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Contents

Foreword

The eight papers in this volume focus on issues of transportation and air quality and discuss a diversity of topics.

A number of papers examine different aspects of the modeling process used to forecast air quality in urban areas. One paper presents the findings of air quality conformity processes in nonattainment areas. Another considers air quality modeling procedures and their impacts on emissions estimates and conformity tests. A third proposes a methodology for determining the proportion of hot and cold engine starts for use in trip forecasting. A fourth proposes a statistical assessment method for vehicle carbon monoxide emission prediction algorithms. Other papers summarize the implications of the Clean Fuel Fleet Act and Clean Air Act Amendments, driving pattern variability and impacts on vehicle carbon monoxide emissions, and sketch-planning tools used to evaluate the benefits of transportation control measures.

Air Quality Conformity Case Studies

ROBERT P. BRODESKY

Case studies of the air quality conformity processes in the Denver, Raleigh-Durham, Philadelphia, and Washington, D.C., nonattainment areas were conducted. The U.S. Department of Transportation's Volpe National Transportation Systems Center conducted these case studies on behalf of FHWA. The case studies focused on travel demand and air quality modeling and included information on regional demographic and economic forecasting, jurisdictional and institutional issues, and technical issues and concerns. This information was intended to help FHWA carry out its responsibilities under the Clean Air Act Amendments of 1990 and set priorities for federal activities in such areas as research and development, development of technical guidance, and information dissemination. Another case study objective was to provide information that other urbanized areas could use to improve their conformity procedures and establish benchmarks for them to assess results.

FHWA recognizes that many metropolitan areas are struggling with how to respond adequately to the Clean Air Act Amendments of 1990 (CAAA) and the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA). Of particular concern is the process for establishing the conformity of the transportation improvement programs (TIPs) and long-range transportation plans. Political representatives and technical staff from state, regional, and local governments have expressed interest in the federal government's providing more information on the air quality conformity processes that different metropolitan areas have adopted. In response to this interest, case studies have been prepared to document the processes in the Denver, Raleigh-Durham, Philadelphia, and Washington, D.C., nonattainment areas. These case studies focus on travel demand and air quality modeling; however, they also include information on regional demographic and economic forecasting, jurisdictional and institutional issues, and technical issues and concerns.

The conformity processes described in each case study were conducted under the U.S. Department of Transportation and U.S. Environmental Protection Agency (EPA) Interim Conformity Guidance. Even since the issue of the Final Conformity Guidance in November 1993, the case studies contain relevant information that could be useful to different metropolitan areas in their preparation of the next round of conformity analyses.

Because each metropolitan area has a distinct approach to resolving issues, these case studies are not intended to be paradigms. Nonetheless, similarities among metropolitan areas exist, and the experiences of each area establish benchmarks for other metropolitan areas to assess their approaches or progress toward meeting federal requirements.

The case studies focus on metropolitan-level planning within the ozone nonattainment area. As a result, the case studies include information about the ongoing air quality conformity processes for each metropolitan area [and their urban transportation planning processes (UTPP)] within any of these ozone nonattainment areas (Table 1). The carbon monoxide (CO) or small particulate matter (PM_{10}) nonattainment areas are also of interest and are included in the case studies; however, these areas are typically smaller geographically than the ozone nonattainment areas.

Three of the case studies—Philadelphia; Washington, D.C.; and Raleigh-Durham—discuss how inconsistencies exist between the geographical designation for the nonattainment areas and the planning boundaries for metropolitan transportation planning. The Philadelphia nonattainment area covers four states and includes four metropolitan planning organizations (MPOs). The Washington, D.C., nonattainment area covers Maryland; Delaware, and Washington, D.C. but has only one MPO. Unlike Philadelphia, the Washington, D.C., nonattainment area includes nonurbanized areas outside the MPO's planning boundaries. Despite the geographical proximity of Raleigh and Durham (25 mi), they have separate MPOs and air quality conformity processes.

The four nonattainment areas that were selected represent a cross section of metropolitan areas with varying air quality, transportation, economic, geopolitical, and planning issues. They also vary in population size from small to very large (Table 1). To a great extent, they represent the mix of metropolitan areas in the United States that must meet CAAA requirements.

For example, Raleigh and Durham, which have been designated moderate for ozone and CO, are smaller metropolitan areas that have experienced high rates of population and travel growth in the past 10 years (Tables 2 and 3). Although bus service is available in both cities, their respective transit mode shares are very low. Consideration is being given to adopting policies that will encourage denser land development; however, highway construction is the focus of Raleigh and Durham's transportation investment programs. Because the respective MPOs have limited staff, the required technical analyses, such as travel demand and air quality modeling, are conducted by the North Carolina Department of Transportation (NCDOT).

In contrast, the Philadelphia metropolitan area, which has been designated as severe nonattainment for ozone and moderate for CO, has experienced an average annual population growth rate of only about 0.4 percent. The region has an old, complex transportation infrastructure that includes the following transit modes: bus, heavy and light rail, trolley, and commuter rail. Thus, the focus of its transportation plan and program is to reconstruct the existing infrastructure. The MPO for the Philadelphia area has in-house staff capable of completing the required transportation and air quality technical analyses, all of which are conducted with cooperation of the Pennsylvania and New Jersey departments of transportation and environment (or natural resources).

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TABLE 1 Overview of MPOs Within Ozone Nonattainment Areas

Ozone Non-Attainment Area	Urbanized Areas	Metropolitan Planning Organizations	U.S. Census MSA 1990 Populations[1]
Philadelphia	Philadelphia	Delaware Valley Regional Planning Commission	4,856,887
	Wilmington	Wilmington Area Planning Coordinating Council	578,587
	Dover	Dover Metropolitan Planning Organization	
	Vineland	South Jersey Transportation Planning Organization	138,053
Washington, D.C.	Washington, D.C.	National Capital Region Transportation Planning Board/Washington Council of Governments	3,923,574
Raleigh - Durham	Raleigh	Greater Raleigh Metropolitan Planning Organization	735,480
	Durham	Durham - Chapel Hill - Carrboro Metropolitan Planning Organization	
Denver	Denver	Denver Regional Council of Governments	1,848,319
	Boulder		
	Longmont		

[1]For consistency purposes, U.S. Census Metropolitan Statistical Area (MSA) estimates are presented in this table; however, the text of this report also includes MPOs' population estimates. The U.S. Census and MPO estimates do not necessarily agree. The MSA and the MPO's planning boundaries do not always coincide and each of the MPOs use different estimation procedures. For example, the Philadelphia MPO includes Mercer County, New Jersey, which is part of the New York CMSA. With the inclusion of Mercer County, the population within the Philadelphia MPO's boundaries is closer to 5.2 million people.

FINDINGS

This section presents an overview of the case studies, focusing on what was learned in each of the four areas. The discussions of procedures are purely descriptive; no attempt has been made to analyze or critique the approaches that have been adopted. The findings are based on reviews of metropolitan air quality conformity analyses and telephone conversations with federal, state, regional, and local planners and engineers who have been involved in the processes. The discussion highlights similarities and differences in the approaches adopted by these metropolitan areas and identifies problems that might be addressed by future federal government action (either by providing additional technical and informational support or determining future policy changes).

Determining Conformity—Transportation Improvement Program and Transportation Plan

Under CAAA, all transportation plans and programs that include federally funded projects must conform to a state implementation plan (SIP). As interpreted in regulations issued to implement the conformity provision of CAAA, this means that the expected emissions from transportation plans and TIPs must be consistent with the implementation plan's required schedule of motor vehicle emissions reductions.

TIP Evaluation

The conformity analyses conducted by the metropolitan areas were based on projects included in TIPs. The project listings in TIPs were used to establish baseline and action ("build" and "no-build") scenarios for evaluating emission levels in the milestone and attainment years.

Plan Evaluation

Although required by the Interim Conformity Guidance, the region's long-range plans and whether they conformed to SIPs were not the focus of the conformity analyses of the participating metropolitan areas. Instead, TIPs were the focus of the evaluations. Because of the traditional relationship between plan and program in the UTPP, this is a reasonable approach. Implicit in this process is the assumption that the projects in TIPs are based on or derived from the policies, goals, and strategies expressed in the long-range transportation plan.

TABLE 2 Air Quality Designations for Nonattainment and Urbanized Areas

Non-Attainment and Urbanized Areas	Air Quality Designations (As Defined by the EPA's National Ambient Air Quality Standards)		
	Ozone	**Carbon Monoxide**	**Small Particulate Matter**
Philadelphia	Severe	Moderate	
Wilmington	Severe	Attainment	
Dover	Severe	Attainment	
Vineland	Severe	Attainment	
Washington, D.C.	Serious	Moderate	
Raleigh	Moderate	Moderate	
Durham	Moderate	Moderate	
Denver	Transitional	Moderate	Moderate

For many of these metropolitan areas, the task of actually conducting a conformity analysis of their long-range plans would have been difficult. This is because their long-range plans are not always developed at a level of specificity that identifies what transportation projects will be in place at different time frames within the planning period.

The requirements of the final rules for conformity and metropolitan transportation planning under CAAA and ISTEA will strengthen the relationship between plans and programs. Long-range plans will have to become more than policy statements; they will have to include a level of project specificity that will enable MPOs to establish whether the plans are financially constrained. As a result, future conformity determinations will shift from the present emphasis of evaluating projects listed in TIPs to a more comprehensive assessment of those projects identified in the long-range plans.

Inconsistency Between Nonattainment and MPO Planning Areas

The nonattainment areas (particularly for ozone) and the geopolitical boundaries of the entities responsible for completing the conformity analyses rarely coincide. This situation arises because the boundaries of designated nonattainment areas relate more to the measurement of emission levels than the metropolitan boundaries that form the basis for planning areas. This inconsistency creates a level of complexity. (For example, more than one MPO or state may compose a nonattainment area, a part of a nonattainment area may lie outside an MPO, and more than one nonattainment area may lie within the planning area.) This complexity also makes it difficult to ascertain the total nonattainment area's progress toward reducing emissions because one conformity determination is not completed for the entire nonattainment area.

The interim and final conformity guidelines permit one conformity determination for nonattainment areas with more than one metropolitan area. Because the focus of urban transportation planning from the federal perspective has been at the metropolitan planning level, this has resulted in each MPO in the nonattainment area completing a conformity determination.

There are also areas (sometimes referred to as "donut" areas) that have not selected to join an MPO but must still meet the conformity requirements because they fall within the nonattainment area. The completion of conformity analyses in these donut areas has in some instances required special agreements with an organization capable of conducting the technical analyses. In addition, areas sometimes exist within an MPO's boundaries that are not urbanized and not covered by the region's transportation demand model. Some jurisdictional and institutional issues that were identified in the case studies include multiple MPOS, donut areas, and multiple nonattainment areas within a planning area.

Multiple MPOs

The Philadelphia ozone nonattainment area covers four states and includes four different MPOs. The Delaware Valley Regional Planning Commission (DVRPC), which serves as the MPO for the Philadelphia area (and covers 9 of the 14 counties that make up the ozone nonattainment area), has in-house staff capable of completing the required transportation and air quality technical analyses. The other MPOs located in the nonattainment area have limited staff and must therefore rely on their respective state departments of transportation to complete the technical analyses.

The Raleigh and Durham areas were newly designated as a single, moderate nonattainment area for CO and ozone in 1991, even though the two urban areas maintain separate UTPPs. To comply with the requirements of CAAA, the Greater Raleigh MPO and the Durham–Chapel Hill–Carrboro MPO made separate conformity determinations based on the respective TIPs and long-range transportation plans.

TABLE 3 Overview of Urbanized Areas' Demographic, Transportation, Institutional, and Planning Features

Urbanized Areas	Compound Annual Growth Rate 1980-1990 (%)	Transportation Infrastructure (includes limited comments about highway networks)	Institutional & Planning Issues
Philadelphia (PMSA) (Phila. Non-Attainment Area)	.4	Extensive, but aging highway & transit networks. Transit includes rail, trolley & bus service. Also, have extensive commuter rail.	Due to its geo-political coverage, the MPO must coordinate closely with state agencies in Pennsylvania and New Jersey. This requires completing emission runs which reflect the policies and conditions of the two states.
Wilmington (PMSA) (Phila. Non-Attainment Area)	1	Bus service	The MPO, which also includes Cecil County, Maryland has limited staff. Consequently, it relies on the Delaware and Maryland departments of transportation for technical support. One of its member counties, Salem County, New Jersey, recently left to join a newly created MPO made up of southern New Jersey counties.
Dover (Kent County) (Phila. Non-Attainment Area)	1 (1980-1986)	Limited bus service	The MPO was recently formed and only has one part time staff person. It relies on the Delaware DOT for completing its conformity analyses.
Vineland (PMSA) (Phila. Non-Attainment Area)	.6	Limited bus service	The MPO is a member of the Southern Jersey Transportation Planning Organization which was recently formed to serve Atlantic, Cumberland, Salem and Cape May counties. It relies on New Jersey DOT for completing its conformity analyses.
Washington, D.C. (MSA)	2	Bus and heavy rail service	The multi-state area is served by one MPO. The conformity technical analyses for donut areas located in southern Maryland are being conducted by the MPO's technical staff. A separate independent regional committee has been formed to focus on the development of the regional air quality strategy and implementation plan.
Raleigh	3 (for Raleigh-Durham MSA)	Bus service	The MPO has limited technical staff. The North Carolina DOT has a strong statewide planning staff which prepares the urbanized area's long range plan and conformity analysis. The area has experienced strong growth. New highway construction is the focus of its capital investment program.
Durham		Bus service	The MPO has limited technical staff. The North Carolina DOT has a strong statewide planning staff which prepares the urbanized area's long range plan and conformity analysis. The area has experienced strong growth. New highway construction is the focus of its capital investment program.
Denver (CMSA)	1	Bus service. Have begun constructing one leg of a proposed light rail system through downtown.	The MPO, which has the responsibility for making the air quality conformity determination, shares responsibility for the technical analyses with the Air Pollution Control Division of the Colorado Department of Health. The MPO does the travel demand modeling and the state generates the emission estimates.

Donut Areas

The Washington, D.C., ozone nonattainment area boundary extends beyond the MPO's planning boundaries to include Charles and Calvert counties in southern Maryland. By agreement, the Washington Council of Governments (WashCOG), which conducts the technical analyses for determining conformity on behalf of the region's MPO (the National Capital Region Transportation Planning Board), has incorporated Charles County into its travel demand and air quality modeling efforts. In the coming year, it will also incorporate Calvert County. Incorporating these two counties is good for Washington, D.C., because considerable suburban development has occurred in southern Maryland as a result of high rates of growth and steep increases in housing values in the counties adjacent to Washington, D.C.

The Raleigh-Durham ozone nonattainment area does not coincide with the combined boundaries of the two MPOs. A rural, unincorporated portion of the nonattainment area currently lies outside Durham's MPO planning area. Although EPA has indicated in writing that it would like this area included in the conformity analysis, the MPO and the state have chosen not to do so because the area is rural and these agencies consider it to have little or no impact on the region's ambient air quality.

In response to the 1990 Census and ISTEA requirements, the Greater Raleigh MPO has recently expanded its boundaries so that they now approximate those of their portion of the ozone nonattainment area. Even so, as a result of a lack of travel data, no adjustments have been made to the region's travel model to incorporate the expanded land area.

Multiple Nonattainment Areas Within A Planning Area

The city of Longmont, which is a member of the Denver MPO (the Denver Regional Council of Governments), is part of a separate nonattainment area for CO. Because it is part of the Denver Regional Council of Government's (DRCOG) regional transportation modeling effort, DRCOG generates socioeconomic and transportation demand estimates for the Longmont urbanized area to use in its air quality planning.

Consultation and Coordination

To meet the requirements of CAAA, MPOs and state agencies (departments of transportation, natural resources, environment, or public health) have had to form close working relationships. Through the Ozone Transport Commission, a group of northeastern states has forged a working relationship for coordinating policy; however, limited consultation or coordination appears to exist among MPOs with conformity responsibility within individual ozone nonattainment areas or in adjacent nonattainment areas. Although it is possible to track the anticipated progress by urbanized area, this would be difficult to accomplish for nonattainment areas with more than one MPO.

Institutional Arrangements for Completing Technical Analyses

In urbanized areas, MPOs are required by CAAA to make the air quality conformity determination. Only the country's larger MPOs appear to have the staff and technical expertise to complete the analysis necessary to support this determination. This means that many MPOs have had to seek technical support from state agencies or consultants. Also, in certain urban areas, political considerations appear to influence the choice of which agencies complete the technical work.

State Support

The research conducted for these four case studies indicates that MPOs covering urbanized areas with populations less than one million do not usually have large staffs or individuals with the technical expertise to conduct the analyses necessary to determine conformity. The MPOs contacted in Delaware, New Jersey, and North Carolina that fall into this category rely on their state departments of transportation to conduct travel and air quality modeling. Without these centralized statewide functions, many MPOs would have had difficulty completing the air quality conformity analyses mandated by CAAA.

The relationship between NCDOT and the state's MPOs illustrates this point best. NCDOT's statewide planning branch supports, develops, and operates regional transportation models and prepares long-range plans, known as thoroughfare plans, for the state's urbanized areas (except Charlotte). It also conducts air quality conformity analyses (i.e., running EPA's MOBILE model) for the state's seven nonattainment areas.

Consultant Support

Among the agencies contacted, the use of consultants for determining conformity has been limited. The Delaware Department of Transportation (Del DOT), which conducts the conformity analyses for the Wilmington and Dover areas, has contracted with a consultant to assist with its MOBILE runs. Also, Del DOT recognized that it needed consultant support to ensure continued progress in meeting the mandated deadlines. Over time, it plans to augment its in-house expertise and rely less on consultant services. Similarly, WashCOG has contracted a consultant to assist in the development of inputs for the MOBILE model and to run the model for conformity analyses.

