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Development of a microscopic activity-based framework for analyzing the potential impacts of transportation control measures on vehicle emissions

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Abstract

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 paper 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. Although the framework, as currently developed, falls well short of actually forecasting changes in traveler behavior relative to policy options designed to encourage emissions reduction, the approach can be useful in estimating upper bounds of certain policy alternatives in reducing vehicle emissions. Subject to this important limitation, the potential of transportation policy options to alleviate vehicle emissions is examined in a comprehensive activity-based approach. Conclusions are drawn relative to the potential emissions savings that can be expected from efficient trip chaining behavior, ridesharing among household members, as well as from technological advances in vehicle emissions control devices represented by replacing all of the vehicles in the fleet by vehicles conforming to present-day emissions technology.

1. Introduction

It is estimated by USEPA (1991a,b) that in a typical US city, the motor vehicle emissions account for 30–50% of hydrocarbon, 80–90% of carbon monoxide, and 40–60% of nitrogen oxide emissions. Advances in technology have played and will continue to play a role in better managing

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both energy consumption and harmful emissions associated with vehicular transport. 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% (compared to a 1971 model car). The corresponding reductions for CO and NO_x have been 96% and 85%, respectively. However, during the period 1981–1992, the total vehicle miles (VMT) traveled for the Nation rose by more than 33% and the number of trips increased by about 25% (USEPA, 1991a, Hu and Young, 1990). 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%, respectively.

The 1990 Clean Air Act Amendments (CAAA) establish rules for gasoline volatility, evaporative and running losses, tailpipe emissions standards, alternative fuel programs, reformulated and oxygenated fuels, and inspection and maintenance programs. It is estimated that 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% annually) will offset much of this reduction (Kessler and Schroeer, 1995).

The CAAA and the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) have, in combination, defined a broad range of transportation control measures (TCMs) and established procedures and requirements for integrating such TCMs as telecommuting, flexible work hours, congestion and parking charges, ridesharing, no-drive days, signal prioritization and expansion of public transport into transportation and environmental planning. 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).

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 reported here 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 result demonstrate an application of the approach to estimate the potential benefits in vehicle emissions reduction that could be achieved with optimal scheduling and linking of the activities performed by the individuals in a household. Specifically, a comprehensive activity-based approach is advanced to address the following question: "Given a set of activities, locations, and various constraints, if ALL individuals were to act to minimize CO emissions by trip chaining and ridesharing in the most efficient way possible, what activity patterns would result, and how would they differ in CO emissions from their observed (i.e., revealed, or chosen) patterns?" [1] The question as posed falls well short of actually forecasting changes in traveler behavior relative to

[1] The authors gratefully acknowledge this suggestion of one of the reviewers (unknown) in phrasing the substantive contribution of this paper with clarity that escaped the authors.

policy options designed to encourage emissions reduction, which is a much more demanding exercise. Rather, the approach, as currently developed, can be useful in estimating upper bounds of certain policy alternatives in reducing vehicle emissions. Subject to this important caveat, conclusions are drawn relative to the potential emissions savings that can be expected from efficient trip chaining behavior, ridesharing among household members, as well as from technological advances in vehicle emissions control devices represented by replacing all of the vehicles in the fleet by vehicles conforming to present-day emissions technology.

2. Base methodology

The methodology used is based on an extension of the mathematical programming approach offered by Recker (1995) in which the household activity pattern problem (HAPP) is posed as a network-based routing model incorporating vehicle assignment, ridesharing behavior, activity assignment and scheduling, and time window constraints. The general approach involves treating the HAPP as an analogy to the so-called pickup and delivery problem with time windows (PDPTW).

In the analogy to the PDPTW, activities are viewed as being 'picked up' by a particular household member at the location where performed and, once completed (requiring a specified service time) 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.

The problem is defined by a network graph $G = (V, A)$, where V is the set of all vertices, and A is the set of all arcs in the network. Physically, V can be a set of demand nodes, and A can be explained as the connections between these demand nodes. The standard vehicle routing problem (VRP), that is applied in numerous studies (Golden, 1984; Desrochers et al., 1988; Solomon and Desrosiers, 1988) is defined on this graph as the visit to each node once and only once by a stable of vehicles with specific capacity constraints. The HAPP is described as: *Minimize a hypothetical objective function* (which generally expresses some 'generalized cost' to the household in order to complete all of the activities needed to be performed by the household members) *subject to the constraints related to transportation supply*, *time windows*, *vehicle capacity*, *and logical connection between activity nodes*. The HAPP, which is more complex than a generic VRP, can be defined on an expanded graph with the addition of temporary returning home nodes, and the replacement of the activity nodes with drop-off and pick-up function nodes, which physically represent the same locations as those of the activity nodes, and logically are used to explain different purposes of that trip. The requirements for the household members to complete all scheduled activities (visiting all activity nodes), which could be performed either by some specific person or by anyone available, are sustained within this model. Each activity in the HAPP must be performed [2] (equivalent to the definition that each vertex of the network in the VRP should be visited once and only once), and there is a limitation on the time period of performing the activity.

[2] Within the HAPP formulation, an activity is defined by a time-line that is invariant with respect to both activity type and space. For example, a morning work activity followed by lunch and then by a return to the work activity for the afternoon period would be classified as three activities – two work activities and a meals activity.

The resulting HAPP formulation is in the form of a mixed integer linear programming (MILP) model. The equations describing the problem are contained in Recker (1995) and are not repeated here. However, the general form of the HAPP mathematical program formulation of the travel/activity decisions for a particular household, say i, during some time period is represented by

$$\begin{aligned} &\text{minimize} \quad Z(\mathbf{X}_i) = \mathbf{B}_i' \cdot \mathbf{X}_i \\ &\text{subject to} \quad \mathbf{A}\mathbf{X}_i \leqslant \mathbf{0}, \end{aligned} \tag{1}$$

where

$$\mathbf{X}_i = \begin{bmatrix} \mathbf{X}^v \\ \mathbf{H} \\ \mathbf{T} \end{bmatrix}, \qquad \mathbf{X}^v = \left[X^v_{uw} = \begin{cases} 0 \\ 1 \end{cases} \right], \quad \mathbf{H} = \left[H^\alpha_{uw} = \begin{cases} 0 \\ 1 \end{cases} \right], \quad \mathbf{T} = [T_u \geqslant 0].$$

The outputs $\mathbf{X}_i$ of the optimization for each household i are specified by the following decision variables: [3]

$X^v_{uw},\ u, w \in N,\ v \in V,\ u \neq w$	binary decision variable equal to unity if vehicle v travels from activity u to activity w, and zero otherwise
$H^\alpha_{uw},\ u, w \in N,\ \alpha \in \eta,\ u \neq w$	binary decision variable equal to unity if household member α travels from activity u to activity w, and zero otherwise
$T_u,\ u \in P$	the time at which participation in activity u begins
$T^v_0,\ T^v_{2n+1},\ v \in V$	the time at which vehicle v first departs from home and last returns to home, respectively
$\bar{T}^\alpha_0,\ \bar{T}^\alpha_{2n+1},\ \alpha \in \eta$	the time at which household member α first departs from home and last returns to home, respectively

The various sets referenced in the above are defined by the following notation:

$A = \{1, 2, \ldots, j, \ldots, n\}$	the set of out-of-home activities scheduled to be completed by travelers in the household
$V = \{1, 2, \ldots, v, \ldots, \lvert V \rvert\}$	the set of vehicles used by travelers in the household to complete their scheduled activities
$P^+ = \{1, 2, \ldots, u, \ldots, n\}$	the set designating location at which each activity is performed
$P^- = \{n+1, n+2, \ldots, n+j, \ldots, 2n\}$	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')
$P = P^+ \cup P^-$	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

[3] The notation used here is the same as that contained in Recker, 1995.

