emissions. The speed correction factors have been revised in MOBILE5 for the mid-range of speeds (between 19.6 and 55 mph). The general curve describing HC and CO emission rates as functions of speed displays very high g / mile emission rates at very low speeds, with emissions decreasing (sharply at first, then more slowly) as average speed increases, until minimum emissions are reached at around 48 mph. The emissions for HC and CO are assumed to be the same for all speeds from 48 to 55 mph in MOBILE5. In the case of speeds above 55 mph, further increases in speed result in increased emissions. The behavior of NO_x emissions as a function of speed have also been revised in MOBILE5.

The speed correction factor coefficients for low altitude Light Duty Gasoline powered vehicles are given below:

$$SCF\ (s, sadj) = SF(s) / SF\ (sadj)$$

$$SF(s) = \exp\ (A + B^* s + C^* s^2 + D^* s^3 + E^* s^4 + F^* s^5),\ HC\ \&\ CO$$

$$SF(s) = (A + B^* s + C^* s^2 + D^* s^3 + E^* s^4 + F^* s^5),\ NOx$$

where:

s = average speed (mph),

sadj = basic test procedure speed; adjusted for fraction of cold start operation x and fraction of hot start operation w, $[1/ sadj = (w+ x)/ 26 + (1- w- x)/ 16]$.

Temperature Correction Factors

There is a variation in the emissions based on the ambient temperature. The value of temperature used to calculate the temperature correction factors for exhaust emissions, hot soak evaporative emissions, refueling emissions, and resting loss and running loss emissions will significantly affect the resulting emission factors. The ambient temperature must be between the minimum and maximum temperatures. This temperature is assumed to be 72^0 F for the Portland area. The effect of the non-exhaust type emissions is not considered important in this analysis. The basic emission rates that underlie the emission factor calculations are developed from emission data from vehicles tested at Federal Test Procedure (FTP) conditions. The temperature correction factors are used to correct exhaust emission factors to temperatures other than 75^0 F. Low temperature (< 75^0 F) correction factors for Light Duty Gasoline powered vehicles are given below:

$TCF(1) = TC(1)*(T - 75.0)$, 1980+ CO,

$TCF(b) = \exp[TC(b)*(T - 75.0)]$, all others

where:

TCF (b) = Low temperature correction factor for appropriate pollutant, ambient temperature (< 75^0 F), and model year, for test segment b,

T = Ambient temperature (Fahrenheit),

TC (b) = Low temperature correction factor coefficient for appropriate pollutant, reference temperature, and model year, for test segment b.

Evaporative and refueling emissions (and exhaust emissions, to a lesser extent) vary with fuel volatility. EPA's vehicle certification program and much of its emission factor testing use gasoline with volatility (as measured by Reid vapor pressure (RVP)) of 9.0 psi. The emission factors are adjusted to account for the effects of fuel with a RVP different from 9.0 psi. Due to lack of data for vehicles in the Portland survey, the fuel RVP is assumed to be 9.0 psi.

High temperature (>75^0 F) correction factor coefficients and fuel RVP correction factors for Light Duty Gasoline powered vehicles is given below:

TCF (b) = exp [TC (b)*(T - 75.0)], Pre-1980

TRCF (b) = exp [RC (b)*(RVP - 9.0) + TC (b)*(T - 75.0) + TRC (b)*(RVP - 9.0)*(T - 75.0)], 1980+

where:

TCF (b) = High temperature correction factor for appropriate pollutant, ambient temperature, and model year, for test segment b,

T = Ambient temperature (Fahrenheit),

TC (b) = High temperature correction factor coefficient for appropriate pollutant, temperature, and model year, for test segment b,

TRCF (b)= High temperature and fuel RVP correction factor for appropriate pollutant, ambient temperature, fuel RVP, and model year, for test segment b,

RC (b) = Fuel RVP correction factor coefficient for appropriate pollutant, fuel RVP, and model year, for test segment b,

RVP = Fuel volatility in psi,

TRC (b) = Combined temperature and fuel RVP correction factor coefficient for appropriate pollutant, fuel RVP, ambient temperature, and model year, for test segment b.

Operating Mode Correction Factors

The mode of operation is an important aspect to be considered in the determination of the emissions performance of the vehicle. EPA's emission factors are based on testing over the FTP cycle, which is divided into three segments (referred to as "bags"), each with differing associated emissions performance. The bags correspond to operating modes:

Bag	Operating Mode
1	Cold Start
2	Stabilized
3	Hot Start

Emission data from each of these bags reflect the fact that the emissions are highest when a vehicle is in cold-start mode: the vehicle, engine, and emission control equipment (particularly the catalytic converter) are all at ambient temperature and thus not performing at optimum levels. The emissions are lower in hot start mode (compared to cold start mode), when the vehicle if not yet completely warmed up but was not sitting idle for sufficient time to have cooled down completely to ambient temperatures. Generally, the emissions are lowest when the vehicle is operating in stabilized mode, and has been in continuous operation long enough for all systems to attain relatively stable and fully warmed-up operating temperatures.

The operating mode of the vehicle at the start of a trip is referred to as either a cold start or a hot start. The operating mode during or at the end of a trip is referred to as either a cold transient, hot transient, or hot stabilized. The EPA has historically defined a cold start as any start that occurs 4 hours or later following the end of the preceding trip for non-catalyst equipped vehicles and 1 hour or later following the end of the preceding trip for catalyst-equipped vehicles. The hot start is defined as any start that occurs less than 4 hours after the end of the preceding trip for non-catalyst equipped vehicles and less than 1 hour after the end of the preceding trip for catalyst-equipped vehicles. The duration of the activity between trips is called the soak period. The shorter time interval associated with the cold/hot start definition for catalyst-equipped vehicles reflects the fact that catalytic converters do not operate at the intended efficiency until they are fully warmed up (to operating temperatures in the 600^0 F range. A vehicle will be operating in either a cold transient mode (corresponding to a cold start) or a hot transient mode (corresponding to a hot start) prior to the attainment of hot stabilized operating mode. The cold start bag (the cold transient) is represented by the first 3.5 miles traveled by a vehicle after a cold start and the hot start bag (the hot transient) is represented by the first 3.5 miles after a hot start. The stabilized mode bag follows the cold transient or the hot transient. The start mode of each trip is thus determined by the duration of the preceding activity and the vehicle type. The vehicles whose model year is 1975 and later are assumed to have catalytic converters.

The normalized bag fractions for Light Duty Gasoline powered vehicles are given below:

NOTE: The fractions given in this table are used in the calculation of the operating-mode/ temperature correction factor (OMTCF).

OMTCF = [(TERM1 + TERM2 + TERM3)/DENOM],

TERM1 = $W*TCF(1)*(B_1+D_{11}*M)$, or $W*[B_1+D_{11}*5.0+D_{12}*(M-5.0)]$,

TERM2 = $(1-W-X)*TCF(2)*(B_2+D_{21}*M)$, or $*[B_2+D_{21}*5.0+D_{22}*(M-5.0)]$,

TERM3 = $X*TCF(3)*(B_3+D_{31}*M)$, or $*[B_3+D_{31}*5.0+D_{32}*(M-5.0)]$,

DENOM = $B_0+D_{01}*M$, or = $B_0+D_{01}*5.0+D_{02}*(M-5.0)$,

W = Fraction of VMT in the cold start mode

X = Fraction of VMT in the hot start mode,

TCF (b) = Temperature correction factor for pollutant/model year/test segment b from Table 1.7A,

M = Cumulative mileage / 10,000 miles.

B_0, D_{01}, D_{02}, B_1, D_{11}, D_{12}, B_2, D_{21}, D_{22}, B_3, D_{31}, D_{32} are the coefficients and the deterioration ratios for the total test and the 3 test segments.

3.7.3 Implementation

The cold transient can be calculated by considering W, the fraction of VMT in cold start mode, to be 100 %. Similarly, the hot transient can be calculated by considering X, the fraction of VMT in the hot start mode to be 100 %. The stabilized mode that follows the transient mode is given by assuming W and X to be zero. Thus for each trip, the emissions are calculated based on the start mode and the temperature, speed and operating mode correction factors. The trip would involve only a cold transient or a hot transient when the total distance traveled is less than 3.5 miles. The HC, CO and NO_x emissions for trips between all activity locations in the household are represented in the form of a matrix in units of 10 grams. This matrix representation is given for all the vehicles in the household.

4. DATA

4.1 Trends in Travel Data Collection

There has been a gradual resurgence of activity by Metropolitan Planning Organizations in the collection of new travel data starting in the mid to late 1980s. These recent data collection activities were in part a response to a recognition that existing databases had become increasingly obsolete and no longer represented either current travel patterns or current socioeconomic and demographic conditions. New data collection activities undertaken in the 1990s, including the conduct of statewide travel surveys, have been motivated in large part by metropolitan and statewide planning provisions contained in the Intermodal Surface Transportation Efficiency Act of 1991 as well as by the Clean Air Amendment of 1990.

The resurgence of interest in travel-related data collection has been led by the metropolitan planning organizations representing larger metropolitan areas, those having a population in excess of 2 million persons. Increasingly though, new travel surveys are now also being conducted in medium-size and smaller urban areas, as well as at the statewide level.

The primary focus of recent and current travel surveys has been the household travel survey. There also, however, has been an increase in the use of other survey types. Most frequently, these include vehicle intercept and external station surveys and transit on-board surveys. However, the number of commercial vehicle surveys, workplace surveys, visitor surveys, and special generator surveys has increased as well. These other forms of travel surveys are being used to supplement the data collected from the household travel survey. Travel surveys, thus, are now becoming a comprehensive set of interrelated survey activities rather than relying primarily on a single data source to support the development and application of a set of travel demand models.

This renewed activity in travel surveys has been accompanied by a refinement in the manner in which household and other types of surveys are being conducted. The in-home interview has now been replaced by use of sophisticated combinations of telephone and mail approaches.

These refinements in survey administration include:

- The geocoding of data and the subsequent introduction of geographic information systems (GIS) as the underlying data management foundation for future travel demand systems.
- The use of computer-assisted surveys that permit more extensive survey branching and thus the collection of greater amounts of information with greater reliability, lower cost and less time.

There has been a broadening of survey scope. This includes the collection of additional data on vehicle characteristics, the inclusion of walking and bicycling as potentially important modes of travel, and the use of activity-based surveys.

Fundamentally new types of travel surveys are now receiving considerable interest and are likely to be increasingly used in the future. In addition to activity-based surveys, these include panel surveys, stated preference surveys, and even the use of traditional market research focus groups. These represent the current leading edge of travel survey techniques. Panel surveys, in which essentially the same sample is repeatedly surveyed periodically over time, permit the development of time-series or longitudinal data that are useful in examining responses to transportation policies and to changing economic conditions. Panel and stated preference surveys are being used both independently from and as a supplement to more traditional forms of travel surveys.

Increasing emphasis in travel surveys is being placed on the interrelationships among all trips that may be taken by individuals, regardless of purpose, time of day, or even day of week. This shift of interest is a response both to the increasingly complex forms of trip chaining that are now occurring and to the potential of in-home activities, including various forms of telecommunications, to substitute for activities requiring travel. Time-use surveys document the linking of household and individual activities and facilitate the development of travel demand models that are based on the household or individual rather that the traffic analysis zone as the fundamental unit of analysis.

4.2 Portland, Oregon Case Study

The data used in the application of the model developed in the previous section are drawn from the Portland, Oregon 1994 Activity and Travel Survey. The survey strategies used in Portland include multi-day activity diaries, in-home and out-of-home activities, full week coverage, transit usage, all household members, and trip ends geocoded to x-y coordinates for application in a GIS environment. In addition, there is close coordination and integration with other relevant databases (such as land use, parking and building permits).

The survey contains revealed and stated preference components. The revealed preference component used in this paper included a two-day (consecutive days) activity diary recording all activities involving travel and all in-home activities with duration of at least 30 minutes, for all individuals in the household. The household and person socio-economic data are also included in the survey.

4.2.1 Revealed Preference Survey

The revealed preference (RP) survey was designed to collect household characteristics and vehicle information for each surveyed household, as well as personal characteristics, activity and travel data for each surveyed household member. Households were defined as "all people currently living in the same dwelling who typically share meals together as well as share at least part of their income." This definition was considered to be more useful for modeling purposes even though it differed from that used by the Bureau of the Census.

Activity / Travel data were collected for every household member, regardless of age (parents were instructed to assist children under 12 years old) over two consecutive days. The travel days assigned to households were varied to capture data representing all the days of the week. In order to observe any differences in travel behavior within households by day of week, the two days' activity / travel data was collected. The Tables below list the household, person, vehicle and activity / travel data elements collected during the RP survey.

Household Data Elements

- Address
- Activity Dates
- Household size and names
- Household structure type
- Household income
- Number of phone lines
- Number of cellular or car phones
- Presence / Absence of household members or visitors on activity day
- Tenure at current address
- Zip code of previous address
- Own or rent
- Number of vehicles
- Shared phone lines
- Transportation disability

Person Data Elements

- Gender
- Race / Ethnicity
- English proficiency
- Employment Status
- Age
- Household Language
- Driver's license status
- Student status

If employed :

- Occupation
- Industry
- Work at home
- Pay for parking ?
- Parking Cost
- Tenure at current job
- Address of primary job
- Zip code of secondary place of work
- Primary employer offers shift work or flex time ?
- Primary employer offers subsidized parking or transit ?
- Number of days traveled by specific modes
- Zip codes of previous employer
- Name of School
- Number of days traveled by specific modes

Activity Diary Data Elements / Questions

What was the activity?

When did it take place?

When did activity start?

Did you have a vehicle available?

Parking costs, if any

How long did it take?

Were you already there?

How did you get there?

Number in party

Start / end times

Bus trip information (e.g. route, transfer)

Vehicle Form Data Elements / Questions

Vehicle year, make, model, type

Year purchased

Fuel type

Vehicle ownership

Purchased as replacement or add-on?

Odometer reading on beginning of 1st day

Odometer reading at end of 2nd day

A total of 4451 households were surveyed in the Portland Metro area using the telephone / mail / telephone method. The first data collection phase took place during the spring and summer of 1994. Additional households were surveyed in the fall and winter of 1994-95 after revisions to the survey instrument and the interviewing procedures were made. The data collection steps included:

- Recruitment of households by telephone

- Mailing survey materials packets to participating households
- Reminder calls to participating households on the day before their designated travel days; and
- Retrieval of data via telephone interviews after the second designated travel day.

4.2.2 Geocoding

Portland Metro geocoded (attach x-y coordinates) activities and employment locations recorded in the final survey data set to an accuracy of 200 feet. Sampled home addresses were also geocoded to allocate sampled households within and among geographic strata. Extensive GIS-based (ARC/Info) files for the Portland area has been constructed and these include mappings of land use, census demographic information, and local employment estimates. Portland Metro has also made available for this cooperative effort 1990 Census Tiger files and tract demographics, as well as EMM/2 coded transportation networks and models.

4.2.3 Stated Preference Surveys

The revealed preference data cannot be used to predict the effects of totally new changes to the transportation environment, though observed behavior forms the basis for transportation demand modeling. The introduction of a new mode, the effect of urban design policies, and various pricing schemes are some of the policy options that are difficult to address with revealed preference data. The stated preference (SP) surveys present a set of hypothetical situations. The data can thus yield the reaction of people in a new situation. A three-part SP survey was administered to a subset of the households that completed the activity / travel survey. The exercise involved preferences with respect to residential location, congestion pricing and travel behavior.