Some MPOs and state transportation agencies also use consultants to identify, evaluate, and quantify the impacts of transportation control measures (TCMs). Conformity and SIP requirements necessitate the quantification of the potential effect of TCMs; however, little is known about what effect different TCM categories will have on emissions.

Shared Responsibilities

In Denver, DRCOG and the Air Pollution Control Division (APCD) of the Colorado Department of Health share the responsibility of conducting the technical analyses that support the conformity determination. DRCOG is responsible for making the air quality conformity determination and conducts the travel demand modeling. The APCD generates emission estimates using EPA's MOBILE model.

As a result of DVRPC's geopolitical coverage, the Pennsylvania and New Jersey state departments of transportation are actively involved in the air quality conformity process. This involvement consists primarily of reviewing or providing input data necessary to complete MOBILE model runs.

Formation of Additional Institutional Arrangements

In the Washington, D.C., and Denver metropolitan areas, additional policy-making organizations have been formed to ensure the regional compliance with CAAA. These organizations focus on meeting SIP requirements instead of on making conformity determinations.

Regionwide Air Quality Committee—
Washington, D.C., Region

The Metropolitan Washington Air Quality Committee (MWAQC), which includes all of the jurisdictions that make up the ozone nonattainment area, is charged with developing and adopting strategies for reducing emissions from mobile and stationary sources to be included in the nonattainment area's 15 percent volatile organic compound (VOC) reduction plan. Its membership includes a number of jurisdictions that do not participate in the MPO as well as representatives from the Maryland, Virginia, and Washington, D.C., departments of transportation. All individuals who represent participating jurisdictions are elected officials.

State Involvement in Establishing Regionwide Air Quality Policy—Denver Region

Air quality planning in the Denver region is a cooperative effort conducted by DRCOG, APCD of the Colorado Department of Health, and the Regional Air Quality Council (RAQC). RACQ, which was created in 1989 by the governor, is designated as the lead agency for air quality planning in the Denver nonattainment area and is responsible for preparing the Denver portions of the SIPs. (As already stated, DRCOG and the APCD share responsibility for conducting the analyses necessary to support a conformity determination.)

The governor formed RACQ after consulting with local units of government in the Denver area. It has a 35-member board, 17 of whom are local elected officials appointed by cities and counties throughout the Denver region. As part of the SIP process, RACQ identifies, analyzes, and recommends control measures to include in the SIP document relating to control of CO and ozone precursor emissions. RACQ accomplishes this by working with the implementing organizations, including the state legislature and local governments.

Transportation Control Measures

Despite their agencies' efforts to evaluate and select TCMs, several participants expressed concern about the focus in CAAA on the use of TCMs to achieve air quality standards. The general sentiment the participants expressed is that TCMs are unlikely to be effective and that too much time is being spent on implementing measures that will not bring air quality results rapidly. Even though TCMs are not perceived to be an effective strategy for achieving air quality goals, they are perceived as a means to influence people's travel choices.

TCM Evaluation

A number of individuals who were contacted said they would like the federal government to provide standardized methods or travel demand modeling tools for evaluating the marginal impact of different TCMs. To quantify the marginal impact of a range of TCMs on future levels of emissions, different MPOs and state departments of transportation have sought outside assistance from consultants.

Identification of Effective TCMs for Large Urbanized Areas with Aging Infrastructure

The Philadelphia metropolitan area has been struggling to identify TCMs that are (a) compatible with its older, multimodal transportation infrastructure, (b) will have a measurable impact on air quality, and (c) will be acceptable to an active and demanding environmental community. The region is not committed to constructing high-occupancy vehicle (HOV) lanes on area-wide expressways because many of the region's expressways are only four lanes and limited room exists to accommodate the addition of HOV lanes. Also, the addition of HOV lanes is difficult to justify in corridors that are already served by rail transit and commuter rail.

Appropriateness of TCMs in Smaller Urbanized Areas with High Growth Rates

NCDOTs long-range planning for Raleigh and Durham focuses on reducing systemwide congestion and emissions by building missing highway links (including freeways), widening roads, and improving intersections and signalizations. TCMs are not included in the thoroughfare plans for the different metropolitan areas. They have not been seriously considered as a means to reduce vehicle miles traveled (VMT) and improve air quality because they are perceived to be expensive with no guarantee of effectively reducing VMT and automobile emissions. Given the nonattainment area's moderate designation for ozone and CO, agreeing to these potentially costly and disruptive actions could be difficult for planners and local officials to justify.

Quantification of Effect of TCMs on Statewide Emission Levels

Recently, the New Jersey Department of Transportation (NJDOT) (with the assistance of a consultant) conducted an analysis to determine the extent TCMs proposed by local governments and MPOs throughout the state and employee trip reduction programs would affect statewide air quality. The analysis, which included 500 to 600 TCMs, concluded that these measures would result in an aggregate statewide reduction of 8.39 tons per day of VOC. According to NJDOT staff, this represents 4 percent of the total VOC reduction that New Jersey must achieve by 1996.

Regional Land Use and Air Quality Planning

ISTEA encourages governmental units to consider the interaction between land use and transportation. In addition, environmentalists have advocated adopting policies that would encourage greater residential densities and other changes in land use patterns as a means of reducing VMT.

The MPOs that were contacted have no regulatory power to affect land use or land development. Through the continuing, cooperative, and comprehensive (3C) planning process, MPOs, along with state and regional transportation organizations, have the mechanism for programming transportation capital investments with potential long-term effects on land development.

Various agencies are also initiating planning activities that could affect land development and transportation supply. Specific activities that are ongoing in North Carolina and Delaware at the regional level are described in the following sections.

North Carolina

In response to the growing economic interaction among Raleigh, Durham, and Chapel Hill, the Triangle Transit Authority was recently formed to provide interurban transit service. It is providing bus service to the cities within the Triangle and studying the feasibility of constructing a regional fixed guideway system. As part of this research, the Triangle Transit Authority is considering alternative land-use scenarios that assume the development of transit-dependent communities and much denser interurban corridors.

Also, a neotraditional neighborhood was recently proposed for the Chapel Hill area. Its developers claimed that this land development concept would produce 60 percent fewer trips than a traditional single-family housing development.

Despite these planning activities, NCDOTs Statewide Planning Branch staff generally do not anticipate significant changes in land-use patterns over the long term. The Raleigh-Durham region continues to experience high growth, and local jurisdictions have not yet adopted land use policies or regulations that would encourage denser development patterns.

Delaware

Del DOT, which is responsible for almost all roads within the state (including many minor collectors), has developed extensive computerized representations of the highway networks serving three of its most urban counties. These networks are being used for travel demand modeling purposes (Del DOT uses TRANPLAN to complete the travel analyses). Del DOT has linked TRANPLAN to a geographical information software (GIS) program (MapInfo), which also allows access to extensive demographic, land use and employment location data. This enables Del DOT to conduct interactive analyses. Analysts can produce highway simulations for the base year and any horizon year and analyze the impact of new development proposals on the transportation network. For example, Del DOT used the system to analyze the potential impact of a proposed Mercedes-Benz assembly plant. It also facilitated analyzing travel and emissions under build and no-build scenarios as part of the air quality conformity analysis process for different milestone years.

Travel Demand Modeling

Generally, the travel demand models used by the planning agencies interviewed for this study represent the state of the practice. For the most part, a four-step travel demand estimation process is being used. Travel demand forecasting packages, such as TRANPLAN and MINUTP (operated on high-performance microcomputers), are the typical means for conducting the analysis. Two different MPOs, DRCOG and DVRPC, continue to use their mainframes for all or part of their analyses.

Availability of Current Travel Data and Model Updates

Many of the travel demand models in use were calibrated by using travel behavior inventories or surveys conducted in the 1960s and 1970s. For example, Del DOTs models are based on a travel behavior survey that was conducted in the 1960s.

The Triangle Transit Authority, which serves Raleigh, Durham, and Chapel Hill, will be conducting a multimodal travel survey as part of its intercity rail study. The survey, which will be used to estimate a new regional travel demand model, will be the first comprehensive travel survey to be conducted in North Carolina in 20 years.

Although many regional technical analysts have been interested in undertaking new travel behavior surveys, they have been unable to secure sufficient funds or support from local policy makers. The Denver region has repeatedly included travel demand surveys in its Unified Planning Work Program (UPWP); however, it has been unable to proceed with extensive survey work because of funding constraints.

Nevertheless, travel behavior surveys that are limited in scope have been conducted in different regions so that their transportation planning models can be updated or enhanced. For example, WashCOG adjusted its trip generation, distribution, and car occupancy submodels in 1992 to conform to data that were obtained from a 1987–1988 home interview survey and traffic counts conducted in 1990. Similarly, DVRPC recalibrated its model using cordon counts, with a home survey that was conducted in the late 1980s.

During 1994, WashCOG planned to update and recalibrate its mode choice model and review the entire model chain as U.S. Census data become available. This will consist of comparing estimated and observed trips and then adjusting the model's constant and coefficients to correspond more closely to observed behavior.

For the Philadelphia region, the 1960 Penn-Jersey Study was the original source for the trip generation data. Since then, these trip rate data have been validated in 1970 and 1980 using screenline counts. A home survey completed between 1988 and 1989 indicates that the basic relationships have remained stable, although the number of trips per household has increased. In response to this, DVRPC intends to increase the trip rates in its cross-classification matrix.

Truck Trip Estimation

Only two of the areas that were contacted, Denver and Washington, D.C., are generating internal truck trip estimates.

Mode Split Estimation

The travel demand models that are used in Raleigh, Durham, and southern New Jersey exclude the mode split step. Because transit represents less than 1 percent of total person trips in Raleigh and Durham, NCDOT subjectively estimates transit shares on the basis of actual route patronage and expected extensions of the bus system.

Model Enhancements

Two of the MPOs—DVRPC and DRCOG—are beginning to consider enhancements (e.g., feedback loops) to their travel demand models, which would enable them to estimate peak-hour travel and assess policy and land use changes. WashCOG recently installed a feedback loop in its modeling process for the purpose of differentiating between peak- and non–peak-hour travel during the trip distribution and trip assignment stages. Another enhancement under consideration by some regions includes modifying the travel demand models so they could estimate bicycle travel.

Even though strong interest exists in making many of these improvements, limited progress has been made. The staffs are hampered by funding constraints and approval from policy makers.

For fiscal year 1994, WashCOG programmed a number of these enhancements in its UPWP. In addition to installing a feedback loop for differentiating between peak- and non–peak-hour travel, work activities included improving trip generation by updating a model to estimate car ownership. The model is based on income, transit service availability, area type (e.g., inner city, urban, or suburban), and land use density.

Interface Between Travel Demand and Air Quality Models

Using EPA's MOBILE model to convert the travel assignment output to an estimate of emissions is cumbersome. To improve the interface between the two modeling processes, three of the organizations contacted developed a post-processor program. These programs are being used to convert the daily travel into hourly estimates and compute VMT and associated speeds.

Air Quality Modeling

Different individuals expressed concerns about the accuracy of EPA's MOBILE model and the current practice of air quality planning. According to planners with NCDOT, MOBILE produces higher emission results for high-speed facilities than it produces for arterials, which have acceleration and deceleration cycles of greater amplitude and frequency. In addition, planners stated that the conformity analysis process attempts to produce results at a level of precision and accuracy far greater than the input data. The input data are based on techniques or methods with considerable variability or error. That is, surveys and travel demand models do not produce exact results.

Future Technical and Informational Needs

The technical and informational needs expressed by the case study participants were comparable. To begin with, the participants expressed interest in the federal government providing more technical training regarding the operation of the MOBILE model. They would also like the federal government to develop better quality transportation and air quality modeling by disseminating information about different modeling procedures that have been adopted by metropolitan areas and states. Additional topics that participants stated they would like more information or technical support on included (a) the roles and responsibilities that different organizations are assuming in SIP development, (b) how TCMs are being modeled to measure effectiveness in reducing emissions, (c) different employee commute option programs that are being developed, (d) strategies being identified for reducing the hydrocarbon baseline emissions as well as nitrogen oxides (NO_x) emissions, (e) how different regions are using congestion management and air quality funds, and (f) what new transportation model packages and corridor-specific air quality models are available.

In addition, many participants expressed interest in the federal government conducting more regional or multiregional meetings with representatives from different state or regional transportation agencies. In this way, representatives of various organizations would have an opportunity to share experiences or approaches to meeting CAAA requirements. Participants also suggested that the federal government should consider (a) issuing a bulletin on a regular basis that reports how various metropolitan areas and states are proceeding with their air quality planning and (b) conducting a survey of metropolitan areas followed by a summary report that highlights successes and problems encountered in attempting to meet CAAA milestones.

CONCLUSIONS

The case studies indicate that the metropolitan areas are implementing the required air quality conformity and transportation planning processes; however, continued guidance and technical support are needed from the federal government. A number of conclusions can be reached regarding the progress metropolitan areas have made in conducting air quality conformity analyses and the support or guidance the areas will need to improve the process.

- Completing the air quality conformity process and demonstrating a region's progress in attaining the National Ambient Air Quality Standards is frequently hampered by (a) the inconsistencies between the geographical designation for the nonattainment areas and the planning boundaries for metropolitan transportation planning areas, (b) the differences among the air quality and transportation policies adopted by states that must work together to reduce emissions in a nonattainment area, (c) the lack of consultation among MPOs located within a nonattainment area that are each conducting conformity determinations, and (d) the limited staff size and technical capabilities among many MPOs, particularly in areas with populations less than one million.
- In many metropolitan areas, particularly those with populations less than one million, the demonstration of air quality conformity depends on the technical capabilities of the in-house technical staffs of the state departments of transportation.
- Because of differences among the metropolitan areas, which stem from economic and demographic growth patterns and existing transportation infrastructure, the approaches to meeting the regions' travel demands and emission reduction requirements vary. In fast growing areas, the construction of missing links in the highway network are necessary to improve traffic flow and alleviate congestion. In contrast, the focus of TIP in areas with complex and older transportation systems is on highway and transit reconstruction instead of implementing TCMs and management systems.
- A considerable amount of concern exists among planners and policy makers about the focus in CAAA on the use of TCMs (other than inspection and maintenance programs) to achieve air quality standards. The concern is that TCMs are unlikely to be effective in contributing to the rapid reduction in emissions that are mandated.
- As a result of inconsistencies between the state-of-the-practice urban transportation models that are used and the MOBILE model, serious questions remain about the accuracy of the emission calculations (by link and speed). Resolving this issue requires the development of additional transportation and air quality modeling enhancements.
- Not all metropolitan areas are estimating truck trips and considering their impact on regional air quality. To accommodate trucks, regions could use traffic counts to adjust hourly vehicle mix and directional speeds by highway classification.
- More technical information and guidelines are needed so that regions can improve their air quality analysis and planning for NO_x and small PM_{10}.

Simplified and Rational Approach To Address New Modeling Requirements for Conformity Analysis

PATRICK DECORLA-SOUZA, JERRY EVERETT, BRIAN GARDNER, AND MICHAEL CULP

Recent conformity regulations require air quality nonattainment areas in serious or higher categories to use many model features that are not currently used in the travel forecasting processes of most urban areas. Many of these requirements are related to speed and travel time estimates. For example, travel times used in trip distribution are required to be in reasonable agreement with travel times resulting from trip assignment, which assumes that reasonable speeds are output from trip assignment. In addition, peak and off-peak travel demand and speed estimates are required. The issues relating to each of these requirements are discussed; procedures to satisfy these requirements in a simple but rational way are developed; the potential impacts of the simplified procedures on emissions estimates and conformity tests are investigated. Another issue relating to speeds and travel time is whether trip speeds instead of link speeds should be used as inputs to emissions analysis. In current practice, a link-based approach is used to obtain speed and vehicle activity inputs for EPA's MOBILE5 emission factor model. Nevertheless, a trip-based approach is more rational because it is consistent with the way speed cycles are used to develop emission factors. The impact a trip-based approach might have on the results of conformity analysis is examined through a case study application of a conformity analysis for a typical large urban area.

The role of travel models has expanded as a result of mandates in the Clean Air Act Amendments (CAAA) of 1990 and conformity regulations issued in November 1993 pursuant to CAAA. The conformity rule has defined certain standards that travel models are required to meet for conformity analyses in urban areas that are designated as serious or above nonattainment areas for ozone or carbon monoxide. These urban areas were required to develop enhanced travel modeling capabilities by January 1, 1995. Issues relating to the new modeling requirements are discussed, and procedures to accomplish these requirements in a simple but rational way are demonstrated. The procedures are suggested for use where improved models have not yet been developed or where improved models do not address the issues satisfactorily.

In serious and above nonattainment areas, the conformity rule either requires or encourages many model features that are currently not used in the forecasting processes of most urban areas. The next section discusses the issues relating to features required in two steps of the travel forecasting process: trip distribution and traffic assignment. A later section, Simplified Procedures, discusses proposed simplified procedures to address the issues.

The issues are all primarily related to the accuracy of estimated speeds, an important variable in conformity tests. Specifically, speeds used as input into trip distribution are required to be in reasonable agreement with speeds output from traffic assignment; free-flow speeds based on empirical observation are to be provided on network links for input into traffic assignment; speeds are to be calculated at the link level; and finally, estimates of speed and vehicle miles of travel (VMT) are to be provided for peak and off-peak periods.

Speed is also an important factor in accounting for differences in emissions estimates if a trip-based approach (*1*) is used for analysis instead of the conventional link-based approach. However, the conformity rule appears to be silent on the approach to be used to calculate average speeds. Therefore, in a later section, Analysis Results, the potential impact of using a trip-based approach for conformity analysis through a case study for a large urban area is investigated. Conformity test results using a trip-based approach are compared with test results using a link-based approach. Also, for the link-based approach, results using link speeds estimated with the simplified procedures were compared with results using "best practice" procedures to estimate link speeds.