$\mathbf{B}_i$ is a vector of coefficients that defines the relative contributions of each of the decision variables to the overall disutility of the travel regime to the household. Descriptively, the constraint sets $\mathbf{AX}_i \leqslant \mathbf{0}$ for this MILP are classified into six groups: (a) routing constraints that define the allowable spatial movement of vehicles and household members in completing the household's activity agenda; (b) scheduling constraints specify the relationship of arrival time, activity begin time, and waiting time, and continuity condition along the temporal dimension; (c) assignment constraints that are applied to match the relations between activity participation and vehicle usage as well as activity performers (household members); (d) time window constraints that are used to specify available schedules for activity participation; (e) coupling constraints that define the relations between vehicle-related variables and member-related variables; and (f) side constraints including budget, capacity, and rules for ridesharing behavior. With the exception of the side constraints (i.e., classification 'f' above), these constraints capture the physical conditions that ensure that each member of the household, as well as each vehicle used by the household, have a consistent, continuous, path through time–space that results in all of the activities on the household's agenda being successfully completed. The reader interested in a detailed derivation and explanation of these constraints is referred to the original work by Recker (op cit).

The solution vector, $\mathbf{X}_n^*$, to Eq. (1) represents the household's utility maximizing behavior, relative to the prescribed objective $Z(\mathbf{X}_i)$, [4] with regard to completing its activity agenda. The solution patterns reveal personal travel behavior and activity participation within a household context, while preserving the concept that the need for travel originates from participation in activities, that travel constitutes the linkage between activities, and in which all of the required components are contained in the activity scheduling problem.

3. Extension to incorporate emissions analysis

The HAPP network-based activity assignment protocol is extended in this study to incorporate emissions based on the Mobile 5 vehicle emissions model (USEPA, 1994). Vehicle emissions depend on a number of factors, including: 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, the vehicle used, and whether or not the vehicle was warmed up when started. All but the last of these factors are explicit outputs of the HAPP optimization process; the last (i.e., cold vs. hot start status) is an implicit aspect of the activity durations, scheduling options, and travel times to/from activities. For example, calculation of the CO emissions produced by any household travel/activity pattern can be captured by the simple linear function:

[4] In the example considered here, the specification of the objective function is prescribed by the analyst; i.e., the minimization of emissions produced by travel. The typical problem in demand modeling (of which the HAPP is a subset) is focused on inferring the relative weights associated with potential components of the utility function that are determinants to a population's revealed selection of the decision variables (in the model estimation phase) with subsequent forecasts made using these weights in conventional application of the model. This particular aspect of the research approach remains a challenge.

$$\sum_{v\in V}\sum_{u\in N}\sum_{w\in N} X_{uw}^{v}\cdot \mathrm{CO}_{uw}^{v}, \tag{2}$$

where CO_{uw}^{v} are the elements of the CO emissions matrix representing the CO emissions for a travel linking activities u and $w \in N$ using vehicle $v \in V$. For any origin–destination-vehicle combination, CO_{uw}^{v} is a function of the travel distance between u and w, network speed characteristics, vehicle v emissions parameters, and the vehicle idle time between successive starts (to determine cold-start or hot-start status). All but the last of these (i.e., vehicle idle time) are system link properties that are directly input as a series of $|N| \times |N| \times |V|$ parameter matrices. Vehicle idle time is dependent on the sequencing of the activities, their respective durations, and the travel time between them. Because of this, CO_{uw}^{v} must be specified in terms of two contingency matrices (one to be applied for cold-start conditions, the other for hot-start) that are solution dependent, i.e.,

$$\mathrm{CO}_{uw}^{v} = \delta_{uw}^{v}\cdot \mathrm{CCO}_{uw}^{v} + \ (1-\delta_{uw}^{v})\cdot \mathrm{HCO}_{uw}^{v}, \tag{3}$$

where CCO_{uw}^{v} and HCO_{uw}^{v} represent cold- and hot-start CO emissions, respectively, for a travel linking activities u and $w \in N$ using vehicle $v \in V$, and δ_{uw}^{v} is a binary parameter that takes on a value unity if travel between activity u and activity w by vehicle v involves a cold start, and is zero otherwise. In effect, CCO_{uw}^{v} and HCO_{uw}^{v} are the elements of cold-start and hot-start CO emissions matrices. 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.

Calculation of HC and NO_x emissions can be found in similar fashion as

$$\sum_{v\in V}\sum_{u\in N}\sum_{w\in N} \mathrm{X}_{uw}^{v}\cdot \mathrm{HC}_{uw}^{v}, \tag{4a}$$

$$\sum_{v\in V}\sum_{u\in N}\sum_{w\in N} X_{uw}^{v}\cdot (\mathrm{NO}_x)_{uw}^{v} \tag{4b}$$

with expressions similar to Eq. (2) defining HC_{uw}^{v} and $(\mathrm{NO}_x)_{uw}^{v}$.

For input to the revised HAPP model, the emissions matrices for CO, HC and NO_x emissions for each vehicle in the household must be determined between the locations of all activities performed by the household (including home). The calculation of these emissions matrices was based on the MOBILE5 emissions model, using appropriate modifications to the basic emissions rates (BERs) based on such factors as travel speed, ambient temperature, and mode of operation (e.g., cold vs. hot start transients and the stabilized portion of the trip). This latter factor (operating mode) is of particular relevance in the current study as the factor most sensitive to the extent of trip chaining present in the optimized versus observed trip patterns. The EPA has historically defined a cold start as any start that occurs 4 h or later following the end of the preceding trip for non-catalyst equipped vehicles and 1 h or later following 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°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 transient is represented by the first 3.5 miles traveled by a vehicle after a cold start and the hot transient is represented by the first 3.5 miles after a hot start. The stabilized mode follows the cold transient or the hot transient.

In the analysis, the start mode of each trip is determined by the duration of the preceding activity and the vehicle type. (Vehicles whose model year is 1975 and later are assumed to have catalytic converters.) For each trip, the emissions are calculated based on the start mode and the temperature, speed and operating mode correction factors. For example, a 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 g. This matrix representation is given for all the vehicles in the household.