4.2.4 In-home activities

The issue of in-home activities has been an important aspect in the development of recent household surveys in the US. The Portland survey has included all activities in-home whose duration was greater than 30 minutes. The modeling of the sequence of activities and its duration, inclusive of the choice of travel and location, requires an accounting for the time spent in a 24-hour period. The approach used in Portland to get great detail of activities led to problems in completing the survey until a threshold of greater than 30 minutes time use was introduced. However, the use of 30 minutes as the threshold led to non-reporting of meals and large amounts of unspecified time.

4.3 Data Classification

The Portland activity data was collected open ended. The activity classification of the Portland activity data is coded to the following set of categories:

Household Sustaining
Meals
Work
Work-Related
Shopping (General)
Shopping (Major)
Personal Services
Medical Care
Professional Services
Household or Personal business
Household Maintenance
Household Obligations
Pick-Up / Drop-Off passengers

Social Activities
Visiting
Casual Entertaining
Formal Entertaining

Personal Enrichment
School
Culture
Religion / Civil Services
Civic

Recreation and Other Diversions
Amusements (at home)
Amusements (Out of home)
Hobbies
Exercise / Athletics
Rest and Relaxation
Spectator and Athletic Events
Out of Area travel

Other
Incidental Travel
Tag along travel

4.4 Data Processing and Conditions

The data files provided by Portland Metro included activity file, file with home address information, geocode file, vehicle file, household file and person file. The activities are classified into 26 activity types as listed in the above table.

The sample included 10,048 individuals. There are a total number of 129,188 activities in the Portland area in the two-day diary. A sub-sample of 2,450 households was drawn with all households headed by opposite sex adult couples. The data involving only two-member households were considered in the analysis. There are 1,273 two-member households in the sub-sample. The starting and ending time of the travel and the activity were converted from 12-hour timing to military timing for both the days of the survey. The activity diaries of the identified couples were processed for the first travel day giving the schedule of activities for all the individuals in the household. There are 64,713 activities listed in the raw data file for the first travel day for all households. The first day of the activity diary begins at 3:00 A.M. The activities listed for day one were given for a period of 24 hours ending at 3 A.M. the following day. All vehicles available to household members are recorded, including their year, make, model and mileage. The vehicle used for each trip is recorded. The beginning and ending odometer readings for the vehicles are also recorded in the survey. The household information available comprises of household size, household income, type of dwelling unit and the number and type of available vehicles. The survey also provides person-level data including age, gender, relation, employment status, occupation, student status and driver license status.

The activity file is then sorted for activities belonging to individuals of 2 member households. The activity locations with x and y coordinates listed in the geocode file are matched to the different activities of the household by the unique identification number of the activity. The unique id includes the sample number, person number, day number and activity number. The activities lacking geocode information were discarded for further analysis. The duration of the activity and travel were computed from the given data for each activity. These values of the duration were represented in hours.

The home locations in the sub-sample were determined from the geocode data and written to a home file. The zeroth activity representing the home location was introduced for all individuals in the activity file with an activity starting time of 3 A.M. The activity ending time is either the starting time of the first activity (if the activity does not involve travel) or the starting time of travel of the first activity (if the activity requires travel). This would ensure the starting time of the activity diary for all individuals to be set at 3 A.M.

The activities requiring transit trips were then listed in a separate file. The transit trips include trips by MAX (Portland Light Rail System), School bus, Public Bus and bicycle. The households having transit trips were not considered further in the analysis. Thus the sub-sample now consisted of households having automobile trips and walk trips only. The data was further reduced to households having only automobile trips by identifying households having walk trips and removing them from the sub-sample. This was done because of the availability of travel times for the automobile trips only. It is difficult to specify the travel times of walk trips for all the individuals in the Portland network. The activities considered in the refined analysis are all out of home activities and all meals activities at home. The non-meal activity types at home are not considered because they can be performed at any time without requiring a vehicle. The focus is on activities that require travel and the most common activity (meals activity).

The cumulative number of activities for the household was also calculated for determining the total number of activities of the household having geocoded information. The number of activities per person was thus computed. The activity relating to the latest return home trip was listed for each individual in the household in a separate file. This activity is either the last activity done by the individual at home if the activity requires travel to home or the last meals activity at home. The total travel time for each individual in the household was computed from the activity data. It is observed that an individual travels for sixty minutes per day on an average in the Portland area. Zahavi et al. (1981) advocated that daily traveling was dependent on people's time and money resources. They supposed that people had a fixed amount of time and money per day for traveling purposes. They had proposed a stable travel time budget. This concept is supported by travel surveys that give average daily travel times of around seventy minutes per day. The possible reason for a lower average daily travel time in the Portland area could be due to the missing geocode coordinates for trips outside of the Portland network. The number of licensed drivers in the household was computed from the person data. This is necessary for further analysis. There are a total of 774 households in the final sub-sample. The number of activities on the first travel day in the sub-sample is a total of 4,738 activities with geocode information.

4.4.1 Activity Starting and Ending Times

The average activity starting and ending times are computed for the whole sample. The activities with geocode information were only considered. There are 91,758 activities with geocode coordinates associated with them. The activities were categorized based on their activity types. The histograms were plotted for the activity starting time, activity ending time and the duration of the activity. This was done for each activity type. The meals activity was further classified as breakfast, lunch and dinner. This classification was made based on the histogram for the meals activity.

Breakfast - Meals activity before 10 A.M.
Lunch - Meals activity between 10 A.M. and 3 P.M.
Dinner - Meals activity after 3 P.M.

The work and school activities are considered to be fixed type activities. These activities cannot be rescheduled and will be done at the same time as reported in the sample. The other activity types are considered to be flex type activities and can be performed within the time window for these activities. The time windows will be described later. The mean starting time and the mean ending time of the activities for all the flex type activities were determined from the histograms of the respective activity types. The following table lists the data for the flex type activities.

Activity Type	Mean Starting Time	Mean Ending Time
Meals - Breakfast	7.47	8.4
Meals - Lunch	12.21	13.03
Meals - Dinner	18.13	19.1
Work-related	13.5	15.4
Shopping (General)	14.8	15.5
Shopping (Major)	14.4	15.4
Personal Services	12.9	14.1
Medical Care	12.3	13.7
Professional Services	14.3	15.0
Household or personal business	13.8	14.7
Household Maintenance	13.6	15.7
Household Obligations	14.9	16.6
Pick-up or drop-off passengers	13.4	13.6
Visiting	16.0	17.8
Casual Entertaining	17.7	20.1
Formal Entertaining	17.4	20.3
Culture	17.5	19.7
Religion / Civil Services	14.4	16.1
Civic	14.3	16.5
Volunteer Work	13.6	15.7
Amusements (at-home)	17.0	19.2
Amusements (out-of-home)	15.8	18.0
Hobbies	14.9	17.0
Exercise/Athletics	14.0	15.6
Rest and relaxation	15.2	17.4
Spectator athletic events	17.6	19.9
Incidental trip	18.6	19.1
Tag along trip	13.8	14.4

Figures 4.1 through 4.9 present the histograms of the duration, starting time and ending time of the meals, work and shopping activities.