CONFORMITY ANALYSIS ISSUES

This section discusses speed-related issues in conformity analysis. These issues are categorized as follows:

- Comparison of assignment output speeds with trip distribution input speeds,
- Peak spreading under congested conditions,
- Assignment input speeds,
- Peak and off-peak speed estimation, and
- Trip-based versus link-based emissions estimation.

Comparison of Output and Input Speeds

The conformity rule requires travel times used in trip distribution to be in reasonable agreement with travel times resulting from trip assignment. It is believed that congestion, in addition to other effects such as shifts in mode use, route choice, and time of travel, causes trips to be sent to closer destinations. Thus, in a "no-build"

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scenario, travel distances (and therefore VMT) could be less than in a "build" scenario. Analysts attempting to implement this feature in the forecasting process face two main questions:

- Do travel time inputs to trip distribution measure the same variable as travel time outputs from trip assignment?
- Are current state-of-the-practice analysis techniques capable of producing accurate post-assignment travel times or speeds?

Unfortunately, the answer to both questions is "no" for the current state of the practice for the reasons discussed.

Do travel time inputs to trip distribution measure the same variable as travel time outputs from trip assignment?

The basic problem is that congested speeds output from trip assignment are peak hour (i.e., low) speeds, even if daily trips instead of peak trips are assigned, whereas trip distribution is generally done for daily trips. Congested travel times, which occur mainly during peak periods, should not be used to distribute daily trips—most of which actually occur in off-peak periods. Although people make decisions on which destinations they should go to during peak periods based on peak period speeds, it is irrational to assume that they make decisions on where they should go at other times of the day based on the same peak period speeds. Therefore, average daily speeds are more appropriate for use as input into trip distribution, because average daily trips, not peak period trips, are being distributed. Consequently, average daily speeds should be obtained from trip assignment before valid comparisons can be made to check for reasonable agreement.

The next section discusses a simple way to estimate average daily speeds from assigned daily traffic volumes based on recently completed (FHWA) research (*2,3*). Note that when urban areas develop advanced state-of-the-art travel models with separate trip distribution models for each time period, estimates of average peak and off-peak speeds will be needed not average daily speeds. The procedures discussed can be extended to calculate such estimates.

Another compatibility problem is that travel times output by traffic assignment are not true travel times but actually "impedances." In other words, they represent more than just travel time; they include other factors that may affect route choice (e.g., preferences by drivers for using different facility classes.) These impedances are developed by adjusting free-flow speed inputs during model calibration to reflect non–time-related factors. Adjustments are made through an iterative process until a good balance of traffic by facility or area type is obtained to match counted traffic. Thus, even in those rare cases where trip distribution may be done by peak and off-peak periods, the impedances output by trip assignment should not be compared with travel times used in trip distribution. Such a comparison would be appropriate only if "true" congested travel times are first estimated using a speed postprocessor. (The next section of this paper discusses a simple procedure to obtain peak and off-peak travel times by hour of the day, directly from assigned daily traffic volumes.)

Are current analysis techniques capable of producing accurate post-assignment travel times or speeds?

The output post-assignment speeds may be inaccurate even if (a) the assignment procedure uses "accurate" relationships of volume-to-capacity (V/C) ratios to speed, including free-flow input speeds based on empirical observation or (b) speeds are corrected through postprocessing. There are two reasons for this. First, most assignment procedures do not incorporate the effects of peak spreading [i.e., the tendency of trip makers to shift from the preferred time of travel (during the peak) to off-peak periods or to shoulders of the peak, when they are faced with peak period congestion.] Therefore, peak-hour volumes are usually overestimated under congested conditions and, consequently, so are V/C ratios. A peak spreading model has been developed in only one urban area—Phoenix, Arizona (*4*). However, even this model is limited in its application, allowing shifts to the 1-hr periods before and after the peak hour, but not to off-peak periods. This may be sufficient if capacity is available within these 1-hr shoulders of the peak period, but not if the total 3-hr travel demand is close to or exceeds the total 3-hour capacity, as is currently the case in many of the largest urban areas.

The procedures proposed in this paper consider the effects of peak spreading, including not only shifts from the peak hour to its shoulders, but also shifts from peak periods to off-peak periods that may occur under severe congestion. Basically, assigned daily traffic volumes are distributed over all hours of the day based on severity of congestion, using the results of previous FHWA research (*2,3*).

Second, speeds output from state-of-the-practice postprocessors do not accurately represent true speeds because these postprocessors do not fully consider queueing. For example, a link may have a low V/C ratio but still have a low speed if it is affected by queueing due to a downstream bottleneck (i.e., spillback) or due to queues formed in a previous time period during which demand volumes exceeded capacity. The procedures proposed in this paper develop appropriate techniques to address the issues raised by queueing due to excess demand from a previous time period.

Peak Spreading Analysis Issues

The conformity rule requires models to provide peak and off-peak travel demand and travel time estimates. There appear to be two relevant impacts of time-of-day (T-O-D) analysis. First, emissions models predict higher emissions at the low and the high ends of the speed range [bottoming out at about 88.7 km/hr (55 mph) for HC and CO and at about 48.4 km/hr (30 mph) for NO_x]; therefore separate (low) peak and (high) off-peak speeds should generate higher modeled emissions than a composite peak/off-peak (mid-range) speed, if all other model parameters are the same for peak and off-peak periods. Second, a no-build scenario might show less congestion and emissions if the T-O-D analysis procedure incorporates peak spreading effects (i.e., the tendency of travelers to shift time of travel in response to congestion, as discussed earlier). In other words, under a no-build scenario for which peak spreading is modeled, estimated peak hour speeds may not be as low, and high off-peak speeds may be moderated, reducing relative emissions. On the other hand, under a build scenario, peak spreading effects may not be as significant because of the reduction or elimination of congestion.

Addressing the T-O-D analysis requirement is not easy if congestion influences are to be considered. One option is to perform T-O-D splits in earlier steps of the four-step process, as is done in a few large urban areas. However, in the few urban areas where this option is applied, peak spreading effects are not modeled (*4*). Instead, observed T-O-D splits are used from base-year home interview surveys to split future daily trips into a.m., p.m., and off-peak trips. Splitting may be done either (a) before trip distribution (i.e., daily trip ends are split), (b) before mode choice (i.e., person trip tables are split), or (c) before traffic assignment (i.e., vehicle trip tables are split). To validate the assigned volumes, traffic counts by T-O-D are needed. Because of its complexity and its data requirements (both travel survey and count data are needed by T-O-D), this type of procedure is probably impractical in the future in many nonattainment areas. Also, because the T-O-D factors used are developed from base-year data, they do not reflect shifts in time of travel in the future as a result of congestion, and additional research will be needed to develop models that relate T-O-D splits to congestion.

The procedures proposed in this paper split assigned daily traffic by hour of the day using simple T-O-D and directional distribution procedures that account for peak spreading under congested conditions, yet avoid the complexity of the above T-O-D analysis procedures.

Input Speeds for Trip Assignment

The conformity rule requires input free-flow speeds to be based on empirical observations. The contention is that many urban areas use posted speeds as inputs instead of observed free-flow speeds. Therefore, these speeds are often underestimated because motorists often exceeded speed limits. Lower speeds tend to underestimate NO_x emissions, and on high speed facilities, HC and CO emissions tend to be underestimated as well.

At first glance, addressing this conformity requirement appears simple. It appears that all that is required is to recode the network speeds to match sampled observed free flow speeds on various facility classes. However, such recoding could result in major shifts in assigned traffic volumes so that they no longer match ground counts. This is because modelers often adjust free-flow speed inputs during model calibration to obtain a better match of assigned volumes to ground counts; the rationale is that the adjustments reflect factors other than travel time (e.g., driver preferences for using some facility types) that affect route choice. In other words, free flow speeds used as input in many assignment models are not meant to be accurate speeds but only calibrated impedance parameters. Using a postprocessor to get more accurate average daily and hourly speeds appears to be a more reasonable approach to address the intent of the conformity rules.

The procedures proposed in this paper do not attempt to adjust input free-flow speeds but instead focus on estimating output speeds more accurately using a postprocessor, which accounts for empirically observed free flow speeds as well as peak spreading and queueing phenomena.

Peak and Off-Peak Link Speeds

Along with estimates of peak and off-peak VMT, the conformity rule requires estimates of peak and off-peak speeds. The conformity rule also implicitly requires estimates of traffic speeds and delays to be based on estimates of traffic volumes and capacities on network links.

A common practice is to average speeds by functional class. Such average speeds tend to be in the middle of the speed range where emission factors are lowest for HC and CO and not usually very sensitive to small differences in speed.

The requirement for more accurate link speeds has been addressed in some areas using sophisticated approaches based on the *Highway Capacity Manual* (HCM) (*5*) with default input parameters (e.g., signal cycle lengths) by functional class. The Houston-Galveston Area Council's procedure (*6*) is a good example. An intermediate level of detail uses relationships of V/C ratios to highway level of service (LOS) and LOS to speed from look-up tables (*7*). However, none of the current approaches can capture the effect of queueing from a previous time period, as explained earlier.

The procedures outlined in this paper may be used to obtain hourly speeds that incorporate vehicular delay due to queueing from a previous time period. A simple postprocessor was developed to obtain queueing-sensitive average daily speeds, and the procedures are being extended under FHWA sponsorship to obtain average hourly speed estimates directly from assigned daily traffic, using relationships that vary by facility type and area type.

Trip-Based Versus Link-Based Analysis

In current practice, estimates of travel activity (i.e., VMT) and speed are link based. However, emission factors in EPA's MOBILE model are based on data that represent trip travel characteristics instead of link-level travel characteristics. In the Federal Test Procedure, which is the basis for developing baseline emission factors, "bags" of pollutants are collected from entire trips about 20 min long. Therefore, developing travel characteristics for limited segments of the highway network is inconsistent with the base from which MOBILE factors are developed (i.e., entire trips.) In particular, average speeds on which MOBILE factors are based represent speed cycles for an entire trip, not speed cycles on any specific link. (This problem could be solved by developing emission factor models based on facility type-specific speed cycles. The California Air Resources Board is attempting to develop such models for freeways and arterials.)

A previous paper (*1*) describes a method to derive VMT and average speeds based on trips instead of links. The application of the procedure to this case study is described in a later section, Case Study.

SIMPLIFIED PROCEDURES

Figure 1 provides an overview of the simplified procedures proposed in this paper to address the speed-related conformity analysis issues discussed in the previous section. The top part of Figure 1 indicates the process used to estimate average daily speeds from assigned traffic volumes, which are used to check for reasonable agreement between output speeds from trip assignment and speeds input into trip distribution. The bottom part of Figure 1 indicates postprocessing procedures to obtain travel demand estimates by time-of-day that are sensitive to peak spreading and obtain peak and off-peak speeds that incorporate peak spreading and queueing effects. The procedures are discussed in greater detail in the following subsections.

Average Daily Speeds

The procedures rely heavily on recent FHWA research (*2,3*) to develop average daily speed determination models based on data for freeways and signalized arterials. The procedures developed in the research effort to estimate average daily speeds involve three steps:

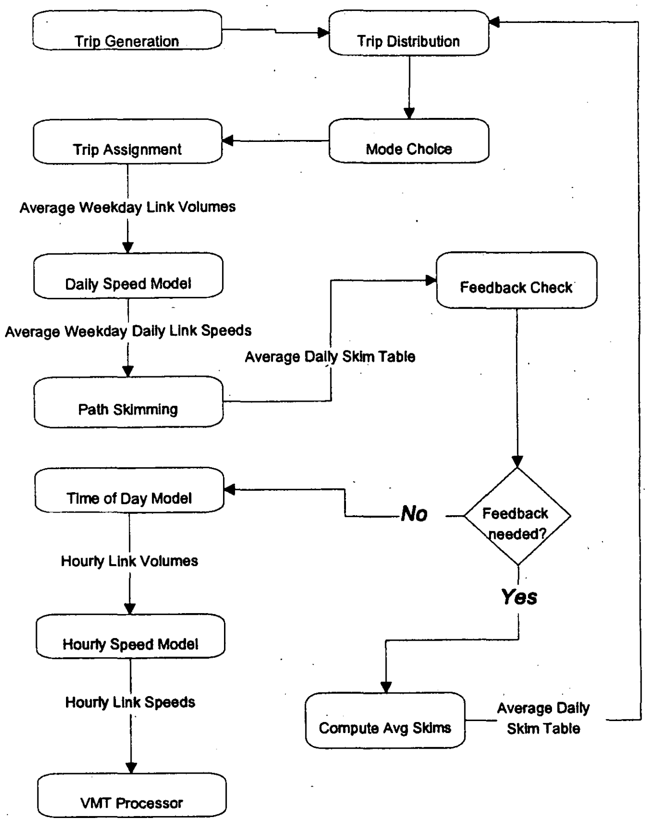

FIGURE 1 Travel analysis procedures.

1. Daily traffic is first split into volumes by hour and direction,
2. Hourly directional traffic is used to estimate hourly traffic delays, and
3. Delays are accumulated over all hours to obtain total delays over a 24-hr period. Average daily speeds are then calculated.

For Step 1, the research used data from automatic traffic recorders to develop T-O-D distribution profiles of directional link traffic for various levels of congestion. Congestion was measured in terms of the ratio of average daily traffic to link capacity (ADT/C). ADT was measured on either an annual average basis or an average weekday basis, AADT or AWDT.

For Step 2, the research used traffic simulation models, i.e., NETSIM and FRESIM (*8*), and the demand estimates by hour (generated by the T-O-D distributions) to simulate queueing delay effects by hour for typical freeways and arterials operating at varying ADT/C ratios.

In Step 3, these delays were accumulated over all hours of the day and aggregated with travel times at free-flow speeds to obtain total daily travel time and average (VMT weighted) daily speeds.

The study developed empirical relationships to estimate hourly link volumes and total daily delay for varying ADT/C ratios (*2*). These equations were later refined (*3*). The refined equations developed to estimate average daily speed for arterials are

$$\text{AADT/C} <= 7: \quad \text{DR} = (1 - e^{-n/24.4})\,(68.7 + 17.7x)$$
$$\text{AADT/C} > 7: \quad \text{DR} = (1 - e^{-n/24.4})\,[192.6 + 14.4\,(x - 7) - 1.16(x - 7)^2] + 0.160\,(x - 7)^2$$

and the refined equations developed to estimate average daily speed for freeways are

$$\text{AADT/C} <= 8: \quad \text{DR} = 0.0797x + 0.00385x^2$$
$$8 < \text{AADT/C} <= 12: \quad \text{DR} = 12.1 - 2.95x + 0.193x^2$$
$$\text{AADT/C} > 12: \quad \text{DR} = 19.6 - 5.36x + 0.0342x^2$$

where

x = AADT/C,
DR = daily vehicle hours of delay/1,000 VMT,
n = signals per mile,
AADT = average annual daily traffic, and
C = highway capacity (vehicles/hour).

For this case study analysis, the earlier unrefined equations to estimate average daily speed were used. Zone-to-zone travel time skims were then developed using these speeds and compared with skims used as input into trip distribution.

T-O-D Traffic Splitting

The T-O-D model uses average daily assigned traffic as input. Daily traffic is split into traffic for each hour of the day using profiles of the hourly distribution of traffic, which vary by ADT/C ratio. Thus, peak spreading effects are automatically incorporated. Examples of the profiles are shown in Figure 2 and in Table 1.

Peak and Off-Peak Speeds

The simplified procedures for estimation of hourly speed presented here are not yet fully developed and computerized. Research sponsored by FHWA is underway to extend the basic procedures used to develop the average daily speed determination models to provide hourly speeds. The procedures will use the hourly delay estimates generated for the purpose of developing the average daily speed equations to calculate hourly speeds. Information on free-flow speeds will be combined with hourly delay estimates to obtain average hourly speeds. Because free-flow speeds vary by facility type and area type, separate delay relationships (based on ADT/C ratios) will be developed by facility type and area type.

CASE STUDY

This case study had four objectives:

1. To demonstrate how the above simplified procedures could be applied in a real-world situation—compute from assigned daily traffic (a) peak and off-peak traffic volumes and (b) average daily link speeds. (Note: The demonstration of the procedures for estimating average peak period and off-peak link speeds is awaiting completion of FHWA research on hourly speed models.)
2. To compare link-based emissions estimates using average daily link speeds (estimated with these simplified procedures) with estimates using best practice speed estimation procedures. (Note: In best practice, emissions are estimated using average peak period and off-peak link speeds.)

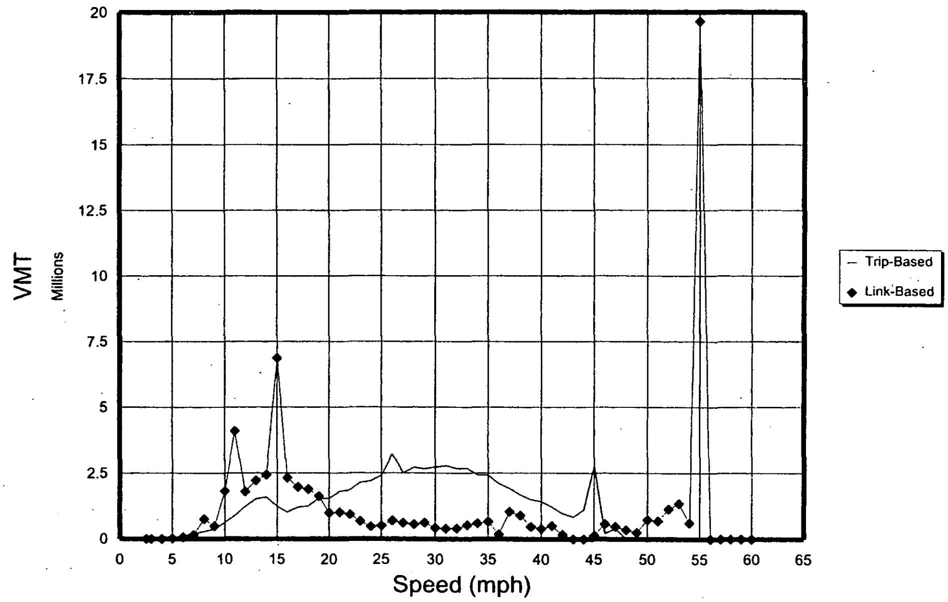

FIGURE 2 Distribution of total daily trip- and link-based VMT for build.