4. Case study

The data used in the application of the model described in the previous sections 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 min, for all individuals in the household. The household and person socio-economic data are also included in the 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. 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. Portland Metro geocoded (attached x–y coordinates to) activities, home addresses, and employment locations recorded in the final survey data set to an accuracy of 200 ft; they also provided EMM/2 coded transportation networks and models.

The Portland activity data were collected open ended, and then classified according to a set of 28 categories shown in Table 1. These categories, as well as the subjective assignment of the respondents' stated activities to the respective categories, were determined by Portland Metro staff as part of their data processing procedures.

The total sample includes 10 048 individuals, who reported a total number of 129 188 activities in the Portland area in the two-day diary; 64 713 activities listed in the raw data file for the first travel day, 64 475 on the second. Of these, 91 758 activities had complete geocode coordinates associated with them.

Table 1
Activity mean start and end times

Activity type	Mean start time	Mean end time
Meals – Breakfast	7.4	8.4
Meals – Lunch	12.2	13.0
Meals – Dinner	18.1	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

4.1. Sample characteristics

For use in this analysis, a random sub-sample of 100 households was drawn from a total of 2450 households headed by opposite sex adult couples; 86 two-member households and 14 three-member households. These households were selected based on the requirement of: complete demographic data for all persons within the household; complete vehicle characteristics for all vehicles available to the household; and complete information on all activities engaged in by members of the household, including geocoded location, start time, duration, and travel mode. To remove complexities in the modeling process associated with public transportation modes, the sub-sample also is restricted to households in which all travel was accomplished using a personal vehicle, and only households having fewer than 10 activities for licensed individuals are considered. [5] The activities considered in the analysis are all out-of-home activities and in-home meals

[5] This latter restriction is employed to reduce computation time, which increases significantly with increase in the number of activities. The current HAPP algorithm limits the total number of activities to 20 and the number of vehicles to four.

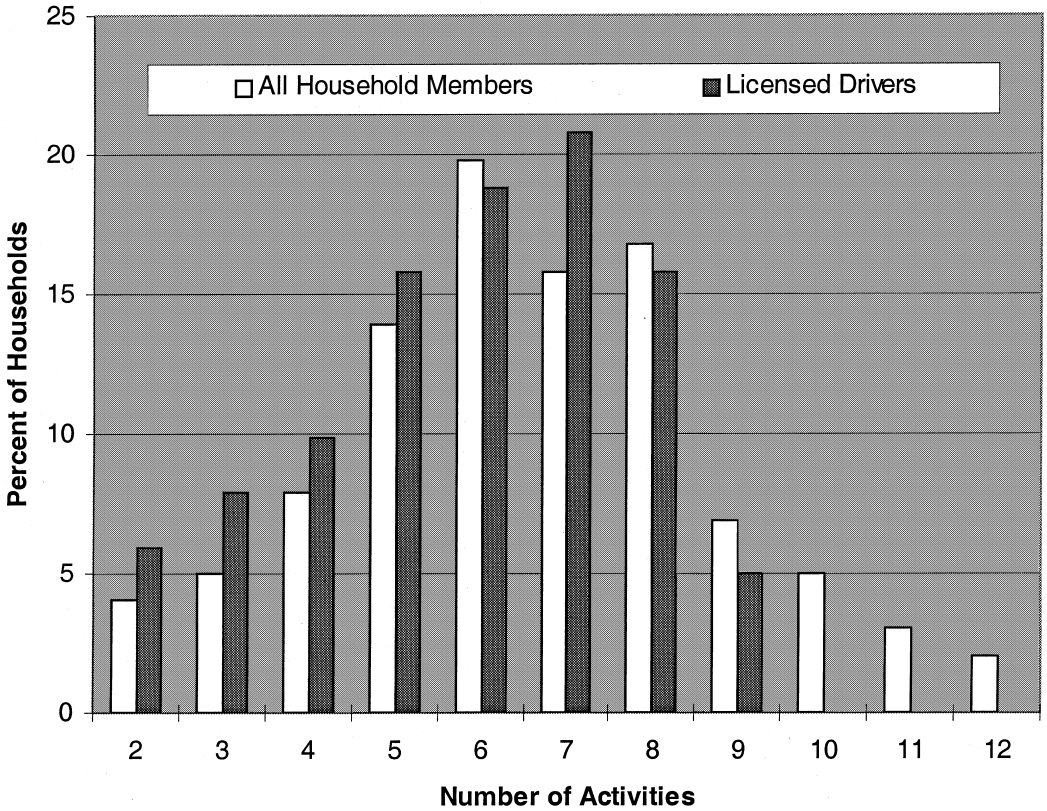

Fig. 1. Frequency distribution of the number of out-of-home activities and in home meal activities completed by households.

for the first day of the two-day activity diary; in-home activities other than meals are assumed to be discretionary and flexible. The activities used in the analysis constituted approximately 56% (17.3% work, 14.6% general shopping and 23.9% from the remaining categories) of all activities reported by two-member households and 58% (27% work, 11% general shopping and 20% from the remaining categories) of all activities reported by three-member households. The frequency distribution of the number of such activities completed both by all members of the households (as well as by only licensed drivers within the households) in the sub-sample is given in Fig. 1. The mean number of activities per household is 6.56 with a standard deviation of 2.23; the mean number of activities performed by all licensed drivers within a household is 5.84 with a standard deviation of 1.87. [6] About 62% of the activities were out-of-home activities that required travel, with an average travel time per activity requiring travel of approximately 18 min. The mean total travel time of those individuals in the household who traveled is 0.95 h. The mean duration of a

[6] These statistics are for the sample considered in the analysis, which is restricted to households having a total of 10 or fewer activities.

meals activity is 1 h and the corresponding mean duration of work and shopping activities is 6 and 0.8 h, respectively.

Approximately 75% of the households have two vehicles and about 93% of the households have more than one vehicle; 90% of the households had two licensed drivers, while 8% had only one licensed driver. The 100 households in the sub-sample comprise 214 individuals, about half of whom are fully employed; 12 households include a child in the household.

4.2. Generation of travel time matrices

Because the HAPP mathematical program optimizes over all feasible sequences of the activities, a full travel time matrix for each household must be specified between the locations of all activities that were performed (rather than simply between the locations reported in the travel diaries that represent the observed activity/travel pattern). A geographic information systems (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. The addresses (or, in some cases, landmarks or nearest intersections) of all activities performed by respondents, as reported, were geocoded on the state plane of Portland. Shortest path travel times between all activity locations of each household in the sub-sample were then generated using TRANSCAD. The activity locations were approximated to the nearest node in the street network. The travel times between all activity locations of a household were determined by matching the unique ID of each activity to the node ID and estimating the travel time between the nodes based on the link attributes (e.g., length, modes allowed, link type, number of lanes, average speed and link capacity) of the links comprising the shortest time path between nodes.