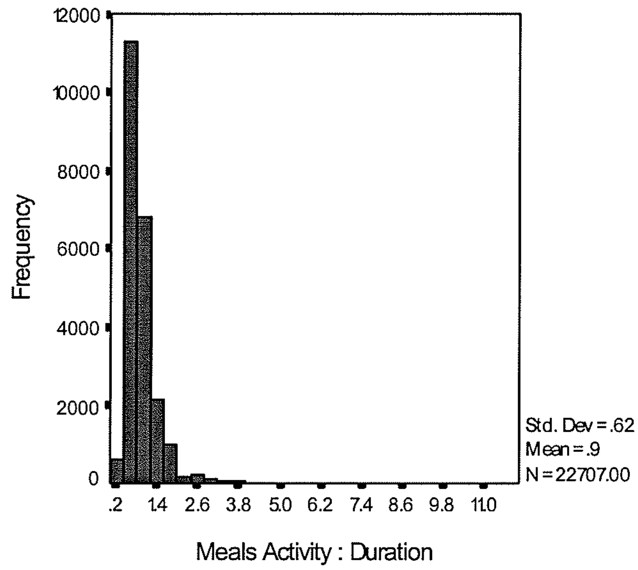


Figure 4.1: Histogram of the activity duration of the meals activity

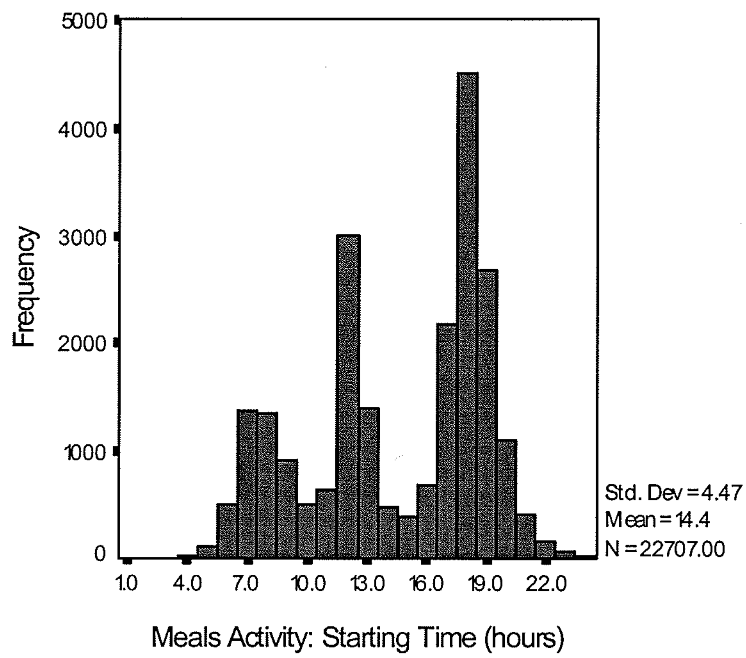


Figure 4.2: Histogram of the starting time of the meals activity

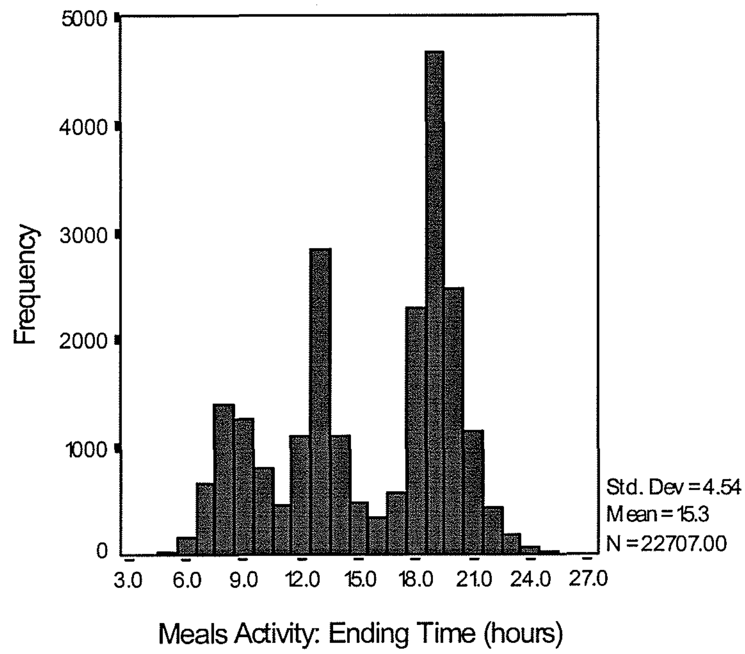


Figure 4.3: Histogram of the ending time of the meals activity

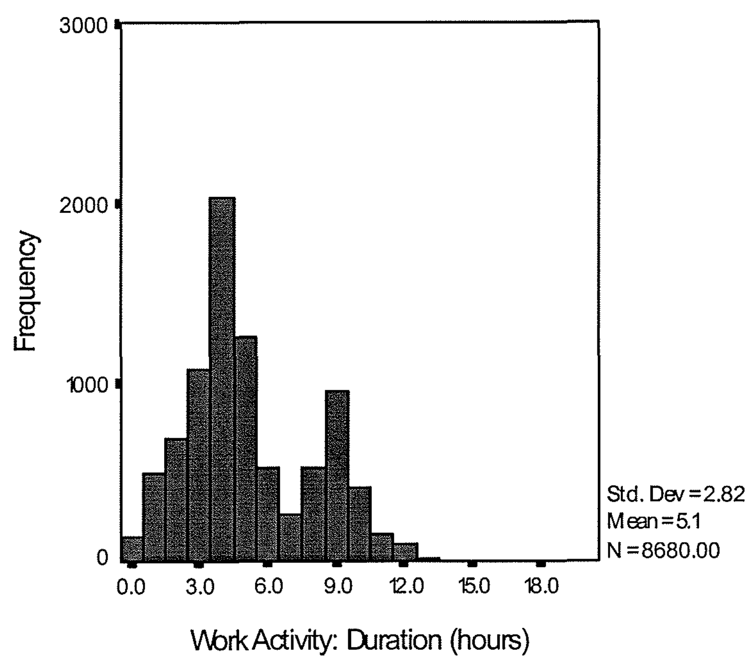


Figure 4.4: Histogram of the duration of work activity

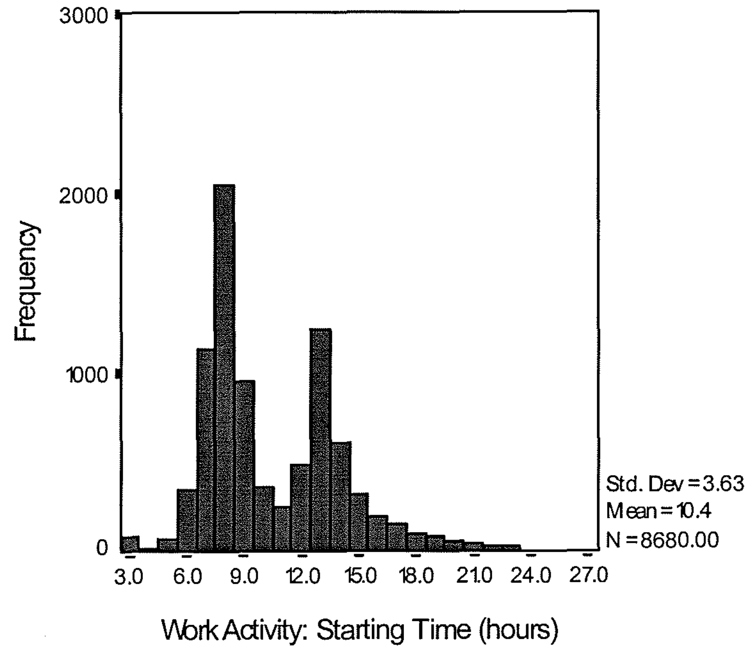


Figure 4.5: Histogram of the starting time of work activity

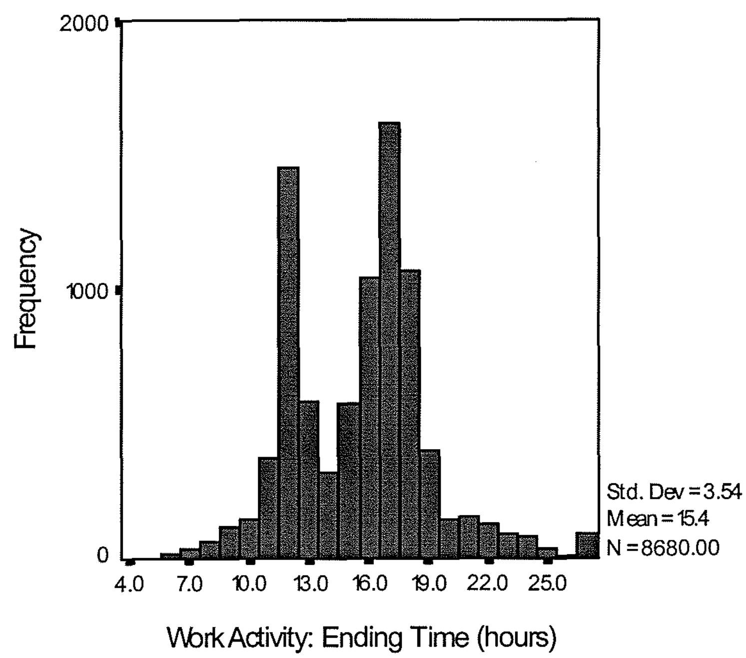


Figure 4.6: Histogram of the ending time of work activity

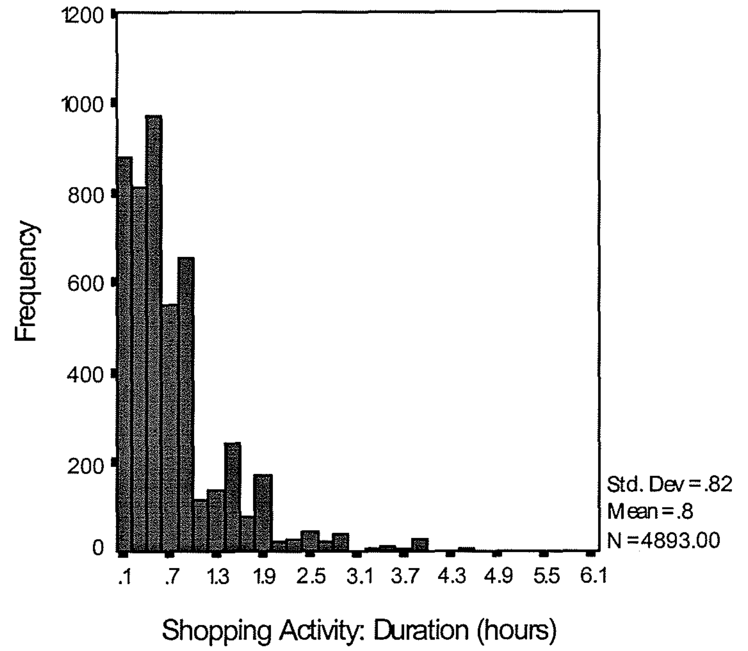


Figure 4.7: Histogram of the duration of shopping activity

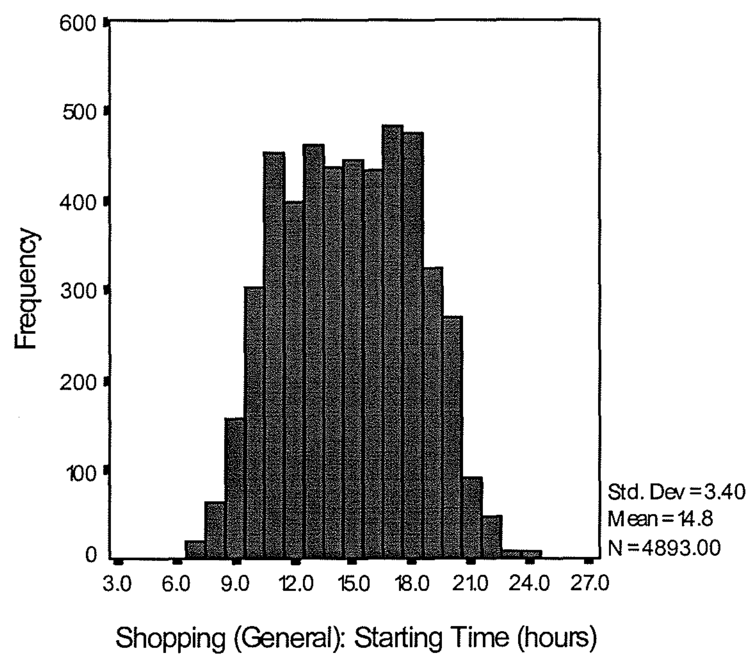


Figure 4.8: Histogram of the starting time of shopping activity

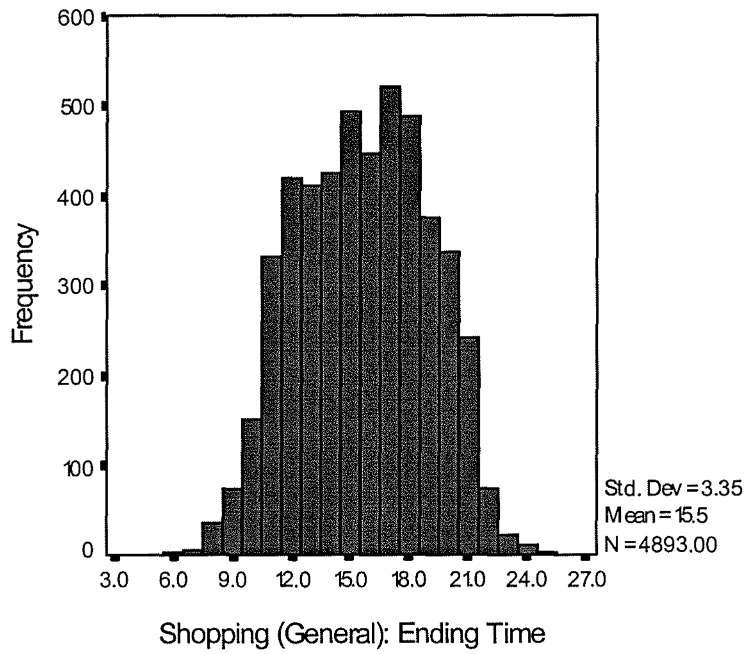


Figure 4.9: Histogram of the ending time of shopping activity

4.4.2 Trip Chains

The trip chaining of activities can be defined as a tour consisting of a series of movements made between successive destination choices over some period of time. This concept of a tour includes complex relations and interdependence of timing, duration, location, frequency and sequencing of activities, nature and number of stops, and trip length. Thus there are complexities involved in the travel pattern of individuals. Using the Portland survey data, the trip chains were generated for all the individuals in the sub-sample. The number of trip chains and the number of activities in a chain for each individual were thus determined from the trip chain data. The chain types were classified into different categories. The trip chain also had information on the number of activities and total duration for each chain type. The chain types were based on non-home activities. It is observed that the average number of activities in a chain (trip length) for the whole sample is 4 activities.

4.4.3 Travel Time Matrices

The Geographic Information Systems (GIS) has been used as an organizing and analytical framework for the collected data in the Portland area. The GIS land-use / network database for the Portland area was provided by Portland Metro. The street address map of the Portland network is based on an enhanced version of the Census Bureau's TIGER files. These files have been edited and inaccuracies were removed. The respondents reported the addresses of all activities performed by them. The activity locations were then geocoded by address matching using the reported data. The survey administrators thus recorded the locations of activities on the state plane of Portland. There is a possibility for errors in address matching due to misreporting of addresses by the respondents. Thus there are activities with missing geocode information in the data. The activity locations were substituted with landmarks or nearest intersections in some cases. The missing geocode information for activity locations could also be due to the activity being performed outside the Portland network area.

The shortest path travel times between all activity locations of a household were generated for all the households in the sub-sample using TRANSCAD. The network is defined as a set of nodes and links. Every node and link in the network has an ID and any number of attributes. The node attributes are x and y coordinates and node centroid number. The coordinates are state plane feet converted to miles. The link attributes are from node, to node, length, modes allowed, link type, number of lanes, midday 1 hour auto time, P.M. 2 hour auto time and link capacity. The activity locations were approximated to the nearest node in the street network. The ID of the node represents the unique ID of the activity. The home location is inserted for all households which do not have an activity at home in the sub-sample.

The travel times were generated between all the nodes of a particular household. The shortest path is the one that minimizes the total value of the midday 1-hour auto time between an origin and a destination. The travel times between all activity locations of a household are determined by matching the unique ID to the node ID and getting the travel time between the nodes. The travel times for all the trips in a particular household are represented as a matrix. The values are converted from minutes to hours.

4.4.4 Person Activity Exclusions

The person activity exclusions include the activities that are personal to an individual and cannot be performed by the other members in the household. These activities are meals, work, work-related, medical care, exercise / athletics and rest and relaxation activity. This is required for the scheduling of activities within the household.

4.4.5 Open Windows for Activities

The open windows for activities were determined based on the following conditions.

- The mean open window using the whole sample for all of the activities including the activity corresponding to the depot (final return to home after the completion of all activities) is 9.40 hours.
- The open window for the zeroth activity (location at home) and the (2n + 1)th activity (where n is the total number of activities in the household) is the minimum of the mean open window and the activity starting time if the activity does not require travel.
- The open window for the zeroth activity and the (2n + 1)th activity is the minimum of the mean open window and the travel starting time if the activity requires travel.
- The open windows for work and school activities are fixed in time and are equivalent to the reported starting time of the respective activities.
- In the case of a meals activity between two work activities, the meals activity is also fixed in time and the open window is equivalent to the reported starting time of the meals activity.
- The open window for the meals activity is the minimum of the average open window for the corresponding meals (depending on breakfast, lunch and dinner) and the reported starting time of the meals activity.
- The open window for all other activities is the minimum of the average open window for that activity type and the reported starting time of that activity.
- The open window for the return home activities (n+1 to 2n) is equivalent to the open window for the corresponding activity of the household plus the duration of the activity

4.4.6 Close Windows for Activities

The close window of any activity is the latest time at which any individual can perform the activity. The close windows for activities were determined based on the following conditions.

- The close window for the zeroth activity is 27.00 hrs (3 A.M. the following day).
- The mean close window using the whole sample for all the activities is 18.10 hours.
- The close windows for work and school activities are fixed in time and are equivalent to the reported starting time of the respective activities plus 0.05 hours. This is to prevent errors in infeasibility in the solution due to the same value for the open window and the close window.
- The close window for a meals activity between 2 work activities is also fixed in time and the close window is equivalent to the reported starting time of the meals activity plus 0.05 hours.
- The close window for the meals activity is the maximum of the average close window for the corresponding meals (depending on breakfast, lunch and dinner) minus the activity duration and the reported starting time of the meals activity plus 0.05 hours.
- The close window for all other activities is the maximum of the average close window for that activity type minus the activity duration and the reported starting time of that activity plus 0.05 hours.
- The close window for the return home activities (n+1 to 2n) is equivalent to either the latest time an individual in the household can return home if the return home activity is a non-meals activity or the ending time of the meals (dinner) activity at home. The close window is updated if a meals activity of an individual ends at an earlier time corresponding to the individual's latest return home trip.

4.4.7 Earliest Departure

The earliest departure from home is the earliest time an individual in the household can leave the home location based on their reported activity schedule. The mean value of the earliest departure from home is 9.40 hours. The earliest departure from home is equivalent to either the starting time of travel for the first activity if the activity is a non-home activity or the starting time of the activity if the activity is at home.

4.4.8 Latest Return

The latest return to home is the latest time an individual can perform all his activities and return to the depot. This limit is given for each individual in the household and is equivalent to either the ending time of the last activity of the individual if the activity does not require travel or the ending time of travel if the activity involves travel to home. This latest return is then updated based on the latest return home trip of each individual. The latest return trip is different because it can result in a non-meals activity at home (which is not considered in the list of activities of a household). The latest return is changed if the value is less than the maximum of the mean close window of the activity based on the activity type and the ending time of the activity (for meals activity) or ending time of travel (for non-meals activity).

4.4.9 Travel Costs

The travel costs of a household is represented in the form of a matrix. The costs for each trip are the number of miles traveled from the origin to the destination of the trip. This is computed from the city block distance between the two locations of any trip. The average speed for any trip is also computed from the travel distance and the calculated value of the network travel time.

5. GAMS AND CPLEX

5.1 GAMS

GAMS (General Algebraic Modeling System) was developed by the World Bank. The design of GAMS has incorporated ideas related to relational database theory and mathematical programming and has attempted to combine these ideas to satisfy the requirements of strategic modelers. Relational database theory provides a structured framework for developing general data organization and transformation capabilities. Mathematical programming is used to describe a problem and present the different methods for solving it. A GAMS model representation is concise and makes the optimum use of the elegance of the mathematical representation. The information needed to understand the model is in one document. The GAMS software includes various modules that deal with mathematical programming formulations that are linear, integer, mixed-integer, non-linear, binary and different combinations of the above. The data transformations are specified briefly and algebraically. The GAMS system is designed to enable the models to be solved on different types of computers with no change.

The basic components of a GAMS model are

Inputs:

- Sets: Declaration and Assignment of members
- Data: Declaration and Assignment of values
- Variables: Declaration and Assignment of type
- Assignment of bounds and/or initial values
- Equations: Declaration and Definition
- Model and Solve statements
- Display statement

Outputs:

- Echo Print
- Equation Listings
- Reference Maps
- Status Reports
- Results

The advantages of using GAMS are that it describes an optimization model to a computer in a simple way. The algebraic description of the problem has generality and is reusable in the case of the same or related problems. The versatility of algebraic modeling languages like GAMS is visible in the creation of inequalities and equations that are used in developing the mixed-integer linear programming formulation. GAMS supports a number of solvers, including CPLEX, the solver used in this analysis..

5.2 GAMS/CPLEX

GAMS/CPLEX is a mixed integer solver within GAMS that allows users to combine high level modeling capabilities of GAMS with the power of CPLEX optimizers. CPLEX optimizers are designed to solve large, difficult problems quickly and with minimum user intervention. This solver accepts both binary integer and general integer variables. Continuous variables are also declared. (In the case of the HAPP formulation, the integer variables are binary in nature.)

The MIPOPT command is used to invoke the Mixed Integer Solver, which employs a branch-and-bound algorithm. A problem may be a mixed integer problem, even if all of its variables are continuous, if its type has been changed to mixed integer.

In the branch-and-bound method, a series of LP subproblems is solved. A tree of subproblems is built; each subproblem is a node of the tree. The root node is the LP relaxation of the original MIP problem. If the solution of the relaxation has fractional-valued integer variables, a fractional variable is chosen for branching, and two new subproblems are generated, each with more restrictive bounds for the branching variable. In the case of binary variables, one node will have the variable fixed at zero, the other node will have it fixed at one. The subproblems can result in an all-integer solution, an infeasible problem or another fractional solution. If the solution is fractional, the process is repeated. Nodes are *cut-off* when the objective function value of the subproblem associated with the node becomes worse than the cutoff value. The cutoff value is either a user-specified value or the value of the best integer solution.

The node is said to be *fathomed* if the subproblem is infeasible, or has an objective function value worse than the cutoff, or gives an integer solution. Once an integer solution is found (an incumbent), its objective function value becomes the new cutoff value, and all subproblems with objective functions no better than the incumbent are pruned from the tree. This is done because the optimal objective function values of the subproblems of a given node can never improve with continued variable bound tightening.