3. To investigate the potential impact of using these simplified procedures for conformity analysis by comparing conformity test results that used the simplified procedures with test results that used best practice speed estimation procedures. (Note: Emissions estimates in both cases would be link based.)
4. To investigate the potential impact of using a trip-based approach for conformity analysis, by comparing conformity test results that used a trip-based approach with test results that used a link-based approach. (Note: Speed estimates in both cases would be average daily link speeds using the simplified procedures; the only difference would be that in the trip-based approach speeds would be averaged over the entire trip instead of on individual links.)

The case study analysis was conducted for a large urban area (Baltimore, Maryland). The case study involved a conformity test for a "theoretical" financially unconstrained long-range plan that would return highway levels of service to those existing in 1990. To focus on the effects of differences in average speed estimates under the various approaches, the no-build network assigned daily traffic volumes (and VMT estimates) were used for both the build and no-build alternatives. Note that the use of feedback loops in travel models generally has the effect of lowering VMT estimates for the no-build alternative (relative to the build alternative), as a result of shortening of trip lengths (distances) by the trip distribution model under congested conditions. Occasionally, this effect may be offset by increases in VMT because of drivers seeking (longer) uncongested routes in trip assignment.

TABLE 1 Daily Emissions for Baltimore Study Area

	VMT	2010 NO-BUILD EMISSIONS(tons)		2010 BUILD EMISSIONS(tons)	
		HC	NOx	HC	NOx
TRIP-BASED:	68,173,072	149.16	117.09	147.47	117.35
LINK-BASED: (Avg Daily)					
NETWORK LINKS	63,694,496				
INTRAZONAL	4,478,576				
TOTALS	68,173,072	162.21	128.66	157.49	126.42
BEST PRACTICE: (Sum of Periods)					
NETWORK LINKS	63,687,736				
INTRAZONAL	4,485,336				
TOTALS	68,173,072	143.22	129.37	139.77	126.74

No-build network average daily speeds were estimated using daily traffic volumes from the no-build network traffic assignment. Build network average daily speeds were estimated using base year 1990 network assigned traffic volumes and capacities because it was assumed that the build network would return ADT/C ratios to 1990 levels. The following subsections discuss the application procedures used for the case study.

Postprocessing Link Data

Postprocessing of assigned daily traffic involved developing.

- Average daily speeds, using the simplified procedures outlined in this paper,
- Peak and off-peak traffic volumes using the simplified procedures, and
- Peak and off-peak speeds using best practice procedures.

The postprocessor used for this study was developed as a stand-alone module outside the travel demand model. Link characteristics were passed between the demand model and the postprocessor using an ASCII data base. Extracting, post processing, and recompiling the network required approximately 10 min of computer time. The post processing procedures will be discussed in greater detail.

Average Daily Speeds

Average daily speeds were calculated as described previously in the section, Simplified Procedures.

Estimating Peak and Off-Peak Traffic Volumes

The postprocessor estimated hourly link volumes using AADT/C relationships developed for the average daily speed determination models (2). Peak and off-peak hours were identified based on the percentage of daily traffic in each hour, and total traffic was then aggregated for three time periods: a.m. peak, p.m. peak, and off-peak.

Peak-direction information was unavailable within the network data for this case study urban area. However, this information was needed for the best practice speed estimation procedures. Therefore, links with odd A-node numbers were assumed to have an a.m. peak direction and links with even A-node numbers a p.m. peak direction. This provides a reasonable estimate of peaking effect and does not affect estimates of aggregate link emissions (i.e., total emissions from traffic in both directions).

Peak and Off-Peak Speeds

The simplified procedures outlined earlier could not be used, pending completion of the FHWA-sponsored research (also described earlier) to extend the average daily speed determination models to hourly speed estimation.

Currently best practice, peak, and off-peak speeds are estimated using HCM procedures. Because one case study objective was to compare emissions estimates that used simplified procedures with emissions estimates that used best practice, a postprocessor was developed to incorporate best practice procedures for estimating hourly speeds. The procedures are complex because they require signal locations to be identified and coded, instead of using defaults by facility type and area type, as proposed in the simplified procedures.

The procedures consist of two submodels, one for freeways and one for arterials. The procedures are derived primarily from the HCM procedures and estimate link speeds by hour of the day. Although the HCM procedures do not explicitly model delays due to queueing in a previous hour or spill-back, they predict through delays on simple signal approaches as well as on freeway links for reasonable V/C ratios (i.e., less than 1.3). Because the input hourly traffic was obtained from the T-O-D model described (which incorporates peak spreading effects), reasonable V/C ratios were estimated on almost all links.

The freeway model used the updated HCM saturated flow rate of 2,200 vphpl (*9*). The speed limit was used as the average free-flow speed for V/C ratios of up to 0.70. A crawl speed of 12.9 km/hr (8 mph) was used for V/C ratios over 1.1. The regime from 0.70 to 1.1 was assumed to be linear.

The arterial model was substantially more complex. Previous studies have shown that traffic control (i.e., signal and stop sign density) governs the travel impedance on signalized arterials (*2,10,11*). The HCM uses signal approach through delay and arterial running speed to estimate average hourly arterial travel times and speeds. This requires data on signal locations, arterial class, access intensity, and approach capacity. Although these data were not explicitly contained within this case study data base, much of it was inferred from available information, and the remaining elements were synthesized. For example, because data on actual signal locations were unavailable, signal density assumptions were made on the basis of area type, facility type, and segment length. Arterial class and running speed were estimated on the basis of area type, segment length, speed limit, and facility type. Approach capacities were estimated on the basis of earlier work by the Florida Department of Transportation (*12*).

Applying the Trip-Based Approach

Figure 3 presents the procedures used to apply the trip-based approach. The Baltimore travel models estimate trips for six trip purpose categories and for a 24-hr period. Using national survey data from Nationwide Personal Transportation Study (*13*), estimates of operating mode percentages (i.e., cold and hot start percentages) and vehicle mix for each trip purpose were derived for the trip-based approach. Trip length (i.e., duration) distributions were obtained for each trip purpose from the travel models, based on post-assignment average speeds. Average daily link speeds were estimated as described earlier.

Emissions estimates were based on daily VMT and average daily speeds. The assigned networks with postprocessed estimates of average daily link speeds were skimmed to obtain zone-to-zone travel times and distances, which were then used to obtain zone-to-zone average speeds. Zone-to-zone daily vehicle trips were obtained from daily vehicle trip tables by purpose output from the mode choice model. Zone-to-zone VMT was computed as zone-to-zone vehicle trips times zone-to-zone distance. A previous paper (*1*) discusses these procedures in greater detail.

Applying the Link-Based Approach

Two different methods were used to estimate daily emissions with the link-based approach: (a) using daily VMT and average daily

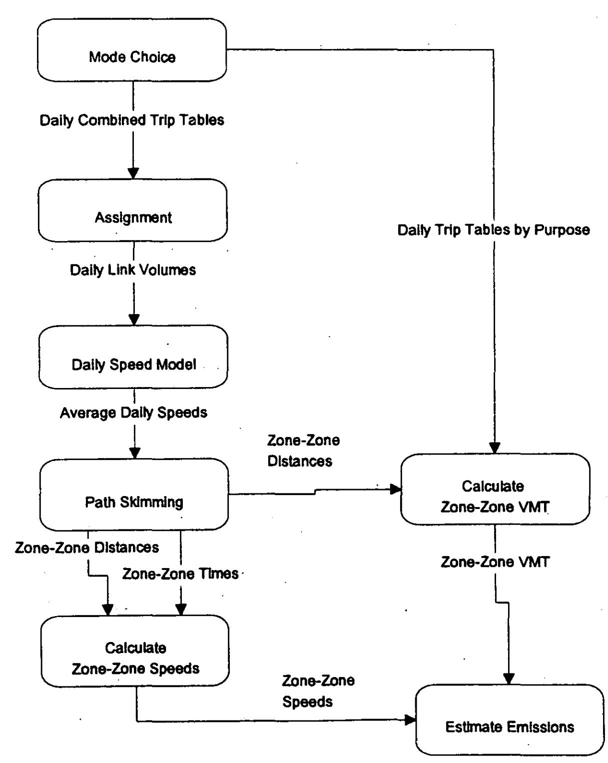

FIGURE 3 Emissions estimation procedure for trip-based approach.

speeds estimated using the simplified procedures and (b) using peak and off-peak VMT estimated using the simplified procedures, along with corresponding peak and off-peak speeds estimated using best practice.

Daily link-based VMT was developed from the "combined purpose" traffic assignment. To ensure consistency with travel characteristics developed for the trip-based approach, the cold and hot start percentages, vehicle mix, and trip length (i.e., duration) distribution were obtained by computing weighted averages of the parameters used by trip purpose in the trip-based approach.

Because this case study focused on evaluating the sensitivity of emissions estimates to differences in speed estimation procedures, operating mode percentages were not varied by time of day for the peak and off-peak application, although recent research by Venigalla et al., in another paper in this Record, could be used to develop such inputs in future work. Vehicle mix was not varied by time of day either.

ANALYSIS RESULTS

Table 1 compares HC and NO_x emissions estimates for the no-build and build alternatives. It should be noted that Baltimore-specific MOBILE settings were not used for technology parameters [i.e., the emission factors used do not reflect inspection and maintenance (I/M) programs]. Thus the emissions estimates developed are not directly comparable to those developed for inventory or other regulatory purposes.

Table 1 indicates that the three approaches, each based on a different speed estimation procedure, result in significant differences in the amount of HC emissions estimated for the no-build alternative. Similar differences are observed for the build alternative. The table indicates that HC emissions are substantially higher if the link-based approach is used with average daily speeds estimated using the simplified procedures. Although the trip-based approach (with average daily speeds) shows lower emissions for HC, they are still higher than emissions estimated with the best practice link-based "sum of periods" (i.e., peak and off-peak periods) approach.

Figures 2 and 4 present profiles of VMT by speed for the three approaches. The profiles suggest the reasons for the significant differences in emissions estimates. In Figure 2, the trip-based approach is compared with the link-based approach. Even though average trip speeds for the trip-based approach are derived from the same link speeds (i.e., based on links on the assigned paths between zones), the trip-based approach results in a concentration of VMT in the center of the speed range, where HC emissions tend to be lower. VMT under the link-based approach tends to concentrate in the low and high ends of the speed range.

Figure 4 compares the simplified procedures, using the link-based approach, with best practice procedures. The best practice procedures result in significantly fewer VMT in the low end of the speed range below 24.2 km/hr (15 mph), where emission factors tend to be highest. The main difference in the two procedures is that queueing delay is handled more thoroughly in estimation of speeds with the simplified procedures, leading to the significantly higher estimates of low speed VMT.

Table 2 presents the results for the build versus the no-build conformity tests for HC and NO_x. The comparison indicates that the build alternative passes the HC test regardless of the approach used. However, the build alternative fails the NO_x test if the trip-based approach is used, although it passes the test if the link-based approach is used with either the simplified procedures or best practice procedures. In other words, for the NO_x test, passing the test depends on which approach is used.

CONCLUSIONS

Serious and above nonattainment areas will need to address specific modeling requirements in the conformity rule issued in November 1993. This paper has developed simple and rational procedures to respond to these needs and demonstrated application of the procedures to the conformity analysis for a large urban area.

The main contribution of this effort is the operationalization of simplified procedures for time-of-day analysis and estimation

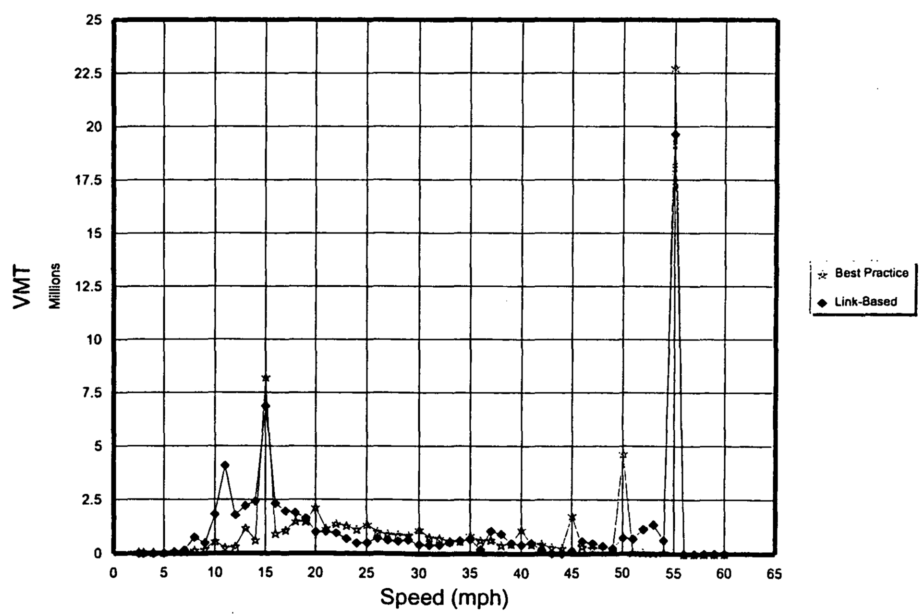

FIGURE 4 Distribution of total daily best practice and link-based VMT for build.

TABLE 2 Conformity Test

	EMISSIONS (tons/day) 2010 BUILD	2010 NO-BUILD	DIFFERENCE Absolute (tons)	Percent	PASS
HC					
TRIP-BASED	147.47	149.16	1.69	1.13%	YES
LINK-BASED	157.49	162.21	4.72	2.91%	YES
BEST PRACTICE	139.77	143.22	3.45	2.41%	YES
NOx					
TRIP-BASED	117.35	117.09	−0.26	−0.22%	NO
LINK-BASED	126.42	128.66	2.24	1.74%	YES
BEST PRACTICE	126.74	129.37	2.63	2.03%	YES

of average daily speeds. FHWA is undertaking further research to extend the capability of the average daily speed determination models to estimate hourly speed.

The paper also demonstrated that using the simplified procedures, which handle queueing delay more thoroughly, can result in significantly higher emissions. In addition, using a trip-based approach to perform emissions analysis can have a significant impact on the results of conformity tests.

The contradictory conformity test results with alternative approaches suggest that further investigation is necessary to determine the cause of these differences and to determine which approach would provide a better conformity test. Further investigation is also needed to evaluate the effect of using peak and off-peak analysis procedures with the trip-based approach (including varying operating mode and VMT mix by time-of-day).

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Cleaner Alternative Fuels for Fleets: An Overview

JON F. ANDERSON

The Clean Air Act Amendments of 1990 (CAAA) and the Energy Policy Act of 1992 (EPact) require conversion to alternative fuels of vehicle fleets in cities with populations greater than 250,000. CAAA and EPact have similar provisions but different requirements. CAAA does not require a specific fuel type but mandates that specific emission levels be met to comply with the regulation's provisions and possibly earn extra emission reduction credits as clean fuel fleet vehicles (CFFV). Key aspects that will facilitate compliance are tax deductions under EPact and marketable emissions reduction credits under CAAA. Fleets were emphasized by Congress because they have a better refueling and maintenance infrastructure, more frequent vehicle turnover, and greater yearly mileage accumulation. CAAA applies to nonattainment areas classified as serious, severe, and extreme. Private and government fleets of 10 or more vehicles capable of being centrally fueled are affected by the program. The program is based on fleet owners purchasing a prescribed percentage of new fleet purchases as CFFVs, which meet lower emission standards. Under CAAA the phase-in period is a purchase rate of 30 percent in 1998, 50 percent in 1999, and 70 percent in 2000 and thereafter for light-duty vehicles. Heavy-duty vehicles remain at the 50 percent level beginning in 1998. The Environmental Protection Agency (EPA) estimates that more than 40,000 private and government fleets will be affected by the CAAA fleets program. EPact, which is administered and enforced by the Department of Energy (DOE), applies to all cities with a population of 250,000 or greater, regardless of air quality nonattainment status. This doubles the number of fleets covered. State fleets are required to be phased in to the program with 10 percent of their purchases in 1996 and 15 percent in 1997. The difference here is that affected fleets must have more than 20 vehicles. At its discretion, DOE may apply EPact to private fleets. Congress directed EPA to exempt qualifying fleet CFFVs, which are called inherently low-emission vehicles, from certain transportation control measures that are time-of-day or week based, such as the ability to use high occupancy vehicle lanes. A state that has a banking and trading program and a low-emission vehicle program would more easily administer and enforce a clean fuel fleet vehicle program.

More than one-third of the United States population breathes air contaminated with pollutants such as carbon monoxide, ground level ozone (known commonly as smog), and potent air toxic carcinogens. One of the primary goals of the National Ambient Air Quality Standards is to reduce ozone-forming pollutants, such as volatile organic compounds (VOC) and oxides of nitrogen (NO_x). Research increasingly implicates vehicle emissions as contributing more significantly to air toxics in urban air than had been previously believed.

Cars, buses, and trucks are responsible for one-third of ozone precursors and two-thirds of carbon monoxide emissions in air quality nonattainment areas. It is not surprising that the Congress and the President have assigned a significant role to the transportation sector to alleviate air quality nonattainment problems in the United States.

The Clean Air Act Amendments of 1990 (101st U.S. Congress), (CAAA) and the Energy Policy Act of 1992 (103rd U.S. Congress) (EPact) each require new purchases and conversions of vehicle fleets to use alternate fuels. EPact applies to all cities with populations greater than 250,000. CAAA applies to air quality nonattainment areas classified as serious, severe, and extreme and carbon monoxide nonattainment areas classified as moderate and serious and have concentrations monitored greater than 12.7 parts per million. CAAA and EPact have similar provisions but different requirements. CAAA does not require a specific fuel type but mandates specific emission levels for vehicle fleets to qualify as clean fuel vehicles (CFVs) and earn tradable credits. Key aspects that will facilitate compliance are tax deductions under EPact and marketable mobile emissions reduction credits (MERCs) under CAAA.