4.3. Activity time window constraints

As noted above, the HAPP optimization algorithm is dependent on the specification of time window constraints that are used to identify available schedules for activity participation. This information is not directly available from survey data. Rather, a procedure was developed to infer estimates of such windows from the observed behavior of the sample. First, the activities were categorized based on their activity types, [7] and histograms were plotted for the activity starting time and activity ending time. An example of such histograms is provided for the shopping activity in Figs. 2 and 3; comparable histograms for other activity types are omitted for brevity.

Work and school activities, and pick-up and drop-off activities associated with either a non-licensed member of the household or a person who was not a member of the household, were considered to be temporally fixed activities; i.e., it was assumed that these activities could not be rescheduled and must be done at the same time as that reported by individuals in the sample; as such, they represent temporal 'pegs' in the activity rescheduling. Activity types other than these were assumed to have temporal flexibility within time-window constraints determined from the

[7] 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.

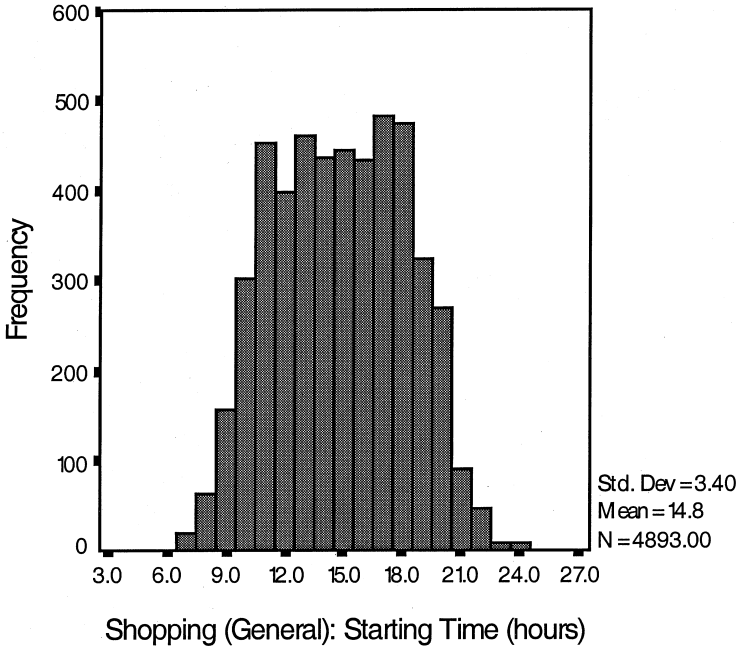

Fig. 2. Histogram of the starting time of shopping activity.

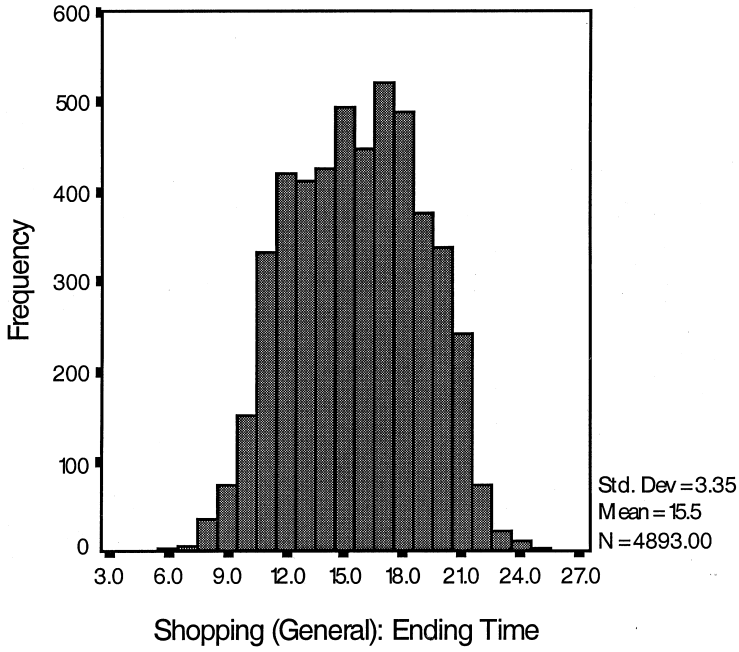

Fig. 3. Histogram of the ending time of shopping activity.

aggregate temporal distributions of activity performance over the entire sample. Based on these distributions, any number of different criteria ostensibly could be employed to infer realistic bounds on the time windows during which any rescheduling would be practical; employing the means, one- or two-standard deviations from the means, or the 85th percentile values are examples. For the empirical application reported herein, the sample means were used as a simple, but arbitrary, example of the approach. The mean starting time and the mean ending time of the activities for all of the activities in the temporally flexible categories were determined from the histograms of the respective activity types (Table 1).

The open windows (the time at which an activity becomes available for participation) for activities were then determined based on the following conditions:

(a) Activities other than work, school, meals between two work activities, and pick-up/drop-off passenger:

$$\text{Open window} = \min \begin{cases} \text{Responents reported activity start time,} \\ \text{Mean activity start time for the sample.} \end{cases}$$

(b) Work, school, meals between two work activities, and pick-up/drop-off passenger: [8]

$$\text{Open window} = \text{Responents reported activity start time.}$$

(c) Individual's first departure from home:

$$\text{Open window} = \min \begin{cases} \text{Responents reported travel start time for his/her initial activity,} \\ \text{Mean reported travel start time for initial activity for the sample.} \end{cases}$$

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:

(a) Activities other than work, school, meals between two work activities, and pick-up/drop-off passenger:

$$\text{Close window} = \max \begin{cases} \text{Responents reported activity end time,} \\ \text{Mean activity end time for the sample.} \end{cases}$$

(b) Work, school, meals between two work activities, and pick-up/drop-off passenger:

$$\text{Close window} = \text{Responents reported activity end time.}$$

(c) Individual's latest return to home:

$$\text{Close window} = \max \begin{cases} \text{Responents reported return-to-home time for his/her final activity,} \\ \text{Mean reported travel return-to-home time for final activity} \\ \text{for the sample.} \end{cases}$$

[8] Pick-up/drop-off activities involving licensed members of the same household are determined through the optimization procedure, and not specified as part of the household's activity program. Pick-up/drop-off activities involving children and/or individuals outside the household are assumed to be temporally fixed.

4.4. Exclusive activities

The HAPP mathematical program 'optimally' assigns both vehicles and individuals to fulfilling the household's activity program. Although it may be assumed that passenger vehicles generally are interchangeable for the purposes of accessing the broad range of activities, [9] certain activity types are not generally interchangeable between household members. The HAPP mathematical program imposes certain restrictions in the form of 'person activity exclusions' that identify the activities that are personal to an individual and cannot be performed by the other members in the household. In this application, these activity types are *meals*, *work*, *work-related*, *medical care*, *exercise/athletics* and *rest and relaxation*; activities of these types are restricted to be performed only by the household member reported in the survey.