The path that CPLEX takes through the branch-and-bound tree is determined by a number of user inputs. Priority orders provide a very powerful mechanism for adding user-supplied problem-specific direction to the branching process. Also, the branching direction preferences (globally or by specific variable) can improve branching based on your specific knowledge of a problem. The use of the MIPOPT command results in the application of the MIP Presolve and Aggregator to reduce the problem. The size of the integer program is reduced in order to strengthen the initial linear programming relaxation and reduce the overall size of the mixed integer program. Bound strengthening can tighten bounds on variables. Coefficient reduction usually helps strengthen the linear programming relaxation and reduce the number of nodes in the branch-and-bound tree, but it can also lead to an increase in the amount of time necessary to solve the linear programs at each node, enough to offset the benefit of fewer nodes.

Cuts are inequalities added to a problem that restrict or cut off non-integral solutions. The addition of cuts usually reduces the number of branches that are needed to solve a mixed integer problem. There are two heuristics available to find integer solutions. The first heuristic is applied at the root node and it fixes variables close to integral values and then proceeds with a restricted branch-and-bound. The second heuristic is applied at nodes during the regular branch-and-bound.

CPLEX reports its progress as the problem is solved. The optimization will terminate when a time limit or an iteration limit is reached. MIP optimization also terminates when an integer solution is reached and all nodes have been processed. There is significant information available about the current branch-and-bound tree when a MIP optimization terminates prior to optimal values.

5.3 Use of the Solver in the Analysis

The HAPP model formulation for emissions reduction, as applied to the activity agendas of a sample of households drawn from the Portland database, was solved using GAMS/CPLEX. The optimal solutions for the different cases of the HAPP formulation were obtained by the GAMS software on a Pentium II 300 with 64 MB RAM. The actual GAMS input files were prepared from the sample's activity diaries using computer code developed specifically to create the input files in the GAMS context language automatically for each observation in the data set. The problem is very complex with tens of thousands of constraints and thousands of variables even for a simple case of a few activities. Thus, the dimensionality of the problem increases tremendously with increase in the number of activities and the number of vehicles in the household; for this reason, analysis was attempted only on households having fewer than ten out-of-home activities.

6. SAMPLE CHARACTERISTICS

The sample characteristics are presented in this section. The reduced sample contains 101 households. They are categorized into 86 two-member households and 15 three-member households. These households were selected based on complete data for the person, vehicle characteristics, activities of individuals, and travel time matrix; they also are restricted to households in which all travel was accomplished using a personal vehicle. The vehicle emissions are modeled only for licensed individuals in the household as it is assumed that the unlicensed individuals do not directly influence the activity schedule and are only involved in pick-up or drop-off activities within the household. The activities considered are out-of-home activities and in-home meals for the first day of the two-day activity diary. The number of activities varies within a household. The frequency distribution of all the selected activities in the household for the reduced sample is given in Table 6.2. The mean number of activities is 6.56 with a standard deviation of 2.23.

Table 6.1: Frequency distribution of the number of individuals in the household

Household Size	Frequency	Percent
2.00	86	85.1
3.00	15	14.9
Total	101	100.0

Only households having fewer than 10 activities for licensed individuals are considered in the final analysis. This is done to take into account the complexity of the problem with increase in the number of activities. The HAPP model formulation limits the total number of activities to 20 and the number of vehicles to 4.

Table 6.2: Frequency distribution of the number of activities in the household

Number of Activities	Frequency	Percent
2.00	4	4.0
3.00	5	5.0
4.00	8	7.9
5.00	14	13.9
6.00	20	19.8
7.00	16	15.8
8.00	17	16.8
9.00	7	6.9
10.00	5	5.0
11.00	3	3.0
12.00	2	2.0
Total	101	100.0

Table 6.3: Descriptive statistics of the reduced sample

	Minimum	Maximum	Mean	Std. Deviation
Number of licensed individuals	1.00	3.00	1.95	.33
Vehicles	1.00	4.00	2.12	.52
Activities of licensed individuals	2.00	9.00	5.84	1.88
Activities in a household	2.00	12.00	6.56	2.23

Table 6.4: Frequency distribution of the number of activities of licensed individuals in the household

Number of Activities	Frequency	Percent
2.00	6	5.9
3.00	8	7.9
4.00	10	9.9
5.00	16	15.8
6.00	19	18.8
7.00	21	20.8
8.00	16	15.8
9.00	5	5.0
Total	101	100.0

This total number of activities also includes the origin of the activity diary (the home location), the return home activity for each activity and the depot. The mean number of activities in the reduced sample is 5.84 with a standard deviation of 1.87. There are a sizeable number of households with 2 vehicles in the selected sample. It is noted that 75 % of the households have 2 vehicles and about 93% of the households have more than 1 vehicle. This can be attributed to the fact that households with two or more individuals prefer to have more than one vehicle. The mean number of vehicles is 2.12 per household with a standard deviation of 0.52.

Table 6.5: Frequency distribution of the number of vehicles in the household

Number of Vehicles	Frequency	Percent
1.00	7	6.9
2.00	76	75.2
3.00	17	16.8
4.00	1	1.0
Total	101	100.0

Table 6.6: Frequency distribution of the number of licensed individuals in a household

Number of licensed individuals	Frequency	Percent
1.00	8	7.9
2.00	90	89.1
3.00	3	3.0
Total	101	100.0

As the reduced sample is restrictive with regard to variation in the household size, it is noted that the number of licensed individuals also does not vary much. The individuals in the two-member households are opposite sex adult couples and those in the three-member households are opposite sex adult couples with a child or a person with or without a driver's license. The mean number of licensed individuals is 1.95 with a standard deviation of 0.33. There are 12 cases with a child in the household. There are 217 individuals in the reduced sample. The mean total day 1-travel time of those individuals who traveled in the household is 0.95 hours. This is in comparison to 1 hour for the whole sample.

Table 6.7: Descriptive statistics of the travel time per individual in the household

Number of persons	Minimum	Maximum	Mean	Std. Deviation
217	0.00	3.47	0.95	0.59

The standard deviation for the travel times is high. This signifies a greater variation in travel times in the reduced sample. There are 22 instances of individuals not traveling on the first day of their activity diary.

Table 6.8: Descriptive statistics of the ages of individuals

Number of valid cases	Minimum	Maximum	Mean	Std. Deviation
206	1.00	84.00	49.98	17.52

The mean age of individuals in the sample is almost 50 years with a standard deviation of 17.51. There are 8 cases of missing data and 3 cases with zero age. The mean age of individuals in the reduced sample varies between two-member and three-member households. It is 55.20 years for two-member households and 29.62 for three-member households. This variation is due to the presence of children and lesser number of retired people in three-member households. The percentage of licensed individuals also ranges from 95.3% for two-member households to 73.3% for three-member households. This is also due to the presence of children. It is interesting to note that the percentage of retired people in two-member households is as high as 30.8% as compared to 4.4% for three-member households. The percentage of fully employed people is 48.8% for two-member households and 51.1% for three –member households. The activities often engaged in are the meals, work and shopping activities. The statistics related to the activities are presented in Tables 6.11 and 6.12. The average travel time is observed to be 0.95 hours for two-member households and 0.97 hours for three-member households with a standard deviation of around 0.60 hours. The activity duration has a large variation as it includes activities ranging from a pick-up and drop-off activity to a work activity of a long duration. About 62% of the activities required travel in the reduced sample. The average travel time per activity in cases where travel was required is around 0.30 hours.

Table 6.9: Age variation between two-member and three-member households

Household Size	Average	Minimum	Maximum	Standard Deviation
2	55.20	23	84	13.62
3	29.62	1	67	17.37

Table 6.10: Person characteristics

Characteristic	2-member households	3-member households
Sample Size	172	45
Male (%)	50	46.7
Licensed individuals (%)	95.3	73.3
Fully employed individuals (%)	48.8	51.1
Retired individuals (%)	30.8	4.4

Table 6.11: Descriptive statistics of the activity types in the reduced sample

Activity Type	2-member households	3-member households
Meals	227 (44.2%)	42 (42%)
Work	89 (17.3%)	27 (27%)
Shopping (General)	75 (14.6%)	11 (11%)
Other	123 (23.9%)	20 (20%)
Total number of activities	514	100

Table 6.12: Activity characteristics for the reduced sample

Characteristic	2-member households	3-member
Number of activities	514	100
Average day-1 travel time per individual (hours) *	0.95 (0.60)	0.97 (0.58)
Activity Duration (hours) *	2.09 (2.49)	2.46 (2.64)
Travel required for an activity	323 (62.8%)	61 (61%)
Average travel time per activity when travel required (hours) *	0.29 (0.20)	0.30 (0.18)

* Standard deviation is given in brackets

The histograms of activity duration for the meals, work and shopping activities are given below. It is observed that the mean duration of a meals activity is 1 hour and the corresponding mean duration of a work and shopping activity are 6 hours and 0.8 hours respectively. The mean travel time to an activity is 0.18 hours. This figure is lesser than those for the average travel time per activity when travel is required because it includes all activities.

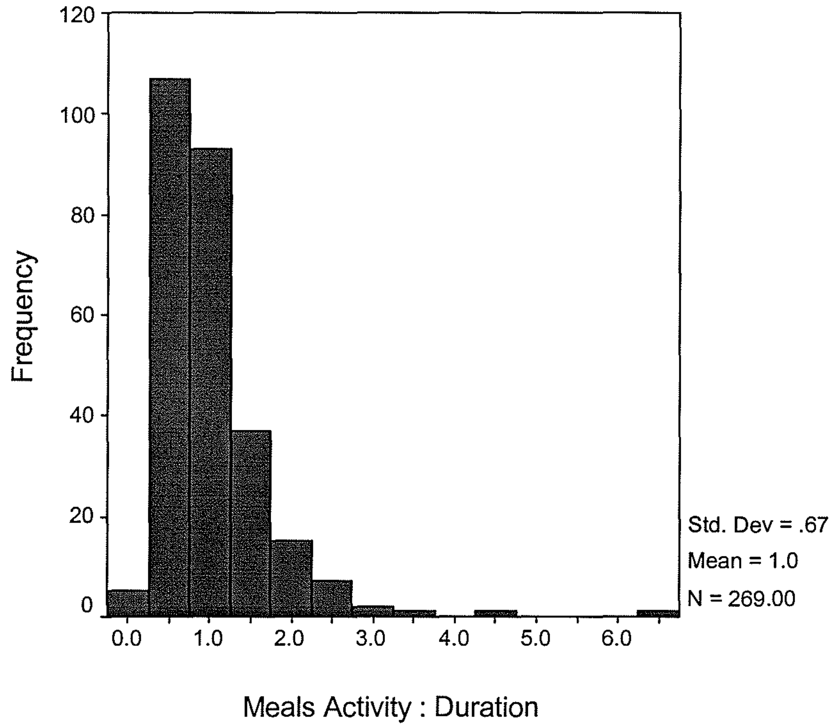


Figure 6.1: Histogram of the duration of meals activity for the reduced sample

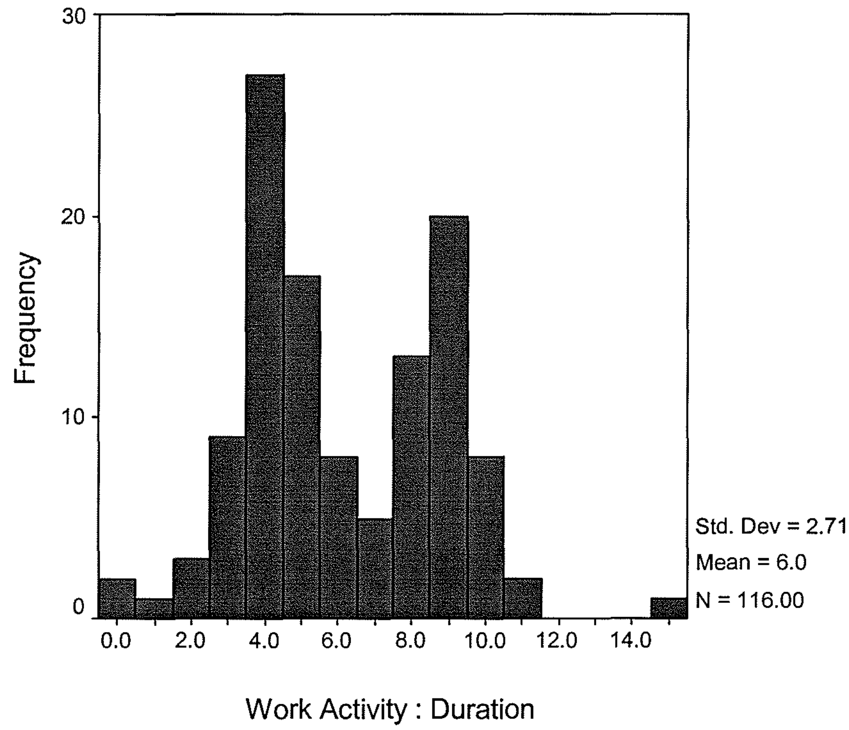


Figure 6.2: Histogram of the duration of work activity for the reduced sample

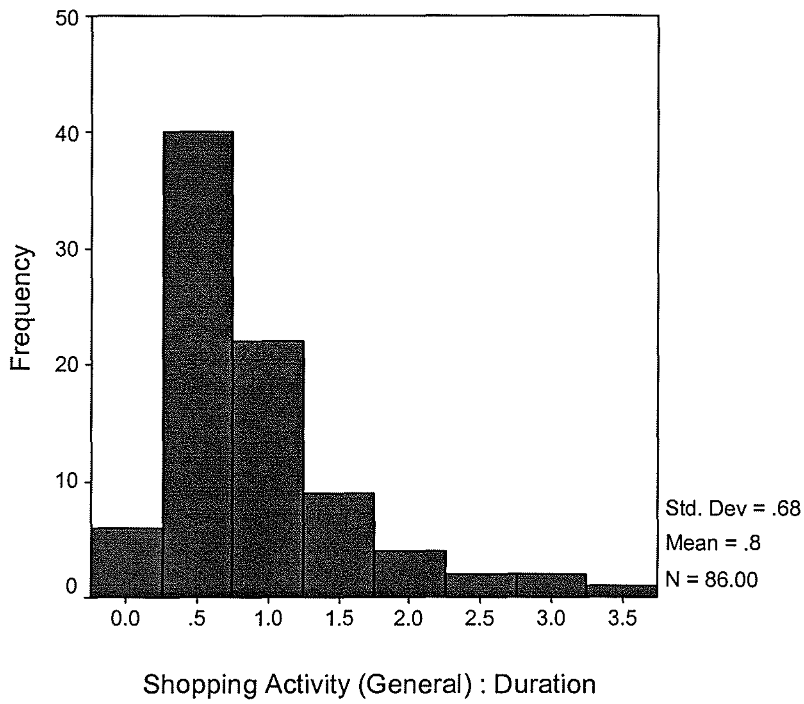


Figure 6.3: Histogram of the duration of shopping activity for the reduced sample

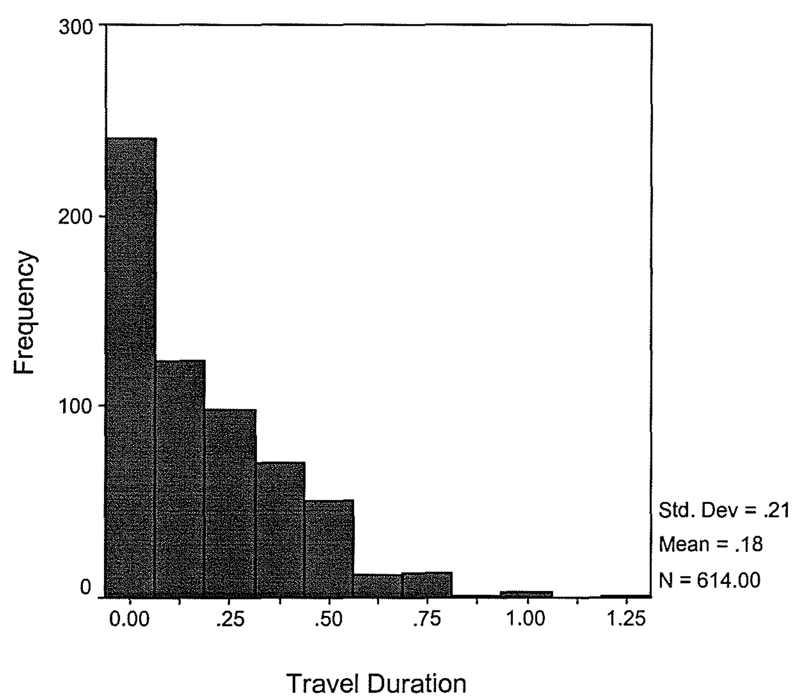


Figure 6.4: Histogram of the travel duration

The reduced sample is further divided into 2 groups: households with children and households without children. The statistics are presented in the tables below.