CAAA and EPact require affected states to begin purchasing cleaner, alternative-fuel vehicles for centrally fueled fleets. As one of the largest sources of carbon monoxide and ozone-forming pollutants, mobile sources were targeted for emission reduction programs under Title II of CAAA. Part C of Title II establishes definitions, requirements, and standards for CFVs. These provisions require affected states to modify their state implementation plans (SIPs) by May 15, 1994, to require that certain portions of the new vehicles purchased by fleet owners meet clean-fuel fleet vehicle exhaust emission standards. These standards are similar to the Low Emission Vehicle Rating (LEVR) program (Table 1). In September 1990, the California Air Resources Board (CARB) approved a low-emission vehicle and clean fuels set of regulations. The regulations established four new classes of emission levels, similar to those in CAAA and the clean fuel fleets emission levels found in Table 1. Note that the Clean-Fuel Fleet Vehicle (CFFV) program does not have a transitional low emission vehicle (TLEV) category as does the CARB program. A controversial aspect of the Low-Emission Vehicle (LEV) program in California and other states has been the zero-emission vehicle (ZEV) sales mandate (2 percent of all sales in 1998, 5 percent in 2001, and 10 percent in 2003). Automobile manufacturers are working with EPA and the Ozone Transport Commission to establish a "49 State Car" which has emission levels similar to Tier II vehicles but with an earlier implementation date and the provision that the ZEV mandate be dropped. Unfortunately, EPA cannot abrogate state legislative decisions in states that have chosen to pursue the ZEV mandate.

Massachusetts and New York have adopted LEV programs. Texas, Illinois, Wisconsin Maryland, Pennsylvania, and Maine have considered adopting the LEV program. In October 1991, the Ozone Transport Commission (OTC) states signed a memorandum of understanding on the California LEV program. In signing this,

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TABLE 1 Emission Standards for Determining MERC Weightings

Light-Duty Vehicle and Truck Emission Levels for Credit Calculation (gm/mi)

	LDV, LDT ≤6000 GVWR, ≤3750 LVW	LDT ≤6000 GVWR >3750 LVW ≤5750 LVW	LDT >6000 GVWR, ≤3750 TW	LDT >6000 GVWR, >3750 TW ≥5750 TW	LDT >6000 GVWR, >5750 TW
Tier 1 Gas					
NMHC[1]	0.25	0.32	0.25	0.32	0.39
CO	3.4	4.4	3.4	4.4	5.0
NOx	0.4	0.7	0.4	0.7	1.1
LEV					
NMOG	0.075	0.1	0.125	0.16	0.196
CO	3.4	4.4	3.4	4.4	5.0
NOx	0.2	0.4	0.4	0.7	1.1
ULEV					
NMOG	0.04	0.05	0.075	0.1	0.117
CO	1.7	2.2	1.7	2.2	2.5
NOx	0.2	0.4	0.2	0.4	0.6
ZEV					
NMOG	0.0	0.0	0.0	0.0	0.0
CO	0.0	0.0	0.0	0.0	0.0
NOx	0.0	0.0	0.0	0.0	0.0

		Heavy Duty Vehicle 8,501-26,000 GVWR
Conventional Vehicle		
	HC+NOx[2]	5.3
	CO	15.5
LEV		
	NMHC+NOx	3.8[3]
	CO	15.5
ULEV		
	NMHC+NOx	2.5
	CO	7.2
ZEV		
	NMHC+NOx	0.0
	CO	0.0

Source: EPA

[1] For MERCs, NMHC = NMOG

[2] For MERCs, HC = NMHC. Also, the conventional HDE standard is not combined

[3] At the time of publication the author could not verify with EPA final HDV LEVR ratings

each member state agreed to propose regulations or legislation necessary to adopt the LEV program in accordance with Section 177 of CAAA. On February 1, 1994, the OTC voted to recommend that EPA mandate the California LEV program in the Ozone Transport Region and shortly thereafter petitioned EPA to do so. EPA was expected to issue a final rule on the LEV program for light-duty vehicles in the Ozone Transport Region in late 1994. However, individual state enabling legislation and regulations may be required for the LEV program. The Environmental Protection Agency (EPA) issued a final rule in January 1993 (58 CFR 11888) that established regulations governing the clean-fuel fleet credit program and the exemption of CFVs from certain transportation control measures (TCMs). EPA issued a notice of proposed rulemaking providing further clarification of clean-fuel fleet emissions standards, conversions, and general provisions (59 FR 32474, June 10, 1993). EPA also finalized the definition of terms used with the Clean-Fuel Fleet program (58 FR 60038, December 17, 1993).

The number of covered fleet vehicles in the nonattainment area will be based on two separate 1-week (7-day) vehicle mileage sampling surveys conducted in 1995 or 1996. This average fleet ratio is determined via the following equation:

$$\frac{\text{miles traveled in nonattainment area}}{\text{total miles driven}} = \text{no. of covered fleet vehicles}$$

This average fleet ratio is used to calculate the number of vehicles that are not centrally refueled 100 percent of the time, not garaged at a personal residence at night, and are capable of being centrally refueled. The operating range of the CFV is the distance a vehicle is able to travel on a round trip with a single refueling.

EPA finalized Emission Standards for Clean-Fuel Vehicles and Engines, Requirements for Clean-Fuel Vehicle Conversion, and the California Test Program (40 CFR Parts 86 and 88) on September 30, 1994. This rule makes conversion kits certify to LEVR standards and allows the converted vehicle to pass the inspection and maintenance (I/M) test. This kit certification and vehicle testing procedure will make post-September 1994 vehicle conversions more economically competitive with original equipment manufacturer (OEM) CFV vehicles. Also, the heavy-duty vehicle NO_x low-emission vehicle standard was relaxed from 3.5 per brake horsepower/hour (g-bhp/hr) to 3.8 g-bhp/hr because of industry concerns about the viability of alternative fuels for heavy-duty vehicles. Further regulations are expected from the Department of Energy (DOE) for EPact, under the alternative fuel fleet program clarifying DOE's intent.

CAAA AND EPACT ISSUES

The key differences between CAAA and EPact requirements as they apply to states are the fuels allowed, the vehicle classes affected, the geographic areas with covered fleets, and the timing of implementation. For example, clean fuels under CAAA include two fuels that EPact does not consider to be alternative fuels: reformulated gasoline and low sulfur diesel fuel. EPact defines alternative fuels as compressed and liquefied natural gas, liquefied petroleum gas, methanol and ethanol (mixtures of 85 percent or more, i.e., M–85, E–85, or "neat" 100 percent fuel), electricity, hydrogen, coal-derived liquids, and fuels derived from biological materials.

In addition to light-duty vehicles (LDVs) and light-duty trucks (LDTs) affected under EPact [vehicles with a gross vehicle weight rating (GVWR) of less than 8,500 lb], the CAAA fleet program includes heavy-duty vehicles with a GVWR between 8,501 and 26,000 lb as a separate affected class. For diesel vehicles, the new diesel NO_x standard beginning in 1998 is 4 g-bhp/hr. The recent low-sulfur diesel fuel regulation in effect combined with the new diesel engine emission standards in 1998 may make diesel engines to LEVR standards. EPA issued a report to Congress in October 1993 on promising diesel engine and fuel improvements to reduce NO_x and particulate matter. A CNG bus has been certified to 2 g-bhp/hr, and many metropolitan planning organizations (MPOs) and departments of transportation (DOTs) are buying these buses for NO_x offsets to pass conformity tests.

APPLICABILITY AND COVERED FLEETS

Congress emphasized fleets because they have a better refueling and maintenance infrastructure, more frequent vehicle turnover, and greater annual mileage accumulation than individually owned vehicles.

CAAA encompasses 22 cities in 19 states (Table 2). The new program affects private and government fleets of 10 or more vehicles that can be centrally fueled. The program requires fleet owners to purchase a prescribed percentage of new fleet vehicle purchases as CFVs, which meet lower emission standards. Certain vehicles are exempt from regulation, such as law enforcement and emergency vehicles and vehicles held for test, rental, or sale. EPA has clarified that vehicles garaged at home are not exempt from the clean fuel fleet provisions if they can be centrally fueled 75 percent of the time. Businesses (usually small) that rely on their employees to use their own vehicles for delivery or sales work would be exempt from the CFFV regulations because those vehicles are garaged primarily at home, and the employer does not provide nonpublic central refueling facilities.

EPact, which is administered and enforced by DOE, applies to all cities with a population of 250,000 or greater, regardless of air quality nonattainment status. EPact doubles the number of fleets covered (Table 3). EPact-affected fleets must have more than 20 vehicles. At its discretion, DOE can apply EPact to private fleets, but if has not yet ruled on this. Small fleet owners with fewer than 20 vehicles but more than 10 can comply with CAAA by using Federal Reformulated Gasoline (RFG), available in many areas in 1995, if the purchased vehicle engine class certifies to LEVR standard. An RFG LEVR vehicle may be possible by electrically preheating the catalyst to eliminate cold-start emissions the first 505 sec after ignition, before the catalyst is heated for efficient pollution abatement.

FUEL TYPES

Although CAAA is an emissions-based program requiring the use of cleaner, alternative fuels, DOE designed EPact to further national energy use goals. Hence, CAAA emphasizes "clean" fuels and EPact refers to "alternative" fuels that would diminish national dependence on petroleum-based vehicle fuels. EPact should affect states before CAAA. However, DOE will not release most EPact regulations until late 1994. DOE has indicated that it generally will consider EPA's lead in development of CAAA CFFV requirements, but it is not certain that DOE regulations will complement those EPA requirements.

TABLE 2 States and Areas Covered by CAAA Clean Fuel Fleet Vehicle Program

1.	Atlanta	Georgia
2.	Baltimore	Maryland
3.	Baton Rouge	Louisiana
4.	Beaumont-Port Arthur	Texas
5.	Boston-Lawrence-Worcester (Eastern Massachusetts)	Massachusetts, New Hampshire
6.	Chicago-Gary-Lake County	Illinois Indiana
7.	Denver-Boulder	Colorado
8.	El Paso	Texas
9.	Greater Connecticut	Connecticut
10.	Houston-Galveston-Brazoria	Texas
11.	Los Angeles-South Coast Air Basin	California
12.	Milwaukee-Racine	Wisconsin
13.	New York-Northern New Jersey-Long Island	Connecticut, New Jersey, New York
14.	Philadelphia-Wilmington-Trenton	Delaware, Maryland, New Jersey, Pennsylvania
15.	Providence (All Rhode Island)	Rhode Island
16.	Sacramento Metro	California
17.	San Diego	California
18.	San Joaquin Valley	California
19.	Southeast Desert Modified AQMA	California
20.	Springfield (Western Massachusetts)	Massachusetts
21.	Ventura County	California
22.	Washington (District of Columbia)	Maryland, District of Columbia, Virginia

Source: EPA

NEW PURCHASE PHASE-IN PERIODS

The phase-in period under CAAA is a purchase rate for new and replacement light-duty vehicles of

- 30 percent beginning in model year (MY) 1998,
- 50 percent in MY 1999,
- 70 percent in MY 2000 and thereafter, and
- Heavy-duty vehicles remain at the 50-percent level beginning in MY 1998.

EPA estimates that the CAAA fleets program will affect over 40,000 private and government fleets.

Under EPact, state government fleets are required to phase in the new vehicle purchase requirements on the following schedule:

- 10 percent of new vehicle purchases in 1996,
- 15 percent of new vehicle purchases in 1997,
- 25 percent of new vehicle purchases in 1998,
- 50 percent of new vehicle purchases in 1999, and
- 75 percent of new vehicle purchases in 2000 and thereafter (Table 4).

Note that in 1998, 5 percent of new state government fleet purchases may be able to operate on RFG, depending on engine class certification results to LEVR standards with RFG as the fuel, and comply with CAAA. In 1999, both new vehicle purchase levels for state government fleets are 50 percent for light-duty vehicles. After 2000, the light-duty vehicle new purchase requirements remain at 75 percent under EPact and at 70 percent under CAAA.

COMPLIANCE ISSUES

The program requirements can be met through new vehicle purchases, vehicle conversions, or credits. The program is administered and enforced by affected state governments. To comply with CAAA, the vehicles must, at a minimum, meet the LEVR standard. The alternative/clean fuel gallon use per month at dispensing facilities will be used by states to determine compliance for both dual- and dedicated-fueled vehicles based on reported average monthly mileage accumulation for the specific fleet.

To demonstrate compliance, EPact defines alternative fuel vehicles (AFV) as either a dedicated or dual-fuel vehicle using an EPact-designated alternative fuel. However, CAAA requires the purchase of CFVs (dedicated or dual fueled) based on their classification of LEVR standards (Table 1). CAAA establishes three classes of low-emission vehicle ratings for fleet purposes:

- LEVs—nonmethane organic compounds (NMOG) at 0.075 g/mi for LDVs,
- Ultra-low-emission vehicles (ULEVs)—NMOG at 0.04 g/mi for LDVs, and
- ZEVs—NMOG at 0.0 g/mi for LDVs (on-road emissions).

(Note that Table 1 is slightly outdated and is derived from CAAA. The light-duty vehicle and truck emission levels have not changed for the LEVR program. However, at the time of this writing, revised data on heavy-duty engine emission levels could not be clarified. Check with the EPA regional office for clarification.)

It is expected that OEMs of alternative-fuel vehicles will certify vehicles according to the EPA-designated LEVR standards.

MOBILE EMISSIONS REDUCTION CREDITS

Purchase credits are available for early/extra CFV purchases (pre-1998) of ULEVs and ZEVs and noncovered category purchases. Credits may be traded for use within the same or contiguous nonattainment area. The purchase credits for this program may be banked with no time limit or depreciation. The only caveat is that MERCs cannot be traded upward between light-duty and heavy-duty vehicles. Small companies may be able to buy credits from larger companies.

CFFV MERCs may be allowed to be traded to other emission sources in the same urban air shed. This could be a big benefit to large utilities with sizable stationary sources and large fleets of vehicles. This is a direct incentive to fleet owners to increase use of clean fuels and purchase dedicated fuel vehicles. Motor vehicle control, especially of fleets, is still an optimal way to effectively control air emissions. The CFFV MERC incentive also provides an added stimulus to develop a CFV/AFV refueling infrastructure that may be available to the general public. Any increased access to alternative refueling facilities could increase demand for clean fuel vehicles. It is important to note that states would administer and enforce this program. Moreover, vehicles may receive credits or TCM exemptions, but not both, for the same emission reduction.

TCM EXEMPTIONS

Congress directed EPA to exempt qualifying fleet CFVs from certain TCMs that are based on use by time of day or week. For example, inherently low emitting vehicles (ILEVs), which have zero evaporative emissions, enjoy the use of HOV lanes even if the vehicle has only one occupant. Clean fuel vehicles most likely will be identified with a large green global decal that reads "ECO." Other possible exemptions for ILEVs are from the Employee Commute Option/Employer Trip Reduction (ECO/ETR) program or congestion pricing. The program is designed to be fuel neutral. In the federal ILEV program, the vehicle must

- Qualify as a CFV,
- Meet the ULEV NO_x standard (0.2 g/mi for LDVs),
- Have no evaporative emissions (even without a control system), and
- Be a dedicated fuel vehicle (run only on clean fuel).

EPA expects significant environmental benefits from the ILEV portion of the program. Vapor emissions are expected to be reduced by about 0.35 g/mi. This reduction is more than twice that achieved by meeting the CFFV exhaust emission standard for the same pollutant. It is hoped that ILEVs provide enough incentive to stimulate the nonfleet demand to broaden the CFV market for automakers. A state that has a banking and trading program and a LEVR program would more easily administer and enforce a CFFV program. This is because familiarity with LEVR-certified vehicles and quantification of MERCs may be more familiar to key state government staff. Also

TABLE 3 Metropolitan Statistical Areas and Consolidated MSAs with 1980 Population of 250,000 or More

Albany-Schenectady-Troy NY	Canton-Massillon OH	Davenport-Moline-Rock Island IA-IL
Albuquerque NM	Charleston SC	Dayton-Springfield OH
Allentown-Bethlehem-Easton PA	Charleston WV	Daytona Beach FL
Appleton-Oshkosh-Neenah WI	Charlotte-Gastonia-Rock Hill NC-SC	Denver-Boulder-Greeley CO
Atlanta GA	Chattanooga TN-GA	Des Moines IA
Augusta-Aiken GA-SC	Chicago-Gary-Kenosha IL-IN-WI	Detroit-Ann Arbor-Flint MI
Austin-San Marcos TX	Cincinnati-Hamilton OH-KY-IN	El Paso TX
Bakersfield CA	Cleveland-Akron OH	Erie PA
Baton Rouge LA	Colorado Springs CO	Eugene-Springfield OR
Beaumont-Port Arthur TX	Columbia SC	Evansville-Henderson IN-KY
Binghamton NY	Colombus OH	Fort Wayne IN
Birmingham AL	Colombus SC-GA-AL	Fresno CA
Boise City ID	Corpus Christi TX	Grand Rapids-Muskegon-Holland MI
Boston-Worcester-Lawrence MA -NH-ME-CT	Dallas-Fort Worth TX	Greensboro-Winston Salem-High Point
Buffalo-Niagara Falls NY		Greenville-Spartanburg-Anderson SC
Harrisburg-Lebanon-Carlisle PA	Lexington KY	New London-Norwich CT-RI
Hartford CT	Little Rock-N. Little Rock AR	New Orleans LA
Honolulu HI	Los Angeles-Riverside-Orange County CA	New York-N. New Jersey-Long Island NY-NJ-CT-PA

(continued on next page)

TABLE 3 *(continued)*

Houston-Galveston-Brazoria TX	Louisville KY-IN	Norfolk-Virginia Beach-Newport News VA-NC
Hungtington-Ashland WV-KY-OH	Macon GA	Oklahoma City OK
Indianapolis IN	Madison WI	Omaha NE-IA
Jackson MS	McAllen-Titusville-Palm Bay FL	Orlando FL
Jacksonville FL	Memphis TN-AR-MS	Pennsacola FL
Johnson City-Kingsport-Bristol TN-VA	Miami-Fort Lauderdale FL	Peoria-Pekin IL
Kansas City MO-KS	Milwaukee-Racine WI	Philadelphia-Wilmington-Atlantic City PA-NJ-DE-MD
Knoxville TN	Minneapolis-St. Paul MN-WI	Phoenix-Mesa AZ
Lakeland-Winterhaven FL	Mobile AL	Pittsburgh PA
Lancaster PA	Modesto CA	Portland-Salem OR-WA
Lansing-East Lansing MI	Montgomery AL	Providence-Fall River-Warwick RI-MA
Las Vegas NV-AZ	Nashville TN	Raleigh-Durham-Chapel Hill NC
Reading PA	Seattle-Tacoma-Bremerton WA	Youngstown-Warren OH
Richmond-Petersburg VA	Shreveport-Bossier City LA	
Rochester NY	Spokane WA	
Rockford IL	Springfield MA	
Sacramento-Yolo CA	Stockton-Lodi CA	
Saginaw-Bay City Midland MI	Syracuse NY	
St. Louis MO-IL	Tampa-St. Petersburg-Clearwater FL	
Salinas CA	Toledo OH	
Salt Lake City-Ogden UT	Tucson AZ	
San Antonio TX	Tulsa OK	
San Diego CA	Utica-Rome NY	
San Francisco-Oakland-San Jose CA	Washington-Baltimore DC-MD-VA-WV	
San Juan PR	West Palm Beach-Boca Raton FL	
Santa Barbara-Santa Maria-Lompoc CA	Wichita KS	
Scranton-Wilkes Barre-Hazleton PA	York PA	

Source: Alternative Fuels Hotline extrapolation of 1980 US Census data

a data base on fleets for the enhanced I/M program may aid state government staff in tracking fleet emissions and compliance with EPact and CAAA.