5. Scenario analysis

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. As a further basis of comparison, the potential gains in emissions reduction through these travel behavioral adaptations are compared to those that might be expected to result from absorption of current emissions technology by the vehicle fleet.

In the analysis, the observed vehicle emissions for each household are calculated based on the actual schedule of activities and vehicle use as reported by the individuals in the household. 'Emissions Optimal' activity patterns are then generated by the HAPP model with an objective to minimize CO emissions; CO emissions are generally regarded as a marker for such other pollutants as HC and NO_x. The analysis considers three different scenarios:

- Optimal scheduling and travel linkages without ridesharing;
- Optimal scheduling and travel linkages with ridesharing;
- Optimal scheduling and travel linkages with ridesharing using vehicles that incorporate present-day emissions technology.

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 emissions 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. In the case of the new vehicle scenario, the best solution for CO emissions, with or without ridesharing, is considered in the analysis.

[9] This is not to say that certain vehicle types may be more or less suited for particular activities. A car with a large trunk, for example, may be more suited for a grocery shopping activity than one with limited storage.

6. Results

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.

Comparisons between the observed CO emissions for the sub-sample of 100 households and those that could be achieved with activity/travel patterns that minimize CO emissions; i.e., the optimal solutions to the HAPP model, are shown in Fig. 4. These figures present scatter plots of the optimal CO emissions on the x-axis with the observed CO emissions on the y-axis. [10]

From these results, it is clear that a substantial number of households in the sample are already practicing behavior that is close to optimal relative to emissions produced by their travel, i.e., those points that hover about the 45° line. It is further noted that for several cases (approximately 10% of the sample in the case of no ridesharing) the observed emissions are less than the 'optimal'. The reason for this occurrence is due either to the presence of ridesharing in the observed activity diary or to 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 sub-optimal or within a specified tolerance of the optimal). As the optimal solution displayed in Fig. 4a 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, leading to an increase in the optimal CO emissions. Fig. 4b and 4c also show negative results for a few observations, partly because the ridesharing heuristic in HAPP is not robust enough to handle some of the more complex variations in ridesharing observed in the data set (those points significantly below the 45° line), and partly due to the solution obtained from the HAPP model either being within a specified tolerance of the true optimal or the best solution obtained by the GAMS/CPLEX software module upon expiration of its execution time limit.

Fig. 5 gives a graphical comparison of the results obtained for the three scenarios in terms of the distribution of percent improvement (over existing) in CO emissions that would be expected under the travel behavior represented by the respective scenarios. Inclusion of ridesharing options in the optimization lead only to minor shifts in the distribution of relative emissions reduction for the sample; only approximately 15% of the sample households had feasible alternative activity/travel patterns involving carpooling among household members, and most of those showed little or no improvement in emissions. Substantial differences, both in the distribution (skewed toward greater improvement) and total emissions (substantially reduced), were found under the scenario in which all household vehicles were replaced by vehicles based on 1998 emissions technology. Figs. 6 and 7 present these results in the form of cumulative distributions for both the percent and

[10] The points of the scatter plot on or above the 45° line have an improvement in the vehicle emissions of the household; points to the left and away from the 45° represent relatively significant improvement in the CO emissions.

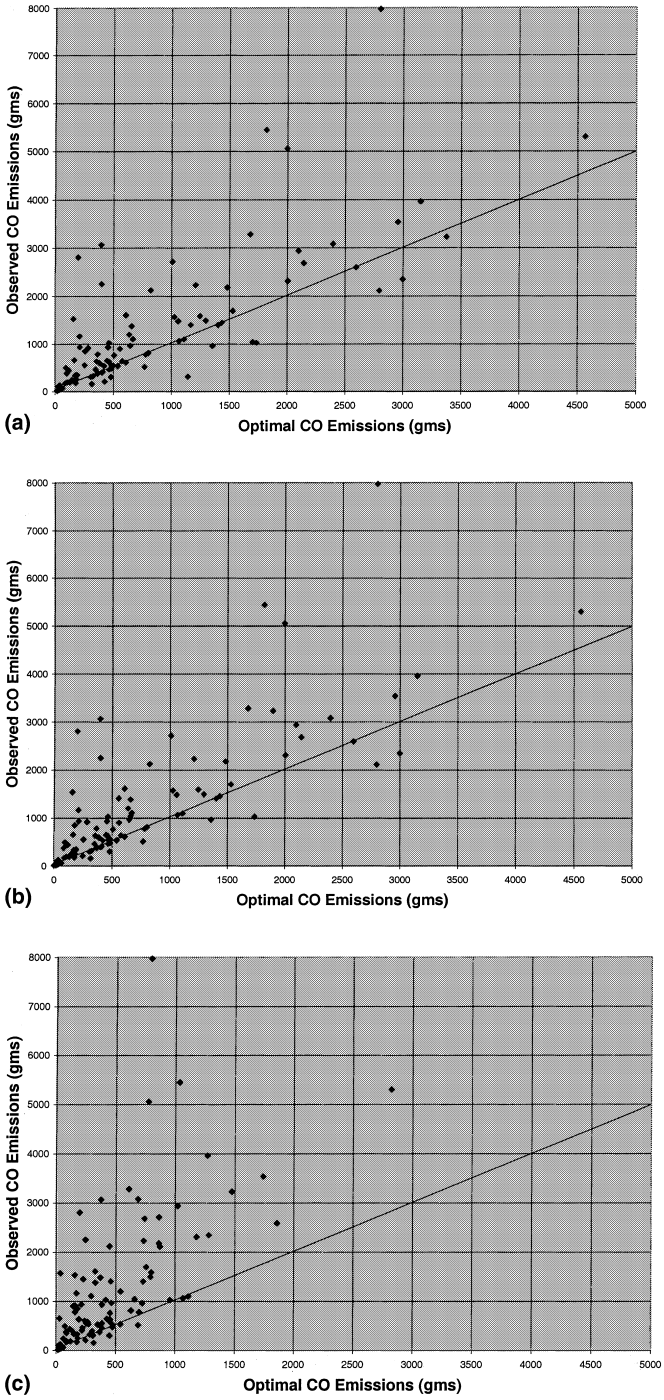

Fig. 4. (a) Observed vs optimal CO emissions without ridesharing; (b) Observed vs optimal CO emissions with ridesharing; (c) Observed vs optimal CO emissions with ridesharing and new vehicle emissions technology.