Table 6.13: Descriptive statistics of the activity types in the reduced sample

Activity Type	Households without children	Households with children
Meals	238 (44.2%)	31 (41.3%)
Work	97 (18.0%)	19 (25.3%)
Shopping (General)	77 (14.3%)	9 (12.0%)
Other	127 (23.5%)	16 (21.4%)
Total number of activities	539	75

Table 6.14: Activity characteristics for the selected group

Characteristic	Households without children	Households with children
Number of activities	539	75
Average day-1 travel time per individual (hours) *	0.95 (0.59)	0.98 (0.60)
Activity Duration (hours) *	2.14 (2.53)	2.72 (2.71)
Travel required for an activity	337 (62.5%)	47 (62.7%)
Average travel time per activity when travel required (hours) *	0.29 (0.20)	0.32 (0.18)

* Standard deviation is given in brackets

The average travel time per individual is almost equal in the sub-groups. There are 12 households with children in the sample. The mean activity duration for households with children is higher than that for households without children. This can be attributed to the fact that there are no retired individuals in the former category and that the activities of the children might be of a longer duration. There is also a possibility that the retired individuals might be engaged in activities of shorter duration and shorter trip distances. The percentage of retired individuals in households without children is 30.2%. This is an important statistic as the activity patterns of retired individuals seems to be different from those of individuals with children. The mean age of individuals in households with children is 23.9 years with a standard deviation of 14.6 years. This is in comparison to 54.6 years for households without children. The mean age is calculated only for valid data.

Table 6.15: Person characteristics for the selected group

Characteristic	Households without children	Households with children
Sample Size	181	36
Average age of individuals (years)	23.9	54.6
Licensed individuals (%)	95.3	73.3
Fully employed individuals (%)	48.8	51.1
Retired individuals (%)	30.2	0.0

7. RESULTS

7.1 Introduction

The HAPP model is used to evaluate the benefits in vehicle emissions reduction based on optimal scheduling of the activities performed by individuals in a household. The TCMs that are considered are the reduction of travel through either substitution or more efficient chaining of trips and the substitution of ridesharing among family members as an alternative to single-occupant vehicle travel. There has been consensus that effective scheduling of trips through trip chaining offers potential to significantly reduce both vehicle emissions and energy consumption. Trip chaining behavior principally affects the non-work travel ranging from trips associated with shopping to maintenance activities. There is a notable contribution of non-work travel to travel demand. These trips are of shorter duration and involve cold starts and frequent changes in speed, thus increasing the vehicle emissions. The effectiveness of TCMs in addressing scenarios pertaining to reduction of vehicle emissions and energy consumption and the potential for regulatory measures to alter travel behavior are unknown. This may be attributed to conventional transportation models being based on single-trip analysis and the inability of such models to take into account the connections and interdependencies of the collection of activities requiring travel in a household.

An application of the HAPP model is employed to remove the problems of traditional modeling approaches in the evaluation of potential improvements in vehicle emissions that may be possible through adjustments in travel behavior. The observed vehicle emissions for each household are calculated based on the reported schedule of activities of the individuals in the household. The optimal activity patterns are then generated by the HAPP model with an objective to minimize CO emissions. (It is assumed that CO emissions are the most important constituent of vehicle emissions.) The potential benefits in vehicle emissions that can be achieved by better scheduling of activities in a household can be studied using this application of the model. The analysis considers three different scenarios:

- Base Case Optimal Solution without Ridesharing
- Optimal Solution with Ridesharing
- Optimal Solution with Present-day Technology and Ridesharing

Under these scenarios, the optimal CO emissions obtained using the HAPP model are compared to the observed CO emissions to determine the absolute and percentage improvement achieved. The third scenario above simulates the use of present-day vehicle technology by replacing the whole fleet in the sample by new vehicles (i.e., vehicles with 1998 emissions characteristics) with the mileage being the same as the actual/reported vehicles in the household; this is to evaluate the benefits that could be achieved by technological means in conjunction with behavioral approaches. The first scenario (comparison of optimal vs observed CO emissions) is tested for 3 groups:

Group 1: Two-member and three-member households
Group 2: Households having two and three vehicles, respectively
Group 3: Households with and without children.

The results are compared within a sub-group to investigate the effect of the segmentation variables on the sub-group's results. The base case solution without carpooling, the base case solution with carpooling and the new vehicle technology scenario are then compared to each other to present the relative effects of vehicle technology and ridesharing among household members. In the case of the new vehicle scenario, the best solution for CO emissions, with or without ridesharing, is considered in the analysis. The results of the analysis are presented in the following sections.

7.2 Scenario 1

In this section, the optimal solution of the CO emissions from the HAPP model for travel without ridesharing is compared to the observed CO emissions in a household. This analysis is done for the reduced sample of 101 households. Figure 7.1 displays the percentage improvement in CO emissions for each household case. The x-axis is represented by the case number and is in an ordinal scale. The percentage improvement is negative for 14 sample cases. The reason for this occurrence is either the presence of ridesharing in the observed activity diary or the resource limit of the GAMS/CPLEX module being exceeded prior to the algorithm finding the optimal solution (i.e., the solution reported is known to be suboptimal). As the optimal solution does not include ridesharing, households in the sample who actually carpooled almost invariably have observed values of CO emissions that are less than the optimal value produced by the algorithm for the non-ridesharing case. The algorithm in such cases would force the household members to use two different vehicles from the same origin to reach a certain destination at the same time. This leads to an increase in the optimal CO emissions. In some cases in which the number of activities that the household completes is near the maximum number of activities permitted (nine, in this anlysis), the complexity of the problem and the computation time increases dramatically. The resource limit (time limit) is set for the GAMS/CPLEX software module. At this limit, the algorithm will terminate and the current (suboptimal) solution is passed on to GAMS. This might lead to worse results for the "optimal" solution than the observed. The optimal solution is close to the observed solution in several of cases that result in negative improvement of CO emissions. Table 7.1 displays the percentage of households having a certain percentage improvement in CO emissions. It is observed that the percentage improvement due to more efficient trip chaining of the activities in a household is quite substantial in some of the cases.

Table 7.1: Percentage improvement in CO emissions

% Improvement in CO emissions	% Households
Less than 0	13.86
0-10	25.74
10-20	5.94
20-30	9.90
30-40	9.90
40-50	8.91
50-60	5.94
60-70	7.92
70-80	5.94
80-90	4.95
90-100	0.99

It can be observed that the percentage of households having 0-10% improvement in CO emissions is close to 26%. The individuals in 19 households behaved optimally with

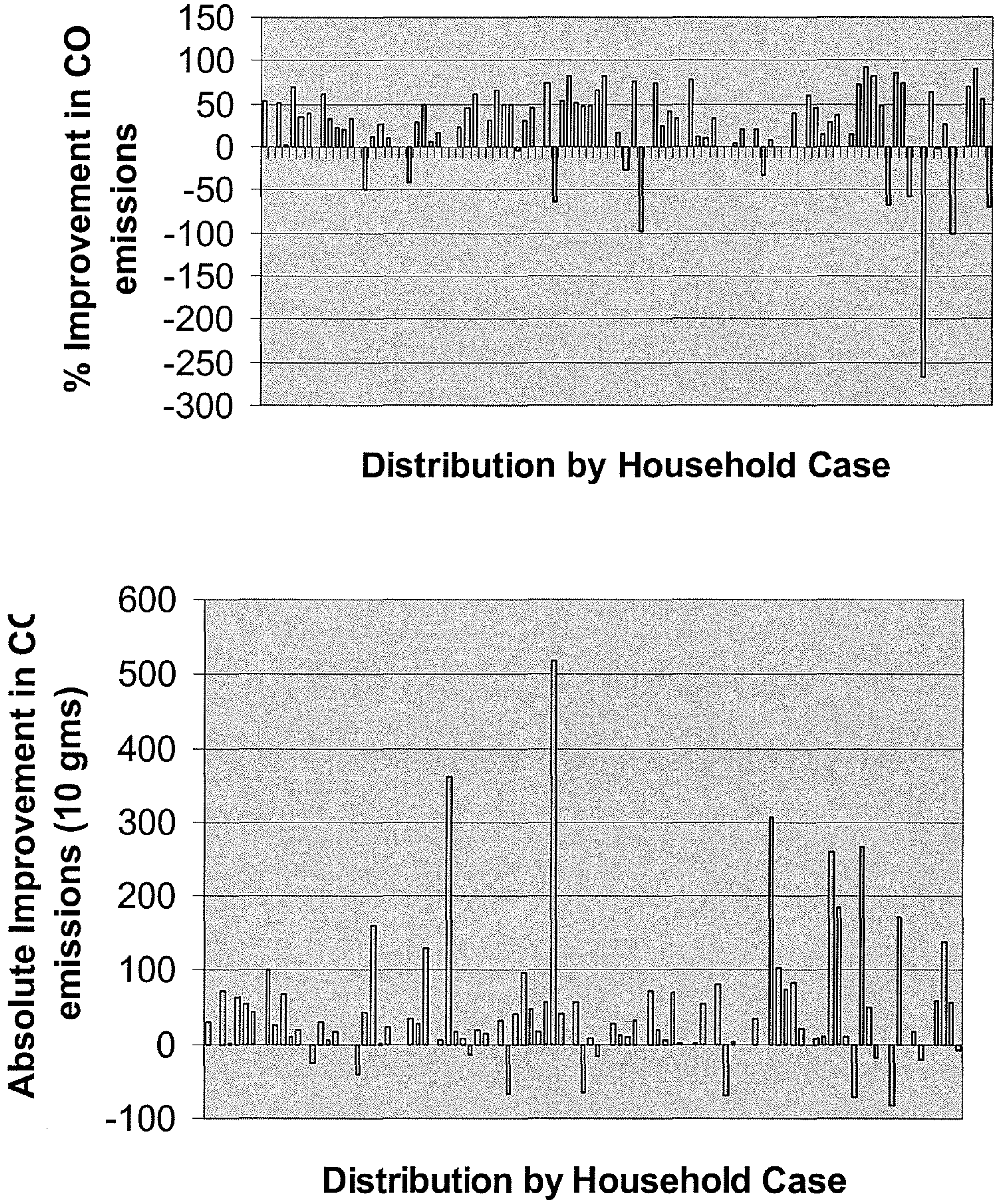


Figure 7.2: Representation of absolute improvement in CO emissions

respect to the objective of minimizing CO emissions, as the observed and the optimal values of CO emissions were equal. There was little improvement in some cases. Figure 7.2 represents the absolute improvement in CO emissions for the sample. It can be noted that the absolute improvement is significant in most of the cases. As mentioned earlier, there are some cases where the absolute improvement is negative due to ridesharing in the observed travel diary of the household. (The resource limit of GAMS/CPLEX was exceeded in several of cases.) The absolute improvement in CO emissions is represented in units of 10 gms of CO. Although these numbers have little intuitive appeal in their own right, it is instructive to compare the optimal CO emissions with the observed CO emissions. Figure 7.3 gives a scatter plot of the optimal CO emissions on the x-axis with the observed CO emissions on the y-axis. The points of the scatter plot on or above the 45º line have an improvement in the vehicle emissions of the household. The scatter plot also indicates that the observed CO emissions values are concentrated below the 100 level. The points to the left and away from the 45º line indicate relatively significant improvement in the CO emissions.

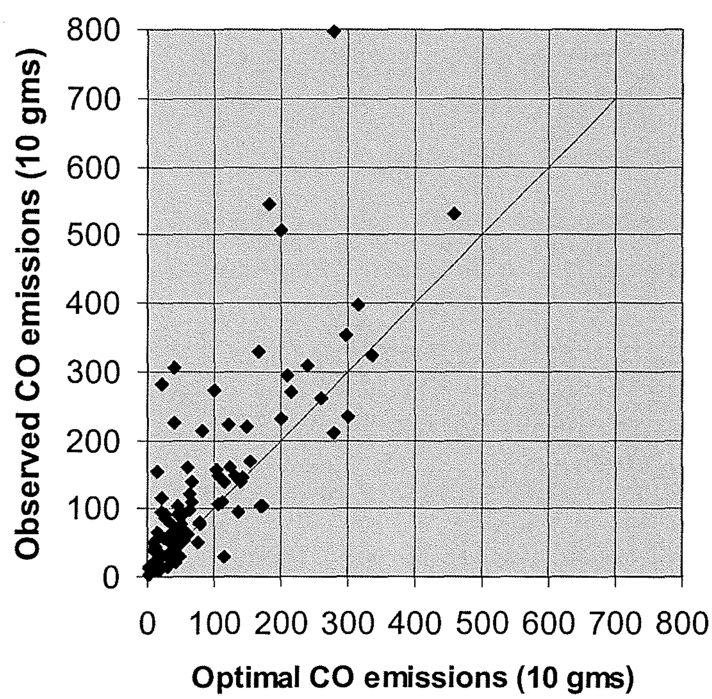


Figure 7.3: Observed vs optimal CO emissions

Figure 7.4 represents the variation of the percentage of households with respect to percentage improvement in CO emissions. The data corresponds to Table 1 and the bar chart representation of the results indicates that the two main categories are those having negative improvement and 0-10% improvement. Figure 7.5 represents the plot of the percentage of households with respect to the absolute improvement in CO emissions. The absolute improvement is less than 250 gms in 44% of the households. This implies that the difference between the optimal and the observed CO emissions is relatively small in a major portion of the reduced sample.