MONETARY INCENTIVES

Monetary incentives provided in EPact are intended to soften the impact of AFV requirements on the private sector. Section 1913 of EPact allows tax deductions for clean fuel vehicles beginning October 24, 1993. The fleet owners are allowed a tax deduction up to $2,000 per LDV or LDT under 8,500 lb. GVWR. Tax deductions of up to $5,000 per truck or van are allowed in EPact for vehicles greater than 8,501 lb. and less than 26,000 lb. For those entrepreneurs building commercial and public alternative refueling stations, property tax deductions of up to $100,000 are allowed until 2002, phasing out the deductions by 2004.

TABLE 4 EPact and CAAA Purchase Requirements in Percentages

	Fed Govt	Fuel Providers	State Govt	Private/ Local*	CAA 90 LDV	CAA 90 HDV
1996	25	30	10	-	-	-
1997	33	50	15	-	-	-
1998	50	70	25	-	30	50
1999	75	90	50	20	50	50
2000	75	90	75	20	70	50
2001	75	90	75	20	70	50
2002	75	90	75	30/20	70	50
2003	75	90	75	40/40	70	50
2004	75	90	75	50/60	70	50
2005	75	90	75	60/70	70	50
2006	75	90	75	70/70	70	50

* Pending DOE rulemaking

Source: EPA

MODEL YEAR COVERAGE PERIOD

The main thrust of the clean fuel fleet provisions under CAAA and EPact is to require fleet owners to purchase a certain percentage (Table 4) of their new fleet vehicles as clean vehicles operating on alternative fuels. An important consideration for government and private fleet owners to understand is when to begin complying with the new laws. For the purpose of this regulation, EPA defines model year as the time period from September 1 to August 31. Because the CFFV provisions under CAAA go into effect January 1, 1998, an affected fleet owner needs to compute its CFFV purchase needs on the basis of the particular budget cycle that covers September 1, 1997, through August 1, 1998. It is assumed that DOE will define model year similarly to EPA. If the EPA definition is adopted for EPact, the 10-percent CFFV purchase for MY 1996 would have to be in place by September 1, 1995. Because the DOE rules affecting state fleets and private fuel provider fleets were not released until late 1994, a delay in new fleet purchases for these two regulated entities may have been prudent.

CONVERSION KIT VEHICLES

A vehicle originally designed to run on gasoline may be retrofitted with a conversion kit to run on an alternative fuel either as a dedicated alternative fuel vehicle or a dual-fueled vehicle capable of operating on either the conventional or alternative fuel. DOE may issue further guidance on the use of dual-fueled vehicles to comply with EPact, but it has yet to do so. EPA allows the CFFV purchase requirements to be met by converting existing or new gasoline-powered vehicles to clean fuel vehicles. The conversion kit will have to meet EPA engine-class certification standards of the LEVR program. An actual converted vehicle will have to pass the I/M test. Enhanced I/M operators are encouraged to find ways to measure emissions accurately from CFV/AFVs to provide SIP credits to state governments. A dual-fuel vehicle must meet the emission standards of the alternative fuel and the fuel to which it was originally certified.

EPA has indicated that an existing converted vehicle may qualify as a CFFV if it can be recertified to LEVR/CFFV emission standards. It is anticipated that post-September 1994 conversion kit manufacturers and installers will certify kits to LEVR standards, but existing conversion vehicles possess no such certification. Thus, they would have to be tested, probably via the federal test procedure, to receive certification, at an approximate cost of $2,000 per test. To achieve LEVR emission standards, most existing conversion vehicles would have to operate on or be upgraded to closed-loop systems (a feedback system operated by an advanced digital processor computer that meters the air-to-fuel ratio for optimal combustion). The costs for such a system are estimated to be $500 to $1,000 per vehicle, including labor. In cases in which an organization has existing conversion kit vehicles, it should be determined whether the kit has passed the EPA certification test and whether it has a closed-loop stoichiometric device. If the existing conversion vehicle does not have both of these features, it is more cost effective to buy an OEM vehicle or a new certified conversion kit that includes the closed-loop device. Recertifying existing conversion vehicles or transferring existing conversion kits to other vehicles is not cost effective at this time for meeting CAAA requirements.

Alternative fuel enhanced I/M testing is an area in which research needs to be conducted immediately. The Flame Ionization Detector, used in the new enhanced I/M programs to measure the NMOG fraction, samples propane to compute emission levels. Apparently, propane is not a significant enough component of most alternative fuels (particularly gaseous fuels, the fuels leading the way in existing production, infrastructure, and new purchase demand) to sample for NMOG concentrations. Proper NMOG sampling would more accurately generate CFV emission credits for the fleet operator and for state SIP credit.

It would not be prudent to exempt alternative fueled vehicles from I/M programs and assume that they meet the LEVR standards without ongoing inspection and, if necessary, maintenance. For ozone nonattainment areas that may demonstrate problems maintaining the EPA enhanced I/M performance standard after the turn of the century in a biennial program, the ability to test fleet emissions and receive SIP credit for additional fleet emissions reductions will remain important.

SELECTING AFV/CFFV

Usually, state fleets are made up primarily of compact sedans but also include mid-sized station wagons, ½-ton trucks, compact pickup trucks, 5-passenger vans, and mini-cargo and passenger vans. AFVs are available for each of these vehicle types, although AFVs are not available in all fuel types per vehicle category. For example, currently available methanol vehicles are almost exclusively sedans. LPG vehicles are primarily vans and medium-duty trucks. Fuel choice will depend on available and planned fuel infrastructures, as well as the desired LEV rating of the vehicle. On a national scale, DOE's Alternative Fuel Data Center reports that most state-planned AFV purchases are for CNG vehicles.

There are currently two fuel choices for compact sedans: M–85 and CNG. Wagons, vans, and trucks are also generally available in only two fuel choices: CNG and LPG (electric vans are still largely experimental and too costly). The additional initial purchase cost per alternative fuel vehicle is approximately

- CNG retrofit, more than $1,600;
- Dedicated CNG, more than $800;
- CNG van/wagon, more than $5,000;
- LNG retrofit, more than $2,780;
- M–85 sedan, more than $150;
- LPG medium-duty truck, more than $800; and
- Electric/hybrid small van, more than $80,000.

These costs, primarily provided by OEMs, are estimates and highly uncertain. (For specific fleet sales information contact the American Automobile Manufacturers Association.) An Air and Waste Management Association paper, Alternative Fuel Vehicles for the Department of the Navy, found incremental purchase costs of $400 for an M–85 vehicle, $800 for a LPG vehicle, and $1,000 for a CNG vehicle.

Another factor that may determine vehicle choice is vehicle operating range. A typical CNG sedan generally has a range of 80 to 110 mi (a dual-fuel sedan would probably have one CNG tank, and a dedicated sedan would have two tanks) or about 40 percent the range of a gasoline vehicle. A Ford Ranger CNG pickup truck has a range of 225 mi with four CNG tanks. CNG has a 3.2-to-1 volume disadvantage at 3,000 lb/in.^{2} compared with gasoline. LNG has only a 1.3-to-1 volume disadvantage compared with gasoline. LNG is thus more favorable in terms of volume disadvantage. However, because of space limitations, refrigeration of the LNG to keep it in a liquefied state may only initially become available for buses. LPG delivers about 50 percent of the mileage range compared with gasoline on a mile per gallon (MPG) basis. Methanol vehicles deliver 60 percent on an MPG basis of the equivalent gasoline vehicles. Electric vehicles deliver 12 to 55 percent the range of gasoline vehicles, depending on the battery type. A new energy storage device is the flywheel-based electromechanical battery. Electricity is converted into rotational energy for storage by a motor/alternator device using magnets and electromagnetic pickup coils. Industry awaits the unveiling of a functional prototype vehicle. In the near term, however, it appears that CNG has the most extensive refueling infrastructure. Hence, many areas are initially leaning toward CNG.

FUEL COSTS

Although natural gas is often less expensive than gasoline, new federal legislative initiatives may tax alternative fuels so not to have a negative effect or impact on the National Highway Trust Fund. CNG costs average about $0.74 a gallon and are generally less expensive than LPG. Methanol is usually the most expensive fuel. The Office of Technology Assessment estimated methanol prices to range from $1.29 to $1.71 per gasoline gallon equivalent in the early years of AFFV/CFFV program implementation. Electricity is estimated to cost about $1.50 per gallon equivalent. Ethanol may range from $1.60 to $2.60 a gallon. The RFG renewable oxygenate mandate could create ethanol supply problems because of ethyl tertiary butyl ether (ETBE) production. As of mid-1994, not many ETBE plants are in production. However, new plants are planned that can produce ETBE, corn syrup, and other corn byproducts to keep the facilities flexible and profitable.

MAINTENANCE

Many AFV OEMs plan to offer maintenance services through their local dealerships. M–85 has some special maintenance considerations: it requires a unique oil and oil change interval (comparable to Schedule A for gasoline vehicles). Because of their corrosive nature, alcohol fuels may remain less attractive until an additive is found to offset the problem. LPG vehicles generally have reduced oil change frequency of 50 percent compared with gasoline vehicles and longer spark plug and engine lives. OEMs report no substantial maintenance differential for CNG vehicles as compared with gasoline vehicles. Under CAAA, states may require more frequent tune-ups of CFFVs (and certification of such tune-ups) to ensure compliance with emission standards certified by the OEM or conversion kit manufacturer.

RECENT STATE EXPERIENCE

At present, most states have experience with experimental programs operating on CNG, often in a dual-fuel mode with gasoline. A few of the positive points from this experience are

- Cleaner air quality effects,
- Increased range of a dual-fuel vehicle,
- Absence of fuel spills during fueling, and
- Absence of fuel evaporation into the atmosphere.

Some negative aspects of CNG use are

- Tuning vehicles to operate on two fuels,
- Working with high pressure,
- Retraining of operators and mechanics,
- Present lack of standards for fuel connections, and
- Initial cost of the program.

CONCLUSION

The implications of fleet provisions in CAAA and EPact are important to the public and private sectors. Although the geographic coverage of CAAA fleet provisions is less than EPact, it is viewed as more stringent. Areas covered by CAAA fleet provisions should more easily comply with EPact provisions. Beginning in 1996 CAAA areas must also comply with the EPact provisions. In those places not affected by CAAA fleet provisions but by EPact, communication, coordination, implementation, and compliance with the fleet provisions will be complicated by the earlier 1996 MY start date. The tight time frame between DOE's final rulemaking and a fleet operator's purchasing needs is important to consider. (A Notice of Proposed Rulemaking for state government fleets and fuel provider fleets was scheduled to be released in November 1994. Consult with the regional DOE office for clarification.) Fortunately, only 10 percent of new fleet vehicle purchases are required to be alternatively fueled in the first year of the program in 1996. Of course, a fleet owner could simply forgo buying or replacing vehicles for 1996.

That EPact is both geographically more pervasive and 2 years earlier than CAAA presents great challenges and opportunities. The challenge is to develop an alternative fuel infrastructure in a great number of U.S. cities in the next 2 years while the government attempts to be fuel neutral. The congressional goal of reducing U.S. oil import dependence for transportation is driving this process.

If alternative fuels are not taxed the same as gasoline, the National Highway Trust Fund, which funds federal and state transportation agencies, is in danger of losing a portion of its solid user fee base derived from the federal gasoline tax. This issue need not concern states if they are willing to replace the existing gasoline tax and user revenues with other sources of revenues, such as registration fees or possibly in the future congestion/emission pricing user fees. However, the public might have a difficult time understanding the nuances and changes in highway funding and probably would resist the pricing initiative without an educational campaign similar to those in the past for safety belts and recycling.

Recent changes in federal law may affect the National Highway Trust Fund. Congress may choose to resolve how to continue funding transportation agencies while providing an incentive to use alternative fuels in the early years of the program, when the risks may appear to outweigh the benefits.

The opportunity presented by the earlier implementation of EPact is the generation of credits in air quality nonattainment areas to apply toward the annual rate of progress in reducing ground-level ozone. For those nonattainment areas trying to determine whether quantifying fleet MERCs is worth the effort in its rate of progress report, they should consider that a fleet vehicle averaging 20,000 mi annually, merely going from NMOG Tier 1 standards (0.25 g/mi) to ULEV NMOG standards (0.04), provides an 84 percent reduction in NMOG, or about a 23 kg/day reduction per 2,000 vehicles. This is approximately a 38-ton-per-day reduction for an area with 3 million ULEV vehicles. Note that actual SIP credit must reflect actual vehicle and fleet emissions and not those specified by the LEVR program (consult MOBILE5).

Nonattainment areas that have been designing EPA's new enhanced I/M programs may have an extensive data base on fleet operators to properly serve fleets in the I/M program. It should be possible to track fleet emissions reductions after 1996 with this data base. State vehicle registration records may not accurately reflect the number of fleets affected, however, because of the voluntary nature of fleet registration and fleet size thresholds. This is further complicated by CAAA fleet-use levels, measured in miles driven in the nonattainment area, which are often not included in current records and complicate enforcement without a computerized trip-log or constant emission monitoring (CEM) type equivalent. This situation is complicated in multiple state metropolitan areas where one of the states may have replaced the CFFV requirement with another program, as was allowed in CAAA. Fleets promise an interesting way to quickly introduce CFVs/AFVs and for fleet owners or state governments to claim the extra emissions reduction credit. An important point for states and private fleet owners is that, unless dedicated fuel vehicles are chosen, they receive very little credit from EPA for the CFFV program. Without an extensive infrastructure in place, fleet owners may be reluctant to purchase more than the required percentage of CFVs or to choose dedicated fuel CFVs. Large commercial interests in urban areas should find it easier to purchase dedicated fuel vehicles because their fleets have a more local operating range. A central refueling facility or a series of them in the urban area should make it easier for dedicated fuel vehicles to operate in urban areas. State fleets and fleets with a wider operating range may prefer to purchase dual-fueled vehicles to avoid the complication of limited refueling facilities during the early years of the programs.

Of more interest, in terms of generating emissions credits, is the maximum credit I/M program, which would return fleet vehicles to near-engine-emission certification levels. This program could yield between 0.6 and 1.2 g/mi VOC reduction, approximately 66 to 132 kg/day per 2,000 vehicles, each driven 20,000 mi/year. A maximum I/M program applied to 3 million vehicles would yield 109 to 218 TPD VOC reduction. The maximum I/M program is clearly an aggressive program, three to six times more stringent than a total ULEV program applied to the entire population. Although, the general public may not approve such a program for all vehicles, it may endorse it specifically for fleets.

Perhaps in the future, ozone nonattainment areas may have difficulty complying with the EPA enhanced I/M performance standard in a biennial testing program. States would have the following choices to remain in compliance:

- Lower slightly the cut-points of the I/M program,
- Adopt a maximum credit I/M program,
- Adopt a LEVR program for the entire vehicle population, or
- Make the I/M program annual.

Before this occurs, states should examine the emissions reductions to be obtained by administering and enforcing the CFFV program and, if necessary, applying the maximum I/M program to fleets instead of the entire vehicle population.

Start Modes of Trips for Mobile Source Emissions Modeling

MOHAN VENIGALLA, TERRY MILLER, AND ARUN CHATTERJEE

An important determinant of vehicle emissions during a trip is the engine temperature at trip start. A trip start may be classified as a cold start or a hot start depending on the emission control equipment and the duration of engine shut-off period before starting the engine. Cold starts are usually associated with higher concentrations of carbon monoxide and hydrocarbons than are hot starts. The emission modeling process uses these start modes as direct or indirect inputs to procedures or models that would be used to determine the portion of vehicle miles traveled in transient and stabilized operating modes. A methodology for determining the operating mode fractions at trip ends is shown. Specifically, a comprehensive analysis of personal travel data available in Nationwide Passenger Transportation Survey data is performed for deriving start mode fractions at trip origins and operating mode fractions at trip destination points. Start mode fractions as cold starts and hot starts are derived for different trip purposes and for each hour of the day. It was observed that the trip purpose is the most important explanatory variable for variance in cold starts, followed by the temporal variables such as the time of day at which the trip is made. The sizes of an urban area and individual metropolitan statistical areas are found to be the two most appropriate spatial variables for which aggregated start mode percentages may be derived. The start mode fractions derived from this methodology will be useful for a variety of mobile source emission modeling exercises.