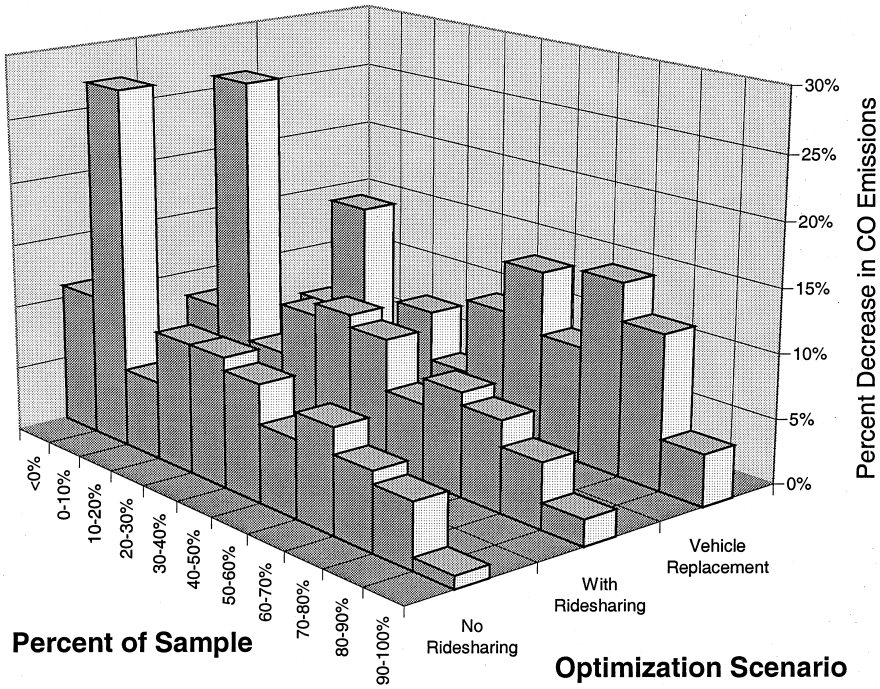

Fig. 5. Histograms of emissions improvement under various scenarios.

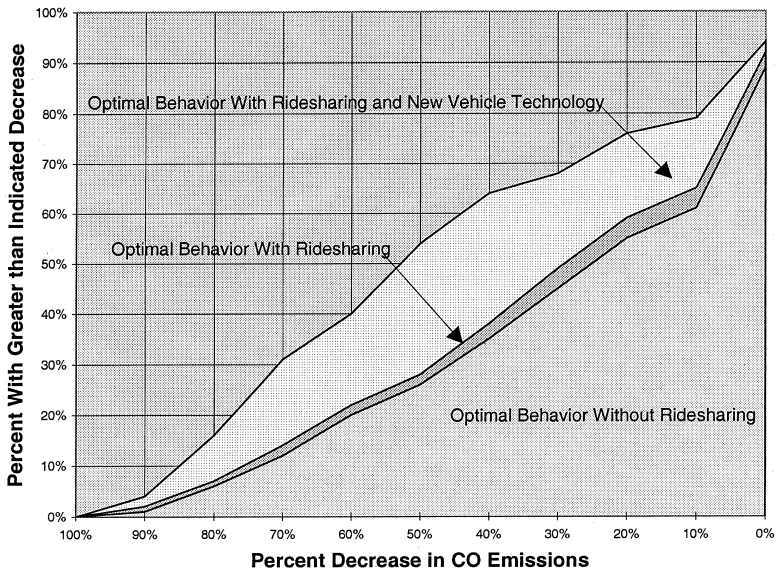

Fig. 6. Cumulative distribution of potential percent emissions improvements.

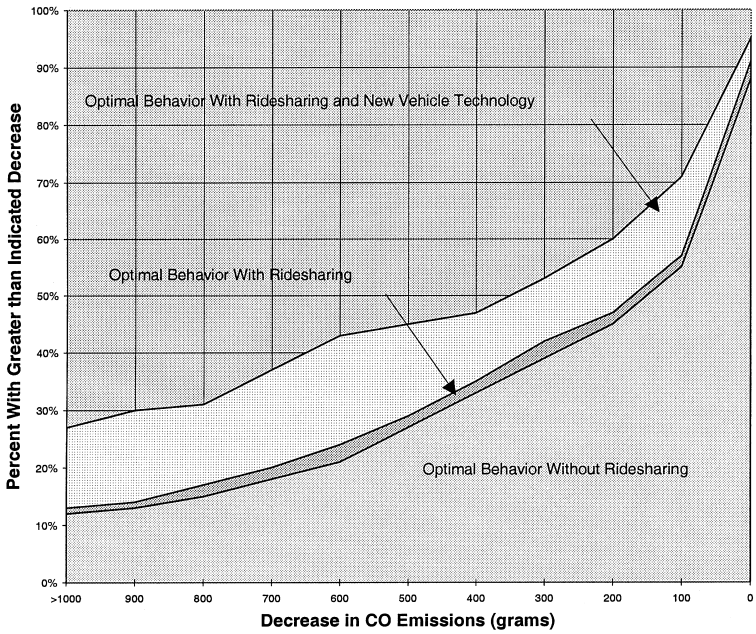

Fig. 7. Cumulative distribution of potential absolute emissions improvements.

absolute improvement in CO emissions that would be expected with optimal activity scheduling/travel behavior. For example, a 50% reduction in CO emissions is achievable for more than 25% of the sample simply by more efficient activity scheduling and travel decisions; with substitution of older vehicles by those with modern emissions technology, more than half of the sample would be expected to achieve this same result. It is notable that ridesharing plays a relatively minor role in contributing to these savings.

The incremental effects of the three optimization scenarios (i.e., optimal travel behavior without ridesharing, ridesharing, and vehicle replacement) are best seen in Figs. 8–11 which portray both the mean and median and median of the individual (i.e., for each household) CO emissions for the sample under the various scenarios, including the observed. Here the results are further broken down according to the number of vehicles in the household. It should be noted that, owing to the small sample size of households in the one- and three-vehicle categories (seven and 17 households, respectively), no statistical inference can be drawn from the breakdown. However, there appears to be at least some preliminary evidence that three-vehicle households tend to benefit more from rearrangement of their activity/travel patterns than from modernization of their fleet of vehicles; the opposite appears true for one- and two-vehicle households. This is also reflected in the differences between the mean and median emissions levels for these particular sample segments, which indicate a disproportionate contribution to mean levels, by relatively small number of households. Expectedly, ridesharing benefits are concentrated among households with multiple vehicles; those with a single vehicle apparently are already constrained to efficient allocation of that vehicle.