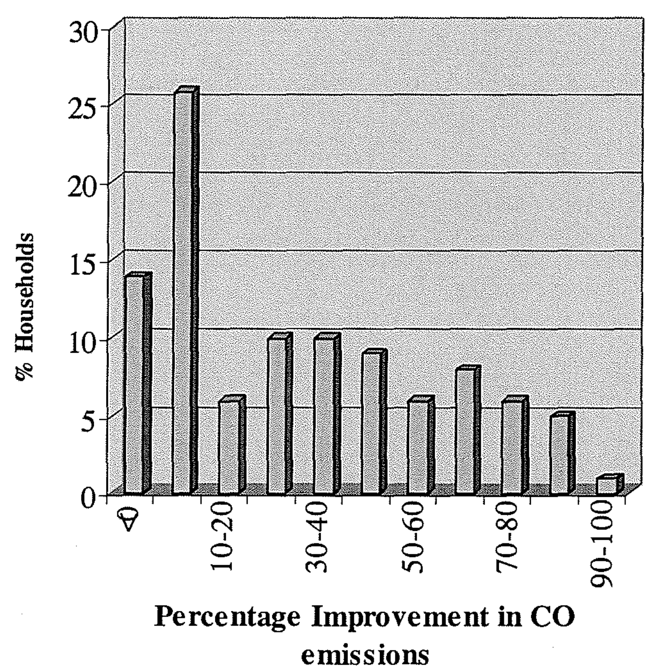


Figure 7.4: Percentage improvement in CO emissions

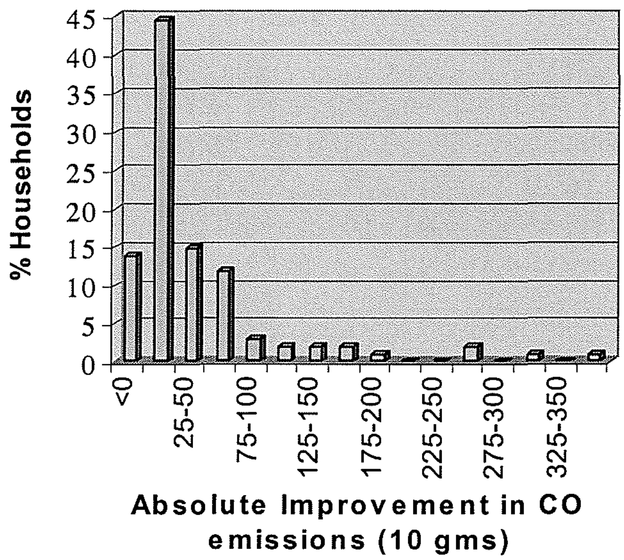


Figure 7.5: Absolute improvement in CO emissions

7.2.1 Group 1 Results: Comparison between Two-member and Three-member Households

The reduced sample is grouped further into two categories of two-member and three-member households respectively. The results of the two sub-groups are compared to illustrate the difference in the benefits achieved in the reduction of CO emissions. The sample size of three-member households is 15 and that of two-member households is 86. The scatter plot of the optimal versus the observed CO emissions for the three-member households indicate that the improvement achieved with optimal behavior as represented by the HAPP model is notable as most of the scatter points are to the left and away from the 45° line. This is in comparison to the presence of most scatter points close to the 45° line for two-member households. This implies that more benefit is achieved in the case of three-member households. There are also more cases of scatter points below the line for two-member households. This might be due to the presence of more two-member households with ridesharing in their travel diary. The scatter plots for two-member and three-member households are displayed in Figures 7.6 and 7.7 respectively.

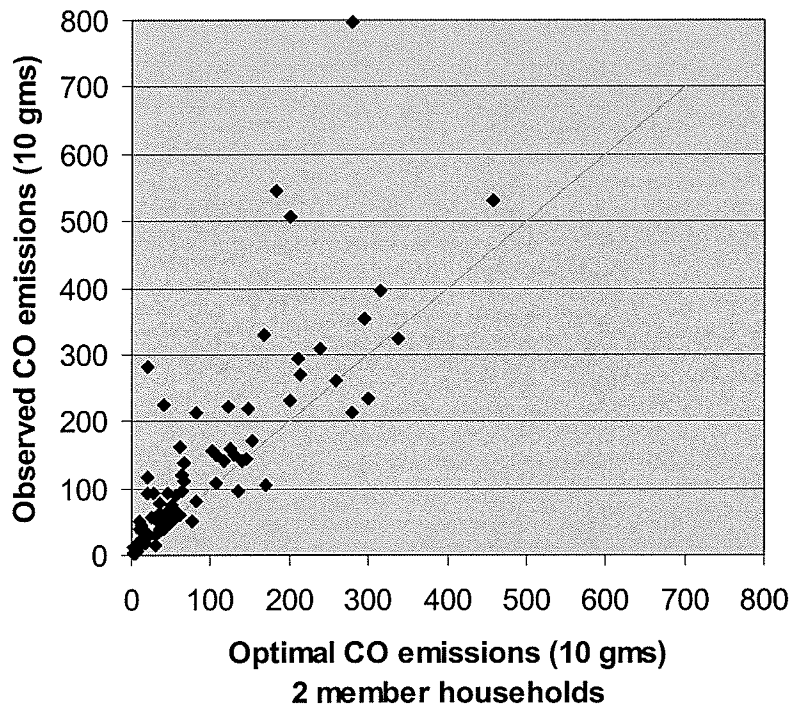


Figure 7.6: Observed vs optimal CO emissions for two-member households

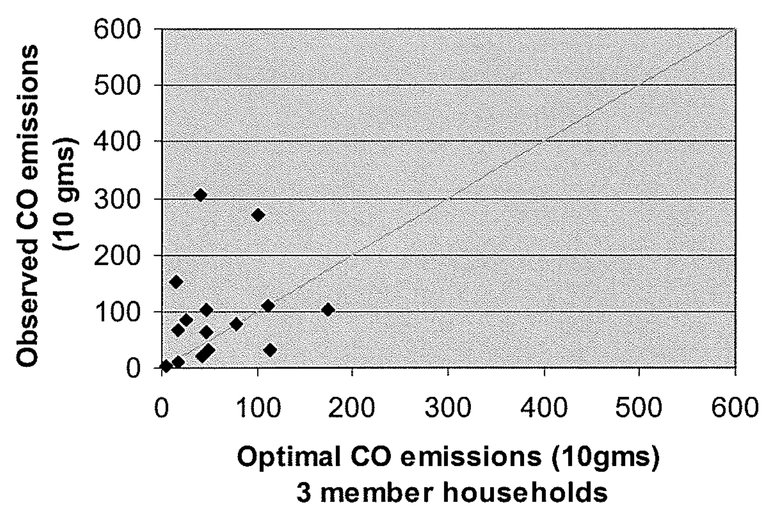


Figure 7.7: Observed vs optimal CO emissions for three-member households

The percentage improvement of CO emissions for the two sub-groups is plotted in Figure 7.8. It can be noted that the percentage of households having a greater percentage improvement in CO emissions is higher in the case of three-member households. The scatter plots also show a similar result.

Figure 7.9 shows the plot of the absolute improvement in CO emissions for the 2 sub-groups. This figure clearly indicates that a greater percentage of three-member households have a higher absolute improvement in CO emissions when compared to the two-member households. In the case of two-member households, 50% of the households have 0-250 gm improvement range of CO emissions when compared to 13.33% for three-member households. The comparative values for 250-500 gm improvement range are 12.79% and 26.67% respectively. This shows that three-person households benefit more from behavior that produces optimal CO emissions than do two-member households.

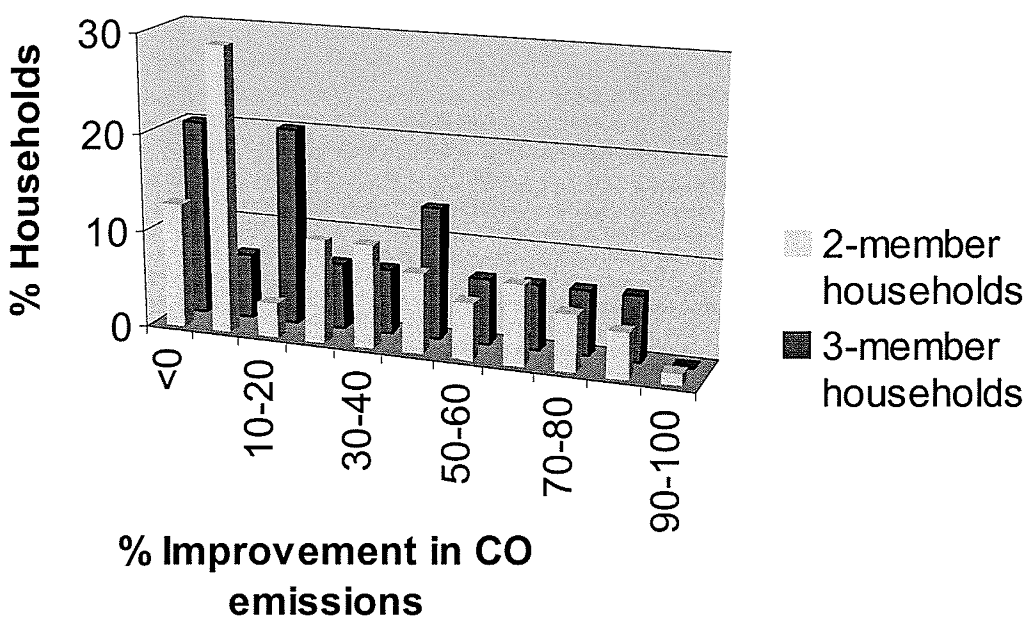


Figure 7.8: Comparison of percentage improvement in CO emissions between two-member and three-member households

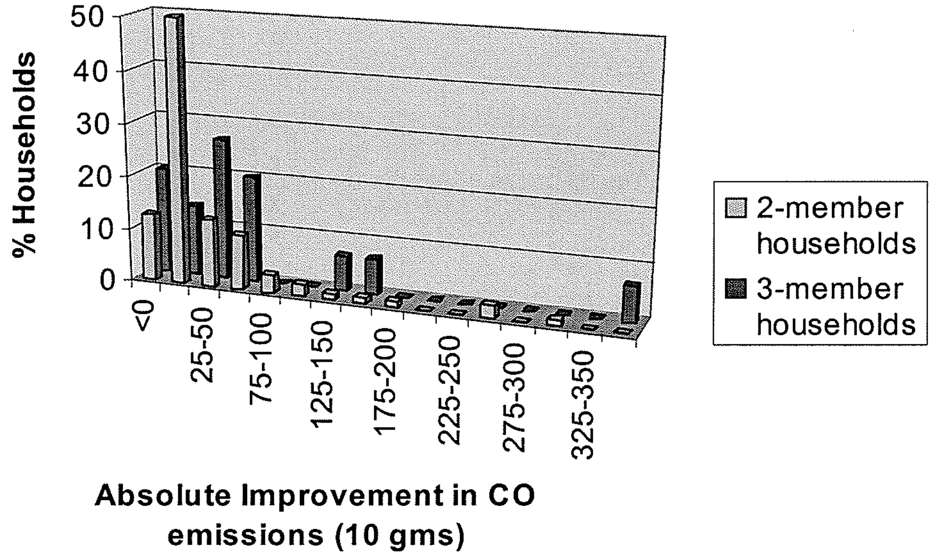


Figure 7.9: Comparison of absolute improvement in CO emissions between two-member and three-member households

7.2.2 Group 2 Results: Comparison of Households with Two and Three Vehicles

The categorizing of the data for this group is done based on the car ownership. The sample sizes with two and three vehicles are 76 and 17, respectively. The scatter plot of the optimal versus the observed CO emissions for households with two vehicles shows a cluster of points closer to the 45° line. This indicates that the difference in the observed and the optimal CO emissions is small in most cases. There are a few cases where the improvement is substantial and a few cases with negative improvement. The scatter plots for households with two and three vehicles are given in Figures 7.10 and 7.11, respectively. Figure 7.11 indicates that there is a tangible improvement in the optimal CO emissions when compared to the observed CO emissions. The percentage improvement of CO emissions for the two sub-groups is plotted in Figure 7.12. The percentage improvement of CO emissions is perceptibly higher in the case of households with three vehicles. There is a probability that at least one of the three vehicles is relatively new and results in smaller values of CO emissions. The optimal solution based on the optimal activity scheduling pattern makes the most efficient utilization of the less- polluting vehicle. It is observed that 26.7% of households with two vehicles has a percentage improvement of 0-10%.

This implies that these households have less flexibility in terms of the vehicle usage and hence the benefit from the optimal solution is relatively lower when compared to households with three vehicles. The data pertaining to the percentage improvement in CO emissions for this group is presented in Table 7.2.

Figure 7.13 shows the plot of the absolute improvement in CO emissions for the two sub-groups. This figure clearly indicates that a greater percentage of households with three