The Clean Air Act of 1970 (CAA) mandates that mobile source emission inventories be prepared as an integral part of state implementation plans (SIP). The CAA Amendments of 1990 (CAAA) require that all major transportation improvement projects be analyzed for air-quality–related impacts. To comply with these regulations, most mobile source emission modeling is performed using either the Environmental Protection Agency's (EPAs) MOBILE model or California's EMFAC. For the MOBILE model, the start mode of a trip is not required to be specified as input; however, the fraction of the vehicle miles of travel (VMT) in cold and hot transient modes must be specified. For the EMFAC model and any procedure based on the modal approach, start modes must be specified explicitly.

In this context, it is important to differentiate the start mode at trip origin from the operating mode during the trip. In this paper, the operating mode 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 historically has defined a cold start as any start that occurs 4 hrs or later following the end of the preceding trip for noncatalyst-equipped vehicles and 1 hr or later following the end of the preceding trip for catalyst-equipped vehicles. Hot starts are those starts that occur less than 4 hrs after the end of the preceding trip for noncatalyst vehicles and less than 1 hr after the end of preceding trip for catalyst-equipped vehicles (*1*). The duration associated with restarting the engine after the end of the preceding trip is called a cold-soak or simply the soak period.

Before attaining the hot stabilized operating mode during which the rate of emissions is significantly lower, a vehicle will be operating in either a cold transient mode (for a cold start) or a hot transient mode (for a hot start). The duration of each of the two transient modes is specified as 505 sec in the Federal Test Procedure (FTP), which is used to test the new vehicles for compliance with EPA emission standards. If the proportion of trips starting in cold and hot modes is known, it is possible to trace these cold start and hot start trips along potential routes taken on the network. The purpose of such analysis using a number of transportation modeling techniques is to derive the VMT-weighted proportions of transient and stabilized modes needed to determine average emission rates (*2*).

The start mode at the beginning of each trip is determined by the duration of the cold soak period and the vehicle type. To derive these start modes at trip origins, data pertaining to cold soak period and vehicle type are needed. Origin-destination data collected for comprehensive urban transportation planning purposes usually contain this information. However, these data sources are localized, tend to be outdated, and are sometimes inadequate for determining start modes. A comprehensive data base on personal travel, Nationwide Personal Transportation Survey (NPTS), available for public use through the U.S. Department of Transportation (USDOT) was examined for this purpose. This paper discusses the analysis of the NPTS data base for deriving start modes at trip origins. Following this introductory section, the state of the art is reviewed. In the remainder of the paper, the analysis of NPTS data base is discussed, followed by a detailed discussion on the start modes by time of day and trip purpose.

STATE OF THE ART

The MOBILE model (version 5A) recommends the use of default operating mode fractions at 20.6 percent cold transient and 27.3 percent hot transient modes. These values are based on the FTP drive cycle and do not consider possible variations due to several factors, such as functional class of a roadway facility, geographic location, and start modes at trip origins. For SIP-related modeling, EPA accepts the use of FTP operating mode fractions, except for small-scale scenarios where their use would clearly be inappropriate (*1*). These operating mode fractions were derived on the basis of the start mode fractions that represented conditions of a typical urban setting (such as Los Angeles) and do not represent variable urban settings (*3*).

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One way to resolve the limitations associated with FTP operating mode mix is to use field observations and measurements. An accurate determination of the operating mode of a vehicle engine requires measurements of the engine temperature, and such measurements are difficult to implement on a vehicle while operating under normal traffic conditions.

Only a few studies attempted to determine operating modes of vehicles traveling on regular roads by field measurements. These include a study in New Jersey (*4*). Data representing six functional roadway classifications were collected at field sites. With the permission of the drivers, engine oil and coolant temperature were measured, and engine run time estimates were obtained from the driver. The collected data were analyzed for determining percentages of hot transient, cold transient, and hot stabilized modes of operation in the traffic.

There is an indirect approach of estimating the operating modes of vehicles traveling on a roadway. This approach uses the travel time from a trip origin as an indicator of the operating mode. The travel time from trip origin can be estimated either by interviewing drivers (as in the case of New Jersey study) or by modeling. The interview technique is expensive and difficult to implement. Therefore, the modeling approach is more feasible.

Venigalla (*2*) and COMSIS (*5*) have developed algorithms to trace transient mode trips on network links. The Traffic Assignment Program for Emission Studies (TAPES) (*2*) and the ASSIGN module in the latest version of MINUTP (*5*) use these algorithms. These models require the analyst to provide data on engine start modes by trip purpose. The portions of cold or hot starts at the beginning of trips will affect the proportions of cold and hot transient modes as well as the hot stabilized modes on various facilities.

Therefore, one of the most important inputs to deriving operating mode fractions using the modeling approach is the start mode fractions at trip origins. Ellis et al. (*6*) have analyzed origin-destination survey data for six Alabama urban areas (Birmingham, Mobile, Huntsville, Montgomery, Tuscaloosa, and Etowah) and Boston, Massachusetts. The study analyzed the beginning and ending times of each vehicle trip and the purpose of the trip. The percentages of cold starts were tabulated for catalyst-equipped vehicles by trip purpose (Table 1) for the six cities in Alabama.

Another study by Garmen Associates attempted to derive the percentage of cold starts to be used as input for assignment models (*2*). The study was aimed at analyzing cold starts VMT for south and north Jersey planning areas in New Jersey. Table 1 also lists the cold start vehicle trip percentages used by this study for north and south Jersey study areas. The study referred to the MOBILE model user's guide and a few test runs as the source of these numbers. However, the study made strong assumptions related to cold starts by trip purpose. For example, it was assumed that work trips are almost always cold start trips, because the car usually sits for hours in the driver's driveway at home or the parking lot at work, whereas shopping and non–home-based (NHB) trips are likely to be hot starts.

It can be seen that there is considerable variation in the numbers derived or used by different studies for cold start proportions. These numbers are either old or derived based on a number of crude assumptions. It is obvious that these percentages significantly influence the operating mode fractions on different facilities. Erroneous operating mode fractions will result in wrong emission factors. Thus, any error in the assumptions made with regard to start modes would carry all the way over to the stage where emissions are estimated.

TABLE 1 Percentage of Cold Starts Used for Different Studies

Trip Purpose	Percent Cold Starts Used for:					
	Alabama/Boston (1978)		New Jersey[1] (1992)		Washington DC (1991)	
	Catalyst	Non-Catalyst	South Jersey	North Jersey	Catalyst	Non-Catalyst
Work	92.3	81.5	90	90	93.7	82.6
Personal Business	52.9	30.3	NI	NI	NI	NI
Social/Recreational	71.6	25.6	NI	NI	NI	NI
School	86.1	63.2	NI	NI	NI	NI
Shop	86.1	23.6	NI	45	NI	NI
Non-Home Based	37.0	14.8	NI	40	NI	NI
Casino Work	NA	NA	90	NA	NI	NI
Casino Visit	NA	NA	75	NA	NI	NI
Beach	NA	NA	85	NA	NI	NI
Other	NI	NI	50	50	66.4	37.0
I/X	NI	NI	0	70	NI	NI
X/I	NI	NI	0	0	NI	NI
X/X	NI	NI	0	0	NI	NI
Average Weighted	*61.5 (Alabama) 56.4 (Boston)*	*40.3 (Alabama) 34.9 (Boston)*	*57*	*59*	*74.1 (Total Daily)*	*49.9 (Total Daily)*
Note:	NA - Not Applicable; NI - Not Indicated; I/X - Internal to External Trips; and X/I - External to Internal Trips [1] Type of emission control equipment was not indicated for the New Jersey Study.					

PREPARATION OF NPTS DATA

NPTS periodically compiles national data on the nature and characteristics of personal travel. It addresses a broad range of travel in the United States providing data on all personal trips for all purposes and by all modes of transportation (*7*). No information on the trips of commercial nature, such as pickup and delivery trips, is available in this data base.

The 1990 NPTS data base includes information on 41,178 vehicles used for 149,546 trips made in a 24-hr travel day. Consult USDOT'S user guide for NPTS data tapes (*7*) for further details on the data base.

The analysis of this data base for determining the operating modes at trip ends was performed in a number of steps while exercising caution at each step with regard to data on questionable trip and vehicle records. The process involved the following distinctive steps:

1. Identify relevant variables in the NPTS data base.
2. Identify vehicles with catalytic converters.
3. Determine cold soak period for each trip.
4. Associate each trip end with an operating mode on the basis of individual mode and trip duration.
5. Perform an analysis for trip duration, operating modes at trip ends, and percentage of vehicle miles of travel in different operating modes.

Relevant variables extracted from the vehicle and day trip files of the data base include the following:

- Household identification number;
- Vehicle identification number;
- Make year of the vehicle;
- Census region, census division, metropolitan statistical area (MSA) variables, and size of urban area;
- Start time and length of each trip in minutes and miles; and
- Trip purpose variables.

Information on emission control equipment mounted on each vehicle is not present in the data base. For this reason, a methodology was devised to identify the emission control equipment on the basis of available information. This methodology assumes that all vehicles manufactured after 1975 are mounted with catalyst converters so that the EPA's emission standards could be met (*2*). Also, it was assumed that about 25 percent of the vehicles manufactured and sold before 1975 were equipped with the converters as a result of lack of sufficient information. Because the total number of vehicles with model year before 1975 was less than 8 percent of the total vehicles (41,178) in the data base, any errors occurring in the overall analysis because of this assumption are minimal. This procedure identifies 2,191 (5.3 percent) vehicles in the data base as noncatalyst equipped and 38,987 (94.7 percent) vehicles as catalyst equipped.

The data base was rearranged so the chain of trips made by each vehicle can be identified individually. The cold soak period between two successive trips was computed by using the data on begin time and duration of each trip. After the emission control equipment of each vehicle and cold soak period of each vehicle trip are determined, each trip start was identified as a cold start or hot start based on the standard definitions mentioned in the introduction section of this paper.

The trip chains used for final analysis were subjected to a series of consistency checks. Questionable trip chains due to insufficient information were discarded. The data screening process reduced the eligible data base size from 149,546 to 105,903 trips. After final screening, the data base was found to adequately represent the sampling characteristics of the original data base.

ANALYSIS FOR START AND OPERATING MODES AT TRIP ENDS

Frequencies were obtained, by trip purpose and hour of day, for cold start, hot start, cold and hot transient, and stabilized modes at the origin and destination points of trips. The analyses were conducted for all trips in the data base, which means that the results should represent nationwide average values. In Table 2, the percentages of cold and hot start modes as well as the frequencies by hour of day and trip purpose are presented. The start modes and the operating modes at the ends of trips for all trip purposes can be derived from Table 2. The operating mode percentages—cold and hot transient modes and hot stabilized modes—at the ends of the trips are presented in Table 3.

The figures presented in Tables 2 and 3 are national averages and do not represent any geographic detail. These figures, in general, indicate that more trips in the morning hours are in a cold start mode. The percentage of trips starting in cold mode falls as the day progresses, a trend that would be expected. On the other hand, most trips appear to be ending in a hot stabilized mode, which also conforms to intuition on travel patterns in general. The numbers presented in Tables 2 are plotted in Figure 1 which indicates the following:

- As expected, most of the home-based work (HBW) trips or home-based other (HBO) trips made in the morning hours (between 3:00 a.m. and 10:00 a.m.) started in a cold mode. As the day progresses, the share of cold starts is reduced.
- On the other hand, for NHB trips between the hours of 6:00 a.m. and 10:00 a.m. more than 60 percent of the trip starts were in the hot start mode. Most of the NHB trips made during this time would perhaps be to leave for work either after stopping for breakfast or after leaving children at schools or daycare centers. Trips of this nature indicate a cold soak period of 0 min to less than 1 hr, indicating the engine start in a hot mode.
- The percentage of hot starts for home-based trips reach a peak during the afternoon hours (2:00 p.m. to 6:00 p.m.).
- The percentage of cold starts for all trip purposes indicates a peaking of cold starts between 4:00 a.m. and 7:00 a.m. Conversely, the percentage of hot starts will be the lowest during this period.

TABLE 2 Start Modes at Trip Origins by Time of Day

	Percent HBW Trips in:		Percent HBO Trips in:		Percent NHB Trips in:	
Time Period	Cold Start	Hot Start	Cold Start	Hot Start	Cold Start	Hot Start
12 AM to 1 AM	87.2 *(170)*	12.8 *(25)*	70.5 *(244)*	29.5 *(102)*	72.4 *(84)*	27.6 *(32)*
1 AM to 2 AM	85.4 *(88)*	14.6 *(15)*	70.5 *(141)*	29.5 *(59)*	73.2 *(41)*	26.8 *(15)*
2 AM to 3 AM	93.0 *(80)*	7.0 *(6)*	72.0 *(85)*	28.0 *(33)*	77.6 *(38)*	22.4 *(11)*
3 AM to 4 AM	91.2 *(93)*	8.8 *(9)*	64.2 *(43)*	35.8 *(24)*	77.3 *(17)*	22.7 *(5)*
4 AM to 5 AM	93.3 *(208)*	6.7 *(15)*	85.0 *(51)*	15.0 *(9)*	80.0 *(12)*	20.0 *(3)*
5 AM to 6 AM	93.6 *(703)*	6.4 *(48)*	79.9 *(119)*	20.1 *(30)*	52.6 *(10)*	47.4 *(9)*
6 AM to 7 AM	91.9 *(2049)*	8.1 *(181)*	72.9 *(415)*	27.1 *(154)*	25.3 *(20)*	74.7 *(59)*
7 AM to 8 AM	86.4 *(3119)*	13.6 *(493)*	63.8 *(1422)*	36.2 *(807)*	21.8 *(70)*	78.2 *(251)*
8 AM to 9 AM	80.4 *(1666)*	19.6 *(406)*	59.0 *(1639)*	41.0 *(1140)*	21.5 *(122)*	78.5 *(445)*
9 AM to 10 AM	78.5 *(672)*	21.5 *(184)*	60.8 *(1887)*	39.2 *(1219)*	27.4 *(230)*	72.6 *(609)*
10 AM to 11 AM	73.0 *(381)*	27.0 *(141)*	60.2 *(2075)*	39.8 *(1369)*	29.8 *(395)*	70.2 *(930)*
11 AM to 12 PM	67.4 *(339)*	32.6 *(164)*	57.5 *(1951)*	42.5 *(1440)*	39.5 *(766)*	60.5 *(1174)*
12 PM to 1 PM	58.8 *(490)*	41.2 *(343)*	53.9 *(2109)*	46.1 *(1804)*	43.7 *(1165)*	56.3 *(1500)*
1 PM to 2 PM	63.0 *(463)*	37.0 *(272)*	53.5 *(1888)*	46.5 *(1640)*	40.4 *(853)*	59.6 *(1257)*
2 PM to 3 PM	73.6 *(706)*	26.4 *(253)*	52.5 *(2006)*	47.5 *(1816)*	41.9 *(852)*	58.1 *(1181)*
3 PM to 4 PM	77.7 *(1437)*	22.3 *(412)*	46.3 *(2073)*	53.7 *(2401)*	48.0 *(1145)*	52.0 *(1241)*
4 PM to 5 PM	75.4 *(1915)*	24.6 *(625)*	45.2 *(1933)*	54.8 *(2346)*	49.9 *(1180)*	50.1 *(1185)*
5 PM to 6 PM	75.3 *(2193)*	24.7 *(720)*	44.1 *(2057)*	55.9 *(2605)*	49.8 *(1147)*	50.2 *(1154)*
6 PM to 7 PM	73.3 *(1136)*	26.7 *(414)*	49.1 *(2357)*	50.9 *(2447)*	40.5 *(649)*	59.5 *(953)*
7 PM to 8 PM	73.9 *(564)*	26.1 *(199)*	50.9 *(2182)*	49.1 *(2101)*	40.3 *(532)*	59.7 *(788)*
8 PM to 9 PM	78.9 *(418)*	21.1 *(112)*	50.3 *(1702)*	49.7 *(1681)*	42.3 *(376)*	57.7 *(512)*
9 PM to 10 PM	79.3 *(414)*	20.7 *(108)*	54.9 *(1388)*	45.1 *(1139)*	52.3 *(345)*	47.7 *(315)*
10 PM to 11 PM	81.9 *(398)*	18.1 *(88)*	60.4 *(892)*	39.6 *(586)*	62.8 *(199)*	37.2 *(118)*
11 PM to 12 PM	84.9 *(338)*	15.1 *(60)*	62.8 *(547)*	37.2 *(324)*	65.9 *(172)*	34.1 *(89)*
Average Daily	79.1 *(20040)*	20.9 *(5293)*	53.4 *(31206)*	46.6 *(27276)*	43.0 *(10420)*	57.0 *(13836)*

Note: Figures in parentheses are number of trips recorded in each cell

The operating modes at the ends of trips, as shown in Figures 2 and 3, indicate the following:

- In general, a large portion of all trips ended in a hot stabilized state. More than 50 percent of all trips ended in this mode during any time of the day.
- The proportions of operating modes at the ends of trips are different for different trip purposes only in the morning, between 5:00 a.m. and 11:00 a.m. During the remainder of the day, the proportions of operating modes are more or less the same for all trip purposes. This can be expected because the length of a trip, rather than simply the start mode at its origin, will be a major determinant of the operating mode at the end of a trip.
- With the exception of non–home-based trips, transient mode trips (Figure 2) peaked during noon hours. This phenomenon indicates that the trips made between 10:00 a.m. and 1:00 p.m. are relatively shorter in duration, a trend that could be expected.