Fig. 12 presents aggregate (across the entire sample) information on the achievable percent reductions in CO emissions. For example, optimal activity scheduling/travel behavior (including ridesharing) would be expected to result in about a 30% decrease in the amount of daily CO

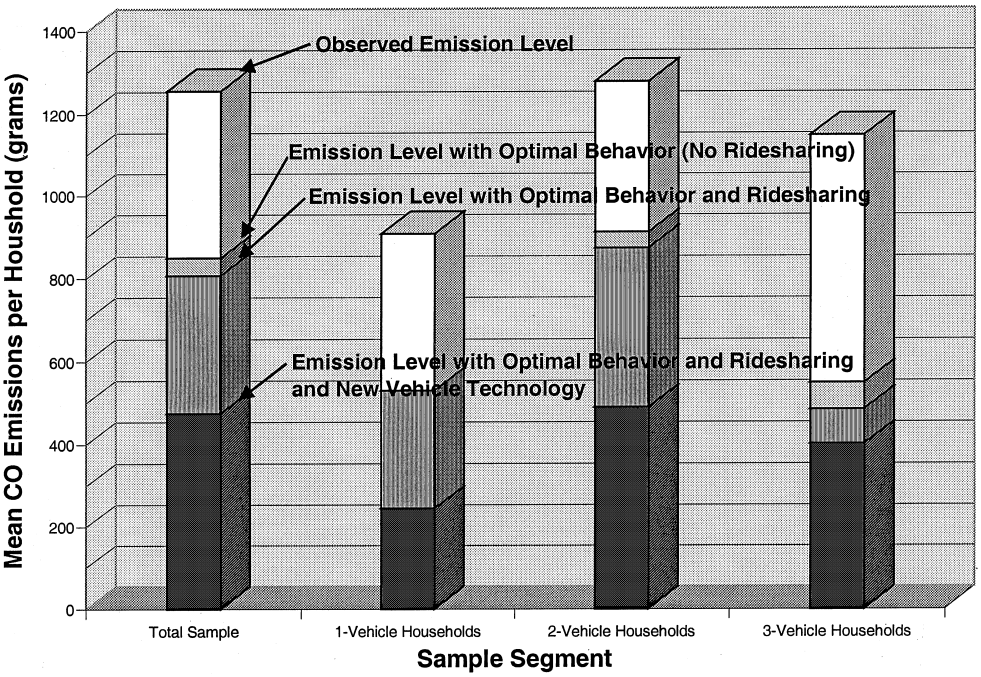

Fig. 8. Comparison of mean of individual CO emissions levels under various scenarios.

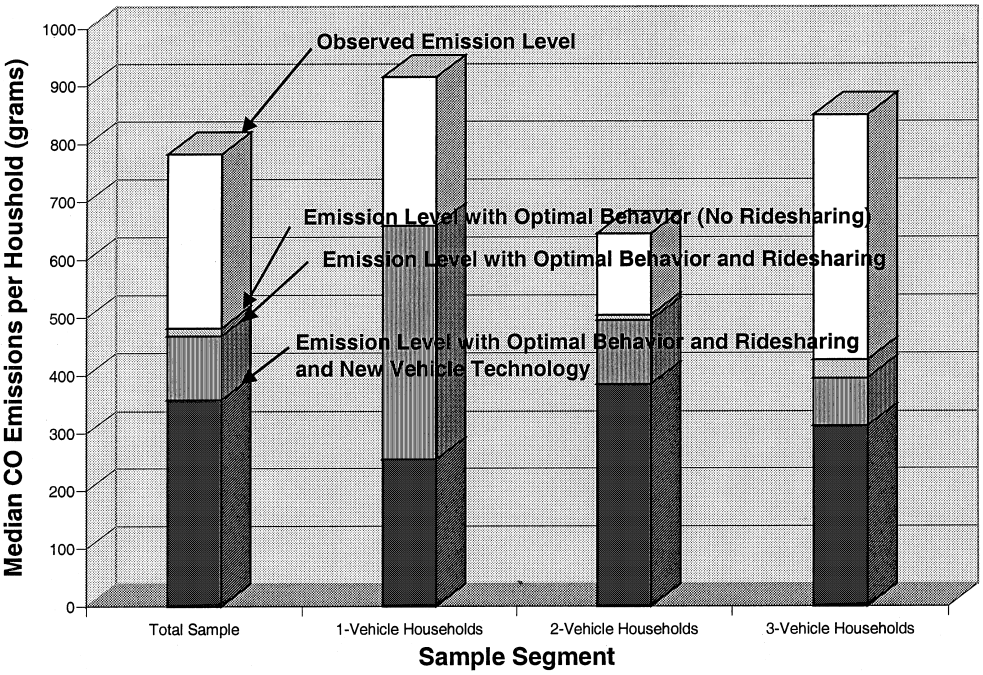

Fig. 9. Comparison of median of individual CO emissions levels under various scenarios.

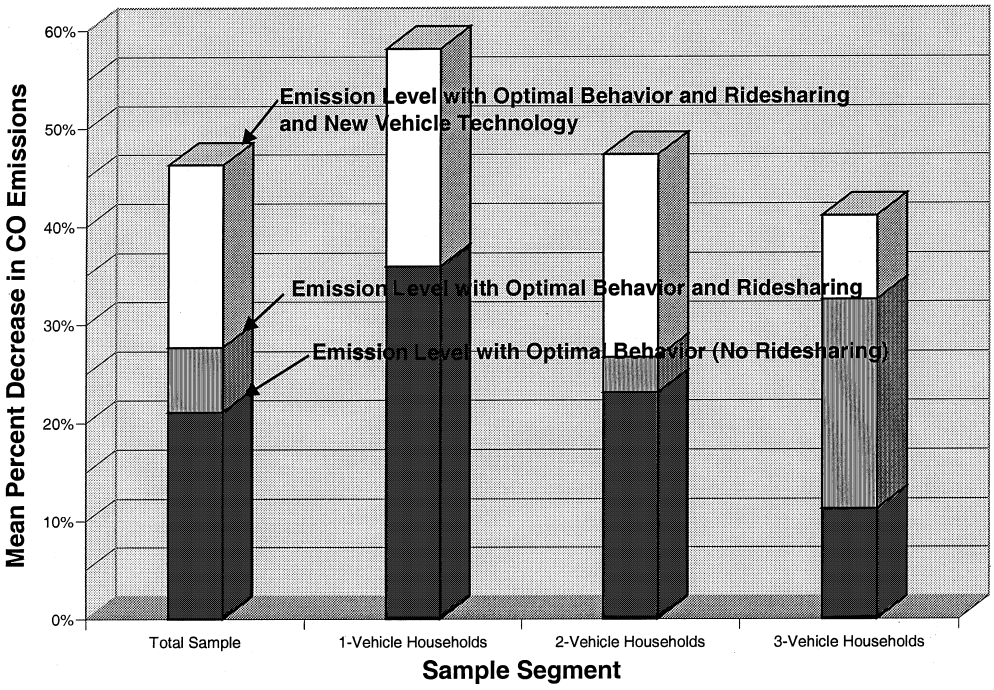

Fig. 10. Comparison of mean of individual achievable percent emissions improvements.