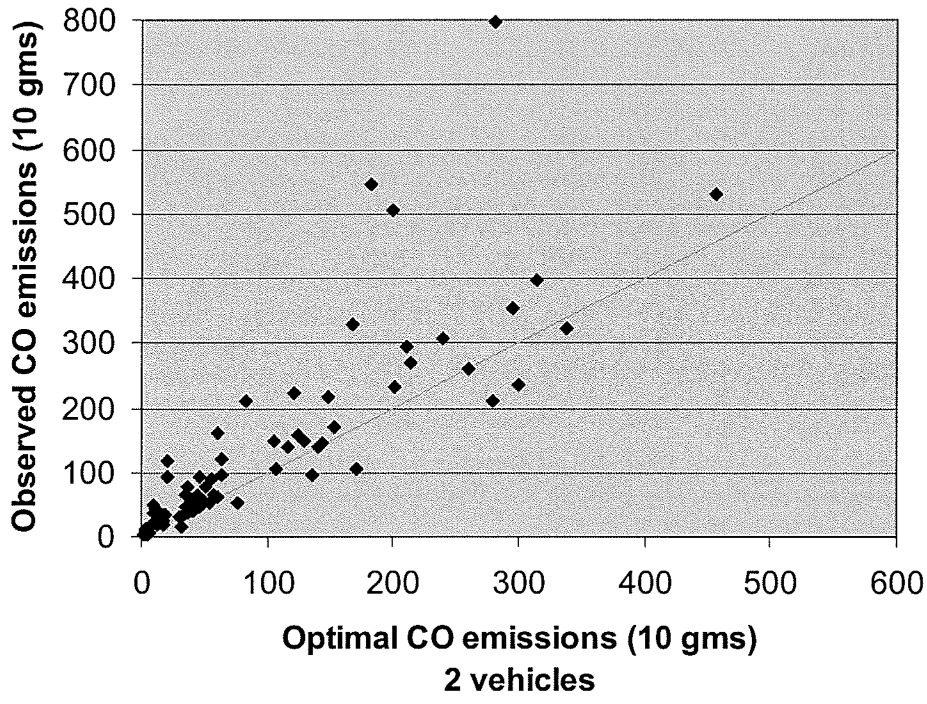


Figure 7.10: Observed vs optimal CO emissions for households with two vehicles

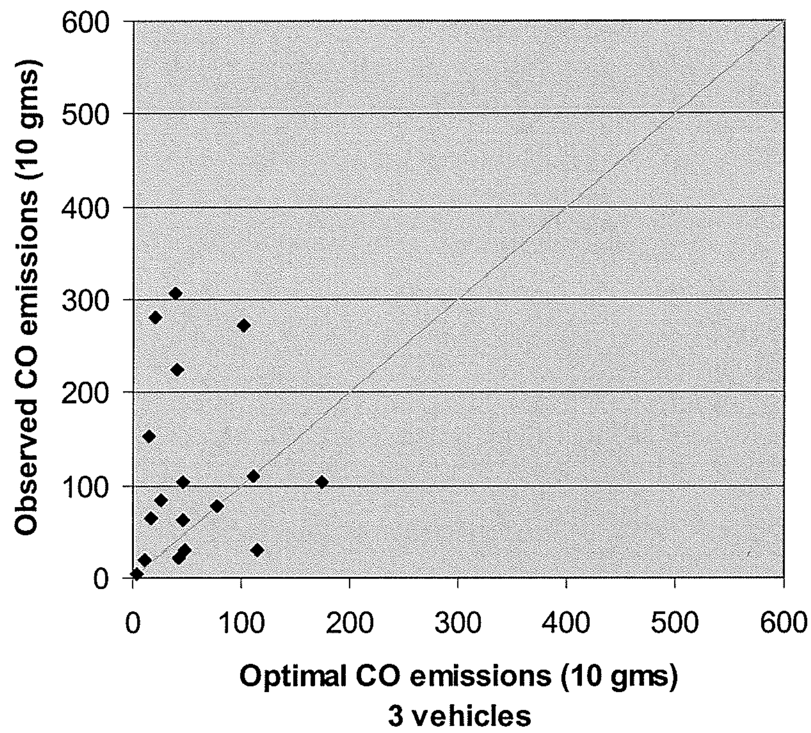


Figure 7.11: Observed vs optimal CO emissions for households with three vehicles

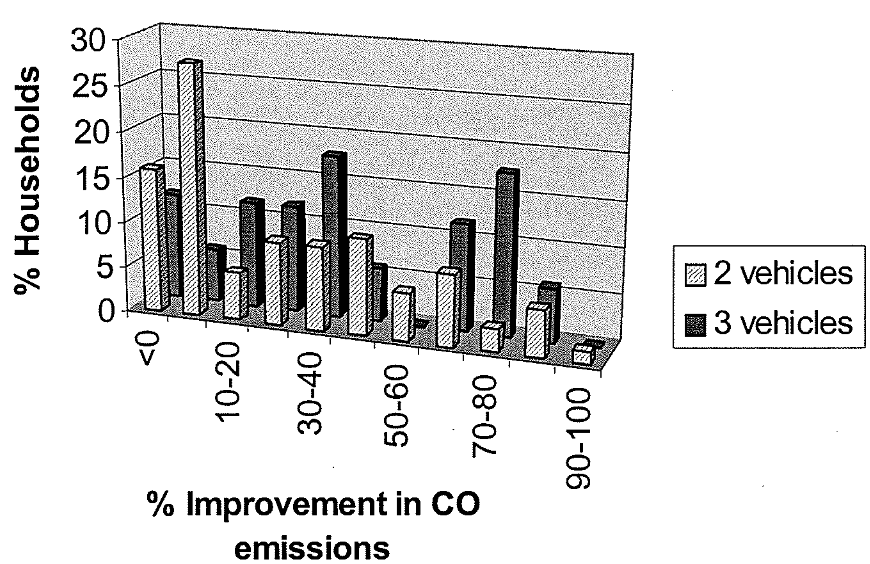


Figure 7.12: Comparison of percentage improvement in CO emissions between households with two vehicles and three vehicles

vehicles have a higher absolute improvement in CO emissions when compared to households with two vehicles.

Table 7.2: Percentage improvement in CO emissions: Comparison of households with two and three vehicles

Number of vehicles	2	3
% Improvement in CO emissions	% Households	
Less than 0	15.79	11.76
0-10	27.63	5.88
10-20	5.26	11.76
20-30	9.21	11.76
30-40	9.21	17.65
40-50	10.53	5.88
50-60	5.26	0
60-70	7.89	11.76
70-80	2.63	17.65
80-90	5.26	5.88
90-100	1.32	0

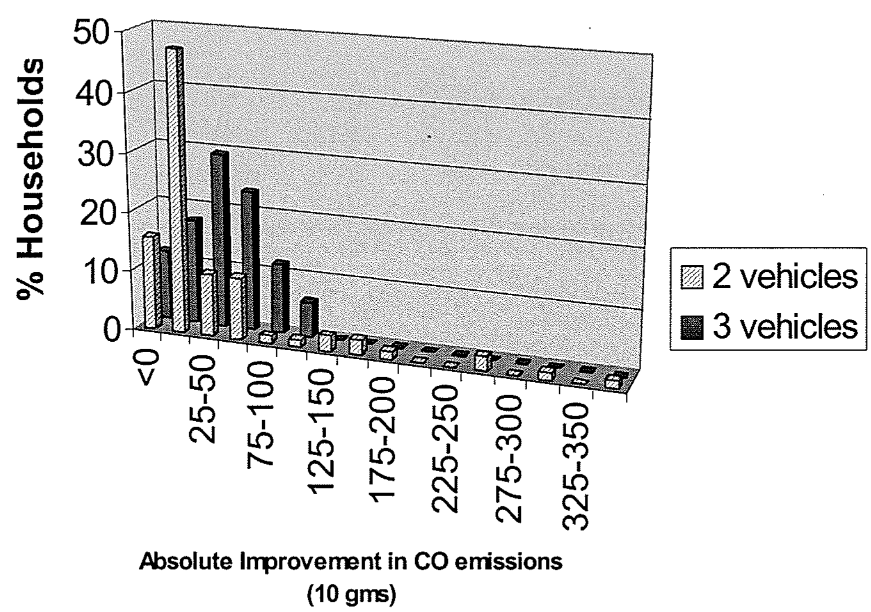


Figure 7.13: Comparison of absolute improvement in CO emissions between households with two vehicles and three vehicles

Approximately 47% of the households with two vehicles have a 0-250 gm improvement range of CO emissions in comparison to 17.65% for households with three vehicles. The absolute improvement is significantly higher for households with three vehicles, as the peak of the bar chart is shifted to the right. The benefit achieved by households with three vehicles is thus greater when compared to households with two vehicles.

7.2.3 Group 3 Results: Comparison between Households with and without Children

The reduced sample data is grouped based on the presence of children in the household. As the maximum household size considered is only three, there are only 12 households with children in the sample. The scatter plot of the optimal versus the observed CO emissions for households without children shows a cluster of points closer to the 45º line and also includes cases where there is considerable improvement in the optimal CO emissions with respect to the observed CO emissions. The scatter indicates that the difference in the observed and the optimal CO emissions is small in cases closer to the 45º line. There are a few cases that show negative improvement in CO emissions due to ridesharing within the household in the observed activity pattern. The scatter plots for households with and without children are given in Figures 7.14 and 7.15, respectively. There is an improvement in the optimal CO emissions when compared to the observed CO emissions in the case of households with children. The percentage improvement of CO emissions for the two sub-groups is plotted in Figure 7.16. The percentage of households with children having a percentage improvement of 10-20% in CO emissions is higher than the percentage of households without children. The converse holds when the percentage improvement is in the range of 0-10%. There is not much variation between the two sub-groups for larger percentage improvements. This is because the households with children are practically limited to households with two licensed individuals. The child does not directly influence travel as it is only involved in ridesharing or pick-up and drop-off activities. Those activities are considered for the licensed individual. Figure 7.17 shows the absolute improvement in CO emissions for the two sub-groups. A greater percentage of households with children have a higher absolute improvement when the improvement is in the range 250-3500 gms.

Approximately 47% of the households without children have an absolute improvement in the range 0-250 gms. This implies that the difference between the optimal and the observed CO emissions is not significant. This also indicates that a greater percentage of households with children have more benefits from behavior dictated by the model.

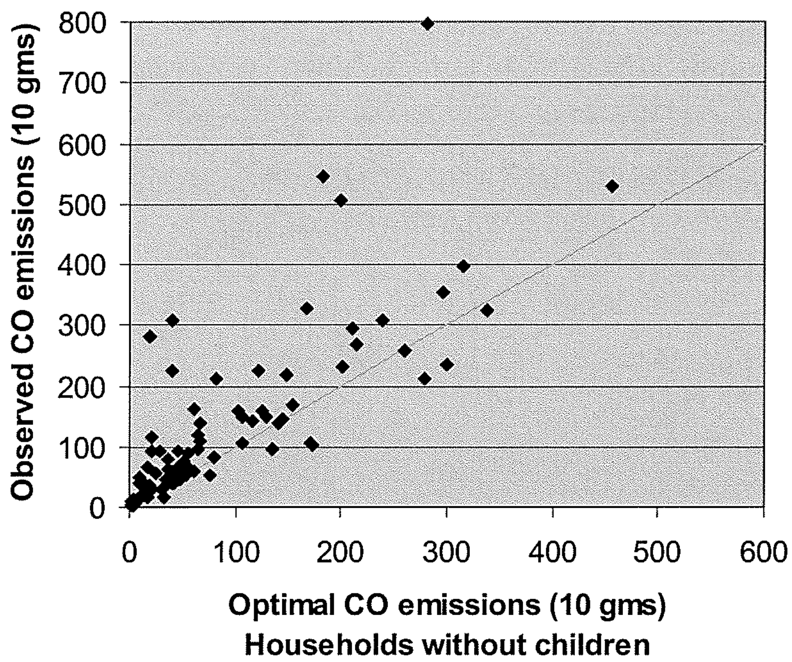


Figure 7.14: Observed vs optimal CO emissions for households without children

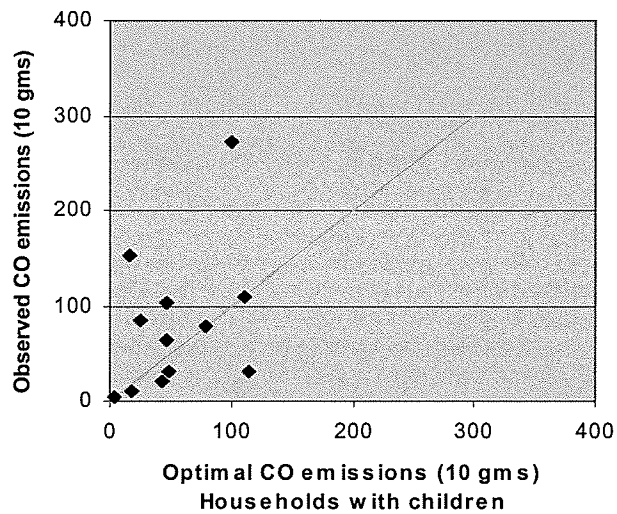


Figure 7.15: Observed vs optimal CO emissions for households with children

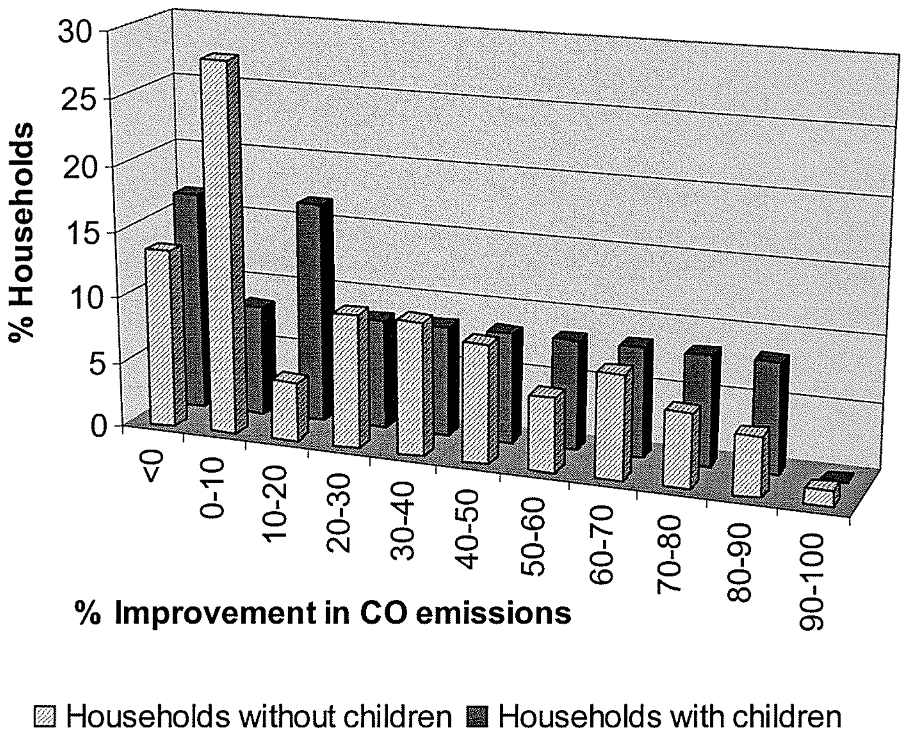


Figure 7.16: Comparison of percentage improvement in CO emissions between households with and without children

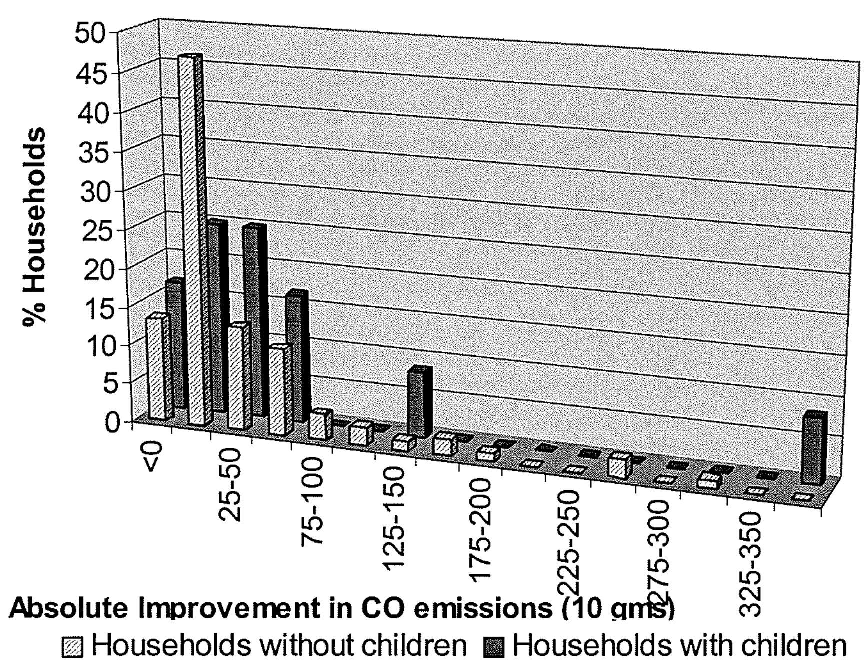
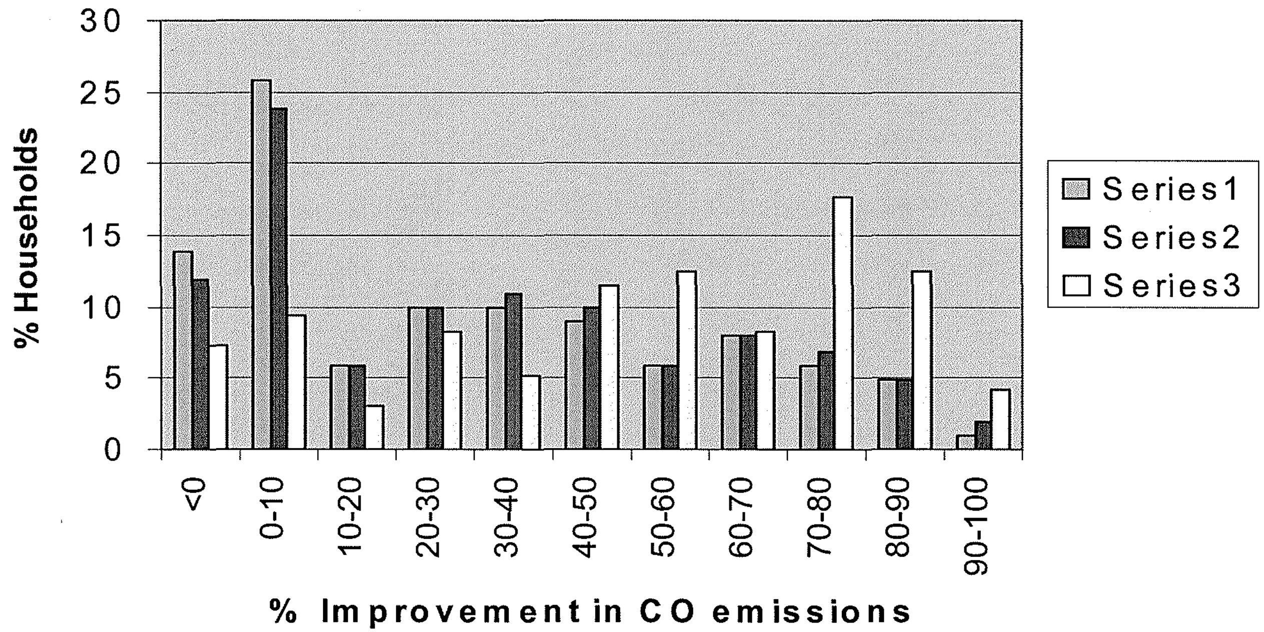