ANALYSIS OF VARIANCE FOR COLD START PERCENTAGES

It would appear that cold and hot start percentages may vary between geographic regions or urban areas by time of day and by trip purpose. However, it is not known a priori whether the differences in cold and hot start percentages are statistically significant for different geographic regions, times of day, and trip purposes.

TABLE 3 Operating Modes at Ends of Trips

Time Period	Percent HBW Trips in:			Percent HBO Trips in:			Percent NHB Trips in:		
	Cold Trans.	Hot Trans.	Hot Stable	Cold Trans.	Hot Trans.	Hot Stable	Cold Trans.	Hot Trans.	Hot Stable
12 AM to 1 AM	19.0 *(37)*	3.6 *(7)*	77.4 *(151)*	19.1 *(66)*	6.1 *(21)*	74.9 *(259)*	27.6 *(32)*	6.0 *(7)*	66.4 *(77)*
1 AM to 2 AM	19.4 *(20)*	4.9 *(5)*	75.7 *(78)*	16.0 *(32)*	5.0 *(10)*	79.0 *(158)*	23.2 *(13)*	14.3 *(8)*	62.5 *(35)*
2 AM to 3 AM	27.9 *(24)*	2.3 *(2)*	69.8 *(60)*	27.1 *(32)*	8.5 *(10)*	64.4 *(76)*	22.4 *(11)*	8.2 *(4)*	69.4 *(34)*
3 AM to 4 AM	21.6 *(22)*	1.0 *(1)*	77.5 *(79)*	16.4 *(11)*	3.0 *(2)*	80.6 *(54)*	31.8 *(7)*	13.6 *(3)*	54.5 *(12)*
4 AM to 5 AM	17.5 *(39)*	0.9 *(2)*	81.6 *(182)*	31.7 *(19)*	3.3 *(2)*	65.0 *(39)*	46.7 *(7)*	. *(-)*	53.3 *(8)*
5 AM to 6 AM	15.6 *(117)*	0.8 *(6)*	83.6 *(628)*	23.5 *(35)*	2.0 *(3)*	74.5 *(111)*	10.5 *(2)*	*(-)*	89.5 *(17)*
6 AM to 7 AM	13.8 *(307)*	1.1 *(24)*	85.2 *(1899)*	31.1 *(177)*	4.2 *(24)*	64.7 *(368)*	7.6 *(6)*	11.4 *(9)*	81.0 *(64)*
7 AM to 8 AM	16.3 *(590)*	2.2 *(81)*	81.4 *(2941)*	27.9 *(622)*	4.6 *(103)*	67.5 *(1504)*	8.4 *(27)*	12.8 *(41)*	78.8 *(253)*
8 AM to 9 AM	20.2 *(418)*	4.8 *(99)*	75.0 *(1555)*	26.6 *(739)*	8.0 *(222)*	65.4 *(1818)*	9.0 *(51)*	21.0 *(119)*	70.0 *(397)*
9 AM to 10 AM	24.2 *(207)*	6.4 *(55)*	69.4 *(594)*	24.5 *(762)*	10.0 *(310)*	65.5 *(2034)*	9.5 *(80)*	23.0 *(193)*	67.5 *(566)*
10 AM to 11 AM	20.3 *(106)*	10.7 *(56)*	69.0 *(360)*	24.0 *(825)*	10.9 *(375)*	65.2 *(2244)*	11.2 *(148)*	27.0 *(358)*	61.8 *(819)*
11 AM to 12 PM	21.3 *(107)*	14.1 *(71)*	64.6 *(325)*	21.2 *(720)*	11.8 *(401)*	66.9 *(2270)*	15.8 *(306)*	22.0 *(426)*	62.3 *(1208)*
12 PM to 1 PM	21.4 *(178)*	19.1 *(159)*	59.5 *(496)*	19.6 *(766)*	12.1 *(475)*	68.3 *(2672)*	19.4 *(518)*	20.1 *(536)*	60.5 *(1611)*
1 PM to 2 PM	22.3 *(164)*	15.9 *(117)*	61.8 *(454)*	18.8 *(664)*	12.9 *(456)*	68.3 *(2408)*	15.1 *(318)*	21.1 *(445)*	63.8 *(1347)*
2 PM to 3 PM	16.9 *(162)*	8.1 *(78)*	75.0 *(719)*	18.4 *(702)*	12.1 *(461)*	69.6 *(2659)*	12.9 *(263)*	20.0 *(406)*	67.1 *(1364)*
3 PM to 4 PM	17.4 *(322)*	7.4 *(136)*	75.2 *(1391)*	15.7 *(703)*	14.3 *(639)*	70.0 *(3132)*	15.9 *(379)*	15.6 *(373)*	68.5 *(1634)*
4 PM to 5 PM	13.6 *(346)*	8.1 *(206)*	78.3 *(1988)*	14.9 *(636)*	15.7 *(670)*	69.5 *(2973)*	15.5 *(366)*	14.7 *(347)*	69.9 *(1652)*
5 PM to 6 PM	14.5 *(422)*	7.3 *(214)*	78.2 *(2277)*	14.5 *(675)*	14.3 *(668)*	71.2 *(3319)*	15.0 *(344)*	15.1 *(347)*	70.0 *(1610)*
6 PM to 7 PM	15.2 *(236)*	7.7 *(120)*	77.0 *(1194)*	17.9 *(859)*	13.7 *(658)*	68.4 *(3287)*	13.0 *(208)*	17.2 *(275)*	69.9 *(1119)*
7 PM to 8 PM	17.3 *(132)*	9.7 *(74)*	73.0 *(557)*	19.1 *(819)*	13.2 *(565)*	67.7 *(2899)*	13.9 *(183)*	17.1 *(226)*	69.0 *(911)*
8 PM to 9 PM	18.3 *(97)*	5.3 *(28)*	76.4 *(405)*	19.5 *(658)*	12.1 *(408)*	68.5 *(2317)*	15.2 *(135)*	18.8 *(167)*	66.0 *(586)*
9 PM to 10 PM	19.9 *(104)*	5.2 *(27)*	74.9 *(391)*	17.1 *(431)*	12.0 *(304)*	70.9 *(1792)*	19.8 *(131)*	12.6 *(83)*	67.6 *(446)*
10 PM to 11 PM	16.0 (78)	5.3 *(26)*	78.6 *(382)*	19.6 *(289)*	10.4 *(154)*	70.0 *(1035)*	22.4 *(71)*	9.8 *(31)*	67.8 *(215)*
11 PM to 12 PM	18.1 *(72)*	2.0 *(8)*	79.9 *(318)*	19.3 *(168)*	7.8 *(68)*	72.9 *(635)*	27.6 *(72)*	10.7 *(28)*	61.7 *(161)*
Average Daily	17.0 *(4307)*	6.3 *(1602)*	76.7 *(19424)*	19.5 *(11410)*	12.0 *(7009)*	68.5 *(40063)*	15.2 *(3678)*	18.3 *(4432)*	66.5 *(16146)*
Notes:	*Figures in parentheses are number of trips recorded in each cell*								

An analysis of the variance of cold and hot start percentages for different spatial, temporal, and trip purpose classifications would not only assess the statistical significance of such a stratification, but would also lead to a more meaningful cross classification. For example, the start percentages may be derived for each hour of the day for a given urban area. However, these percentages may be statistically similar for several consecutive hours such as morning peak period, night hours, and so forth. To minimize the level of effort required to model mobile source emissions, it is necessary to identify such similarities and combine those levels into one class.

Analysis of Variance for Cold Starts

The percentage of cold starts was used as the response variable to analyze the variance of start modes. Because the percentage of hot starts is related to the percentage of cold starts, the inferences drawn from the analysis of cold start percentages apply to hot starts as well. Three groups of variable categories were included as independent variables in the analysis of variance for cold start percentages. These groups are spatial variables, time-of-day variables, and trip-purpose variables. The spatial resolution in the NPTS data includes the following categories:

- Census region (four levels—Northeast, North Central, South, and West);
- Census division (nine levels—New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific);
- Urban area size (six population levels—50,000 to 199,999; 200,000 to 499,999; 500,000 to 999,999; 1,000,000 or more with

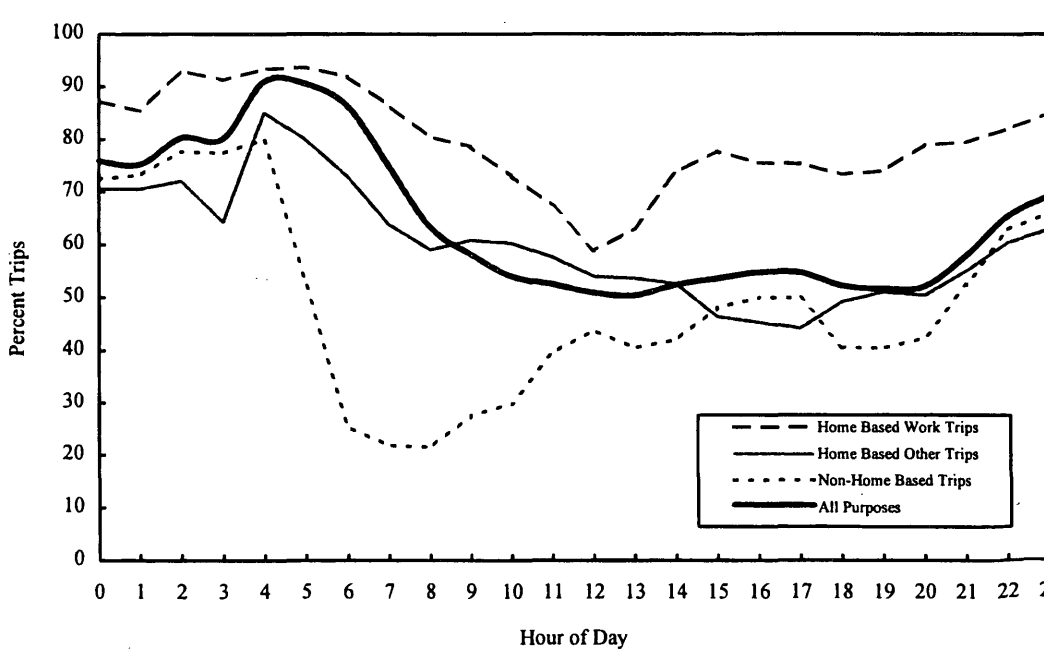

FIGURE 1 Percentage of cold starts by time of day.

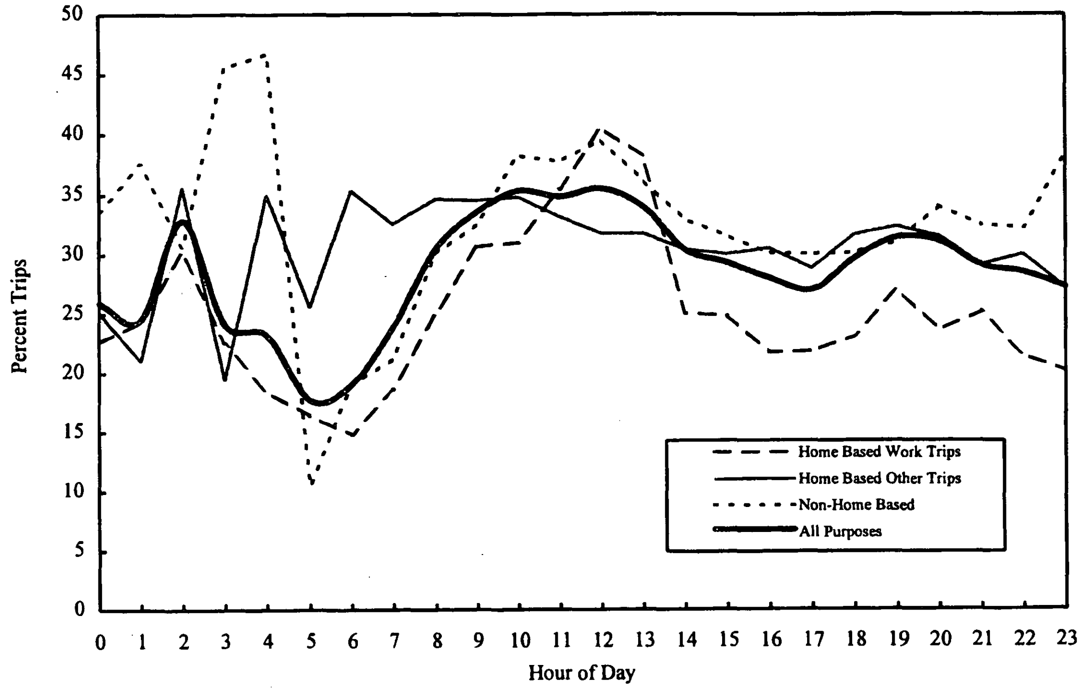

FIGURE 2 Percentage of trips ending in transient mode.

subway/rail; 1,000,000 or more without subway/rail; and not in urbanized area);

- MSA size (six population levels—fewer than 250,000; 250,000 to 499,999; 500,000 to 999,999; 1,000,000 to 2,999,999; 3,000,000 or more; and not in an MSA); and
- Individual MSAs.

All these spatial variables were considered for analysis of variance. Because the time each trip started was recorded in the 24-hr time format, it was possible to derive cold and hot start percentages for each hour of the day. With regard to trip purpose variables, no additional data processing was necessary to identify the purpose of each trip because all the trips in the data base were already identified with a trip purpose. Another variable in the NPTS data base (whytrip) describes the purpose of each trip in further detail than the three variable categories, such as to or from work, school, or church, and pleasure driving. Because trips are often classified as HBW trips, HBO trips, and NHB trips for transportation planning studies,

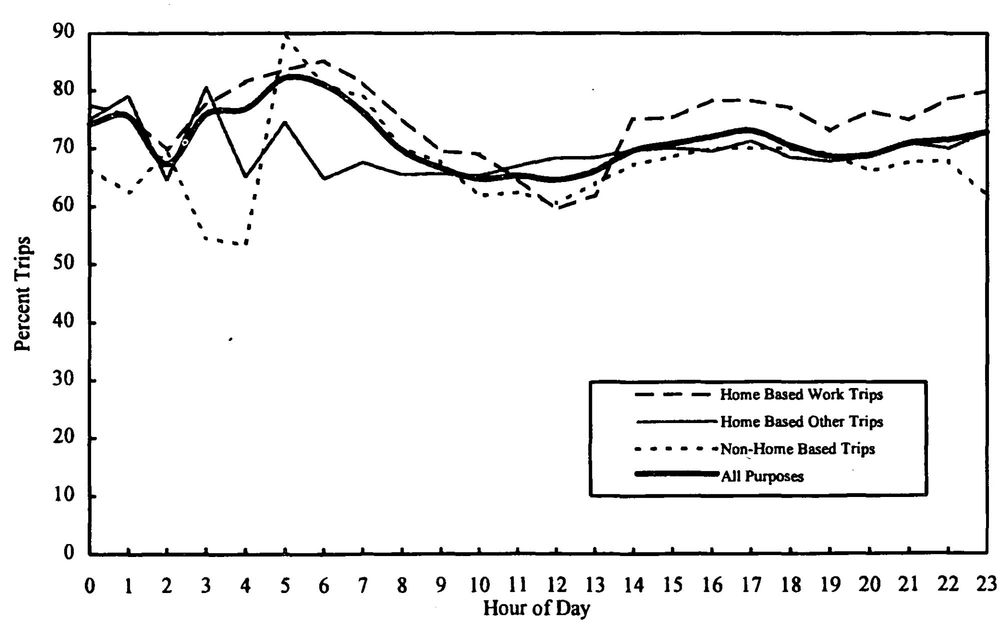

FIGURE 3 Percentage of trips ending in hot stabilized mode.

only the previously mentioned three trip categories were considered for this analysis. Home-based shopping, social/recreational, and other trips were grouped as HBO trips.

Thus, from the NPTS data, cold and hot start percentages may be computed across several levels of spatial, temporal, and trip-purpose variables. There will be only one value for the response variable Y_{ijk} in each cell ijk, which is the percentage of cold starts. Because the response variable is a proportion, it is necessary to transform the dependent variable to stabilize the variance. An appropriate transformation for this case is the arc sine transformation, which is performed as follows (*8*):

$$Y' = 2 \arcsin \sqrt{Y}$$

Thus, the final analysis of the variance on the percentage of cold starts was conducted using the general linear model procedure, and the results are summarized in Table 4. The model included the main effects of the three independent variables and only two-way interactions. Because there was only one observation in each cell, no three-way interaction term was specified. In situations like this, the general model uses the three-way interaction term as the error term. The results of the analysis indicate the following:

- Except for the spatial variables, MSA size, and the census division, all other main effects have significant influence on the percentage of cold starts. Therefore, it may be inappropriate to group trips by census division and MSA size for composite values of cold start percentages.
- Trip purpose is the best explanatory variable for variance in the percentage of cold starts.
- The time-of-day variable closely follows the trip-purpose variable as the second most significant main effect.
- The crossed or interaction effects of time-of-day and trip-purpose variables are highly significant. That is, there is a statistically significant reason to believe that the percentage of cold starts does vary by each hour for a given trip purpose.

Even though the census region proved to be a statistically significant main effect, it may not be appropriate to use it to group cold start percentages because this class variable represents a very coarse level of aggregation (four regions for the United States). Individual MSAs, on the other hand, provide a finer resolution for presenting start mode fractions. However, the results can be used only by the MSA in question and may not be transferable to any other MSA. Thus, on a nationwide basis, the most appropriate classification for presenting transferable results is the size of the urban area. The start modes at trip origins were derived for urban areas of different sizes and are presented in Tables 5 to 10.

TABLE 4 Summary Analysis of Variance for Percentage of Cold Starts

Source of Variance	Spatial