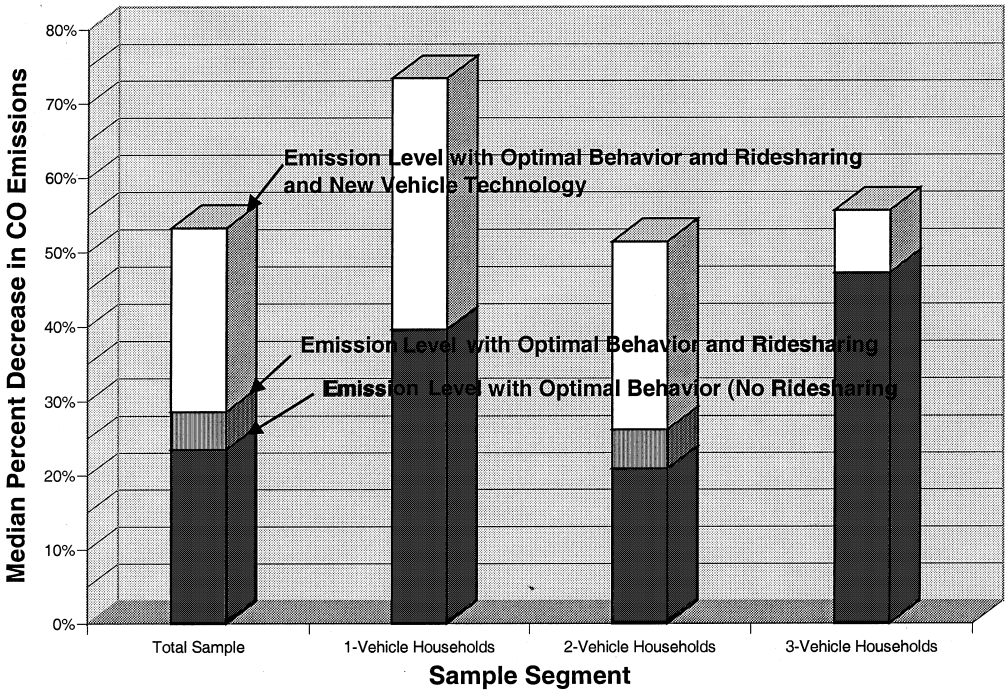

Fig. 11. Comparison of the median of individual achievable percent emissions improvements.

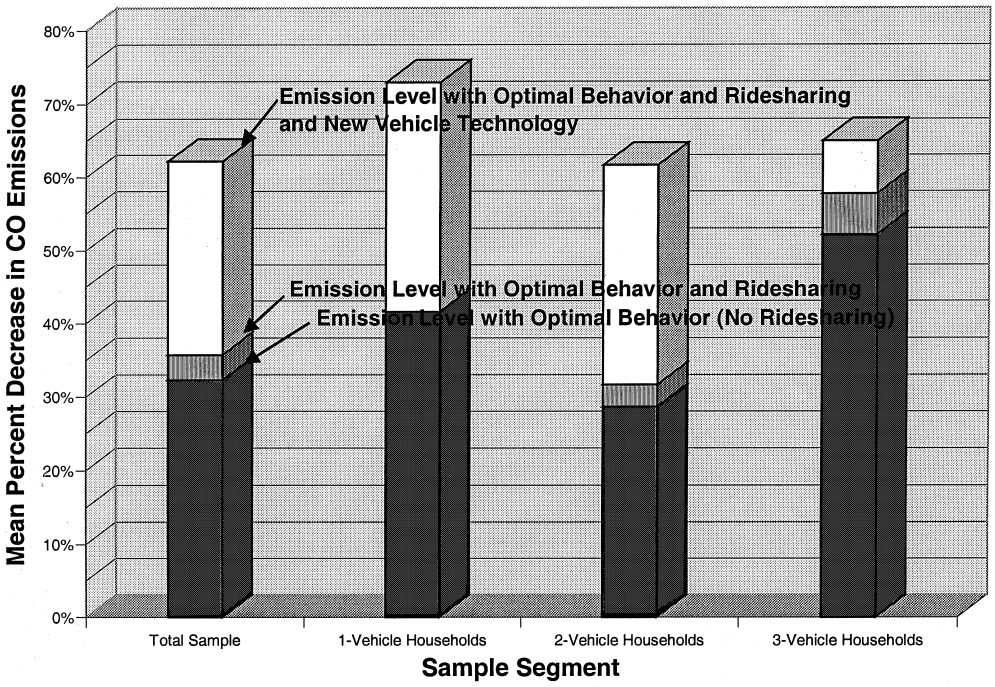

Fig. 12. Comparison of total achievable percent emissions improvements for sample.

emissions generated by the sample of one hundred households; with the replacement of aging vehicles, the decrease would be greater than 60% of current levels.

7. Conclusions

This paper 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 the study is to estimate the maximum vehicle emissions reduction that could be achieved through optimal scheduling and linking of the activities performed by individuals in a household. A vehicle emissions model has been incorporated in the model formulation and the resulting framework is tested under different scenarios, including an evaluation of the potential benefits achieved by replacing all of the vehicles in the fleet by vehicle conforming to present-day emission technology. The results generally support the contention that policies aimed at encouraging efficient trip chaining and scheduling of activities have the potential to lead to significant reductions in vehicle emissions – reductions that are comparable to those that may be expected with fleet modernization. It is again emphasized that these results indicate only the potential, and in no way forecast that the attendant behavior could be influenced sufficiently by policy to actually achieve the potential.

This has been an exploratory study to demonstrate the potential usefulness of activity-based analysis in addressing policy-sensitive issues reliant on modeling complex travel behavior. It is

offered that questions that inherently involve the linkages between a set of travel decisions and the activities that they support can best, and perhaps only, be examined from such an approach.

There are many limitations of the study and, correspondingly, as many areas of improvement that would be needed to operationalize the approach presented here. As indicated, the ridesharing option has not been tested effectively in this analysis, primarily due to limitations in the heuristic used in the ridesharing form of the optimization model. It would be both interesting and important to derive the improvements in vehicle emissions reduction with a more robust ridesharing heuristic. Only households having nothing other than automotive trips were considered in the analysis. The inclusion of transit modes in the modeling framework, although conceptually not difficult, greatly increases the dimensionality of the mathematical program, principally because of fixed schedules and routes; the walk mode, however, can easily be accommodated by assuming an average walk speed. The specifications of the constraint space in general, and the time window constraints in particular, is a source of probably significant, and unknown, bias. The constraints, as presently incorporated in the modeling framework, are dominated by physical time–space and continuity issues. Since information regarding the feasibility of performing activities at alternate times is generally not available in travel diaries, time window constraints will continue to have to be inferred, and done so absent the full context of the socio-psychological machinations of the household. Incorporation of these 'soft' aspects within the constraint specification remains a formidable challenge.

The emissions model used in this study gives the emissions for an average vehicle in that model year, with vehicle emissions based on average speed for an O–D pair. In reality, speed may vary substantially during any trip due to the stop–go traffic, possibly leading to higher emissions levels. Moreover, the reported travel times were used for all the trips with available travel time data, while the shortest path network travel times were used for all other O–D pairs. Discrepancies between these two measures, as well as tendencies on the part of respondents to both over-estimate in cases with low travel times and to round-off, may lead to erroneous results in some household cases. Both of these shortcomings can be ameliorated by wedding the HAPP activity/travel model to a microscopic traffic simulation model with emissions calculations based on accelerations and stops, as well as speed; work to accomplish this is currently underway.

Acknowledgements

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