Figure 7.17: Comparison of absolute improvement in CO emissions between households with and without children

7.3 Scenario 2

The objects of comparison in scenario 2 are the base case optimal CO emissions (without ridesharing), base case optimal CO emissions (with ridesharing) and the best solution for CO emissions with new vehicle technology. The ridesharing option in the base case solution gave a result in only 13 cases. The negative improvement in few cases in scenario 1 was not considerably changed by the ridesharing option. This is because the ridesharing heuristic is not robust enough to handle the complex variations in ridesharing observed in the data set. The ridesharing option gave positive results in 4 of those cases. The model gave solutions that were close to the observed CO emissions in some cases. The new vehicle technology assumed that the fleet in the household is replaced by a vehicle of model year 1998 with the mileage being the same as the original vehicle in the household. The results of the percentage improvement in CO emissions are presented in Figure 7.18. It is observed that there is a slightly higher percentage of households with greater percentage improvement in the CO emissions for the base case optimal solution with the ridesharing option when compared with the base case optimal solution without ridesharing for the improvement range of 30-100%. The converse holds for an improvement range of 0-30%. The negative improvement cases exists due to the inability of the ridesharing heuristic to detect possibilities for ridesharing within the household in most cases. The percentage of households having a greater percentage improvement in CO emissions is much higher for cases with new vehicle technology. This is expected because of the reduction of the CO emissions based on the new vehicles. The peak for the new vehicle technology case is to the right and gives the best result in scenario 2. The variation in absolute improvement in CO emissions is also plotted for the three categories in Figure 7.19. There is less variation in the absolute improvement in CO emissions for the three categories. The cumulative distributions of the percentage improvement and absolute improvement in CO emissions are shown in Figure 7.20 and Figure 7.21, respectively. These results indicate that the new vehicle technology usage will produce the best results in scenario 2 and that the ridesharing option is not used to any effective degree.

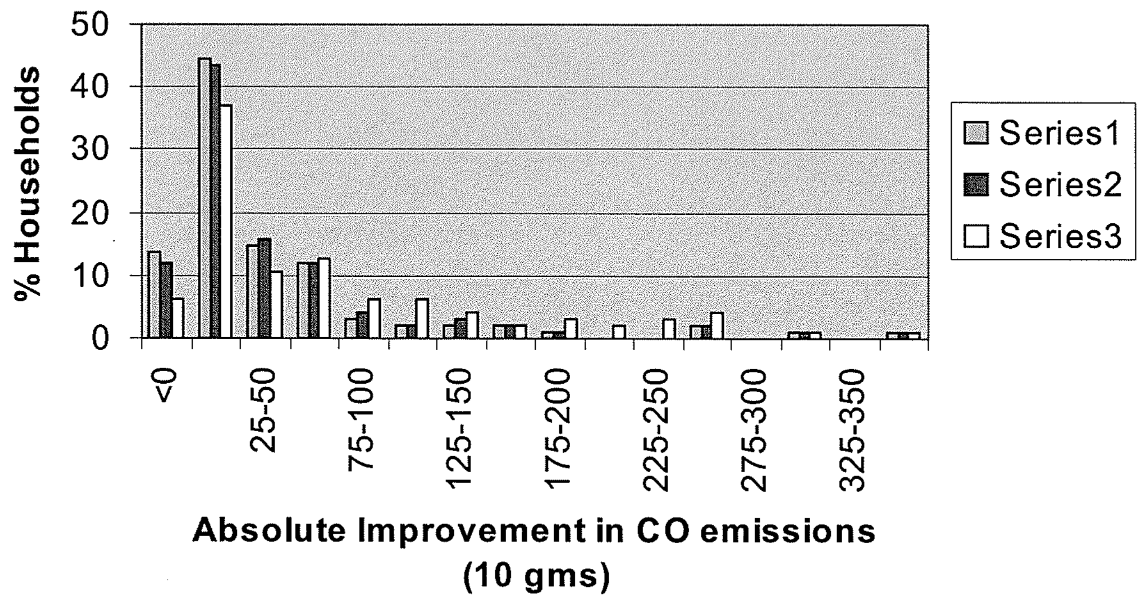


Series 1: Percentage improvement in CO emissions for base case without ridesharing

Series 2: Percentage improvement in CO emissions for base case with ridesharing

Series 3: Percentage improvement in CO emissions with new vehicle technology

Figure 7.18: Comparison of percentage improvement in CO emissions

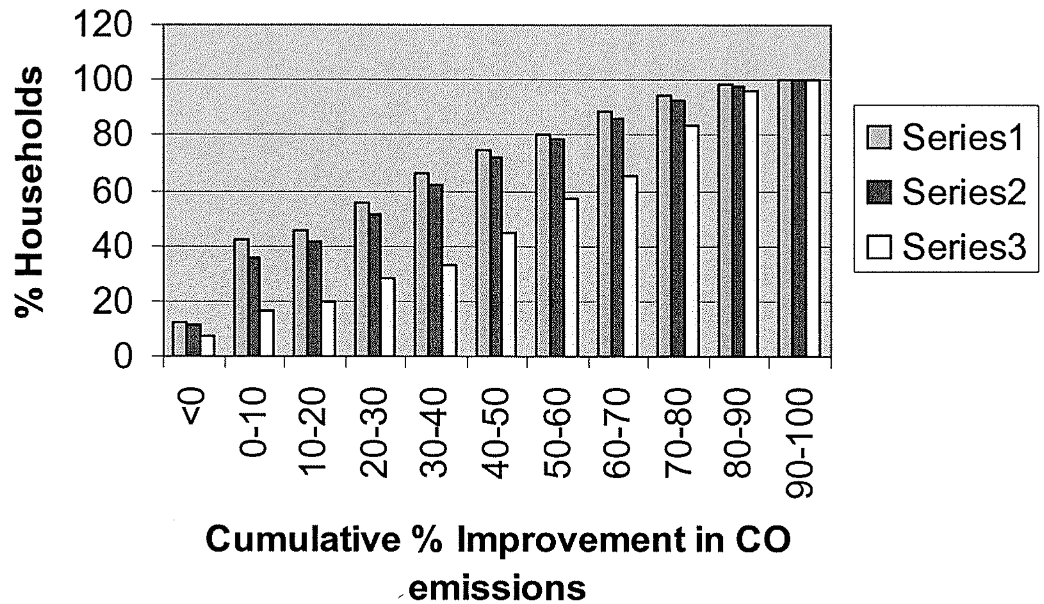


Series 1: Absolute improvement in CO emissions for base case without ridesharing

Series 2: Absolute improvement in CO emissions for base case with ridesharing

Series 3: Absolute improvement in CO emissions with new vehicle technology

Figure 7.19: Comparison of absolute improvement in CO emissions

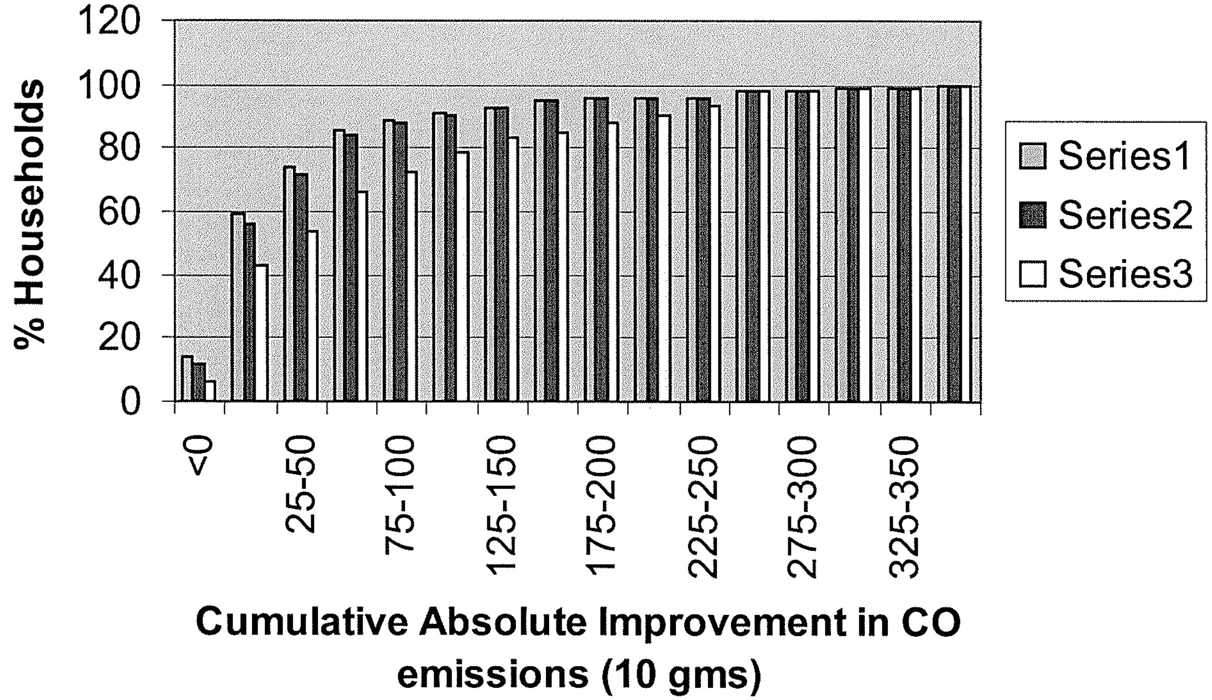


Series 1: Percentage improvement in CO emissions for base case without ridesharing

Series 2: Percentage improvement in CO emissions for base case with ridesharing

Series 3: Percentage improvement in CO emissions with new vehicle technology

Figure 7.20: Comparison of cumulative percentage improvement in CO emissions



Series 1: Absolute improvement in CO emissions for base case without ridesharing

Series 2: Absolute improvement in CO emissions for base case with ridesharing

Series 3: Absolute improvement in CO emissions with new vehicle technology

Figure 7.21: Comparison of cumulative absolute improvement in CO emissions

8. CONCLUSIONS AND FUTURE RESEARCH

8.1 Conclusions

This study presents an application of the Household Activity Pattern Problem to remove the problems in traditional modeling approaches in the evaluation of potential improvements in vehicle emissions that may be possible through adjustments in travel behavior. The main objective of this study is to demonstrate the benefits in vehicle emissions reduction based on optimal scheduling and linking of the activities performed by individuals in a household. The vehicle emissions model is incorporated in the model formulation and the resulting framework is tested under different policy scenarios, including an evaluation of the potential benefits achieved by replacing all the vehicles in the fleet by vehicle conforming to present day emission technology. Section 7 presents the results of the different scenarios with the comparisons among sub-groups. It is observed that the benefits achieved with the new vehicle scenario is substantial. The policy of old-vehicle "buy back" schemes will thus be effective for reduction in vehicle emissions as the highly-polluting cars are tracked down. The sample had a significant percentage of retired individuals in two-member households. These individuals may be involved in short trips and it might be difficult to change the activity patterns of such individuals. The results also showed that the potential benefits were much higher for households with three vehicles when compared with households with two vehicles. The ridesharing option has not been tested effectively in this analysis, primarily due to limitations in the heuristic used in the ridesharing options. It would be interesting to derive the improvements in vehicle emissions reduction with a more robust ridesharing heuristic.

8.2 Directions for Future Research

This study has provided a framework for analyzing the benefits of the vehicle emissions reduction. The different directions for future research are listed below:

1. <u>Modeling the vehicle emissions for other vehicle types:</u>

   The existing model framework is used only for modeling the emissions of light-duty gasoline vehicles. The vehicle emissions can be modeled using MOBILE5 for the other vehicle types.

This would result in more household cases having valid data. Also, the potential benefits can be compared over the vehicle type.

2. Trips using other modes:

   Only households having nothing other than automotive trips were considered in the analysis. It will be interesting to determine the changes in the activity patterns of individuals when another mode (e.g., transit) is available to the individuals in the household. The transit network has to be modeled to generate the transit travel times to be used in the modeling framework. In the case of walk trips, the travel time matrix can be generated by assuming an average speed. The objective function will correspondingly change to include other variables.

3. HC and NO_x emissions:

   The effect of reduction of HC and NO_x emissions can be considered in the objective function. It has been assumed in the analysis that CO emissions are the important constituent of vehicle emissions. The percentage and absolute improvements for these variables might shed some light on the relative importance of the reduction of CO emissions. The results can be compared by changing the objective function.

4. Integration with traffic microsimulation:

   The existing emissions model gives the emissions for an average vehicle in that model year. This is an approximate representation of the vehicle emissions as we assume an average speed for an O-D pair. In reality, speed may vary substantially during any trip due to the stop-go traffic. This could lead to higher emissions levels. If the traffic signal data is available in the Portland network area, the traffic can be simulated for a given O-D pair in a traffic microsimulation model and the emissions can be tracked for flagged vehicles. This would improve upon the estimation of vehicle emissions values used in this analysis considerably.

5. Travel time matrices:

   The reported travel times were used for all the trips with available travel time data. The shortest path network travel times are used for all other O-D pairs. There can be discrepancies in reporting and this might lead to erroneous results in some household cases. A comparison between the network travel time and the reported travel time gives the perceived difference in travel time. It is observed that the travel times are over-estimated in cases with low travel times as there is a tendency to round-off. The network travel times need to be adjusted if there is a significant perception error in the sample.

6. Better ridesharing heuristic:

   The inability of the present ridesharing heuristic to detect the possibilities for ridesharing within the household in most of the cases led to negative percentage improvement in CO emissions. The existing modeling framework can be updated with a more robust ridesharing heuristic and the ensuing results might provide more efficient vehicle emissions reduction.

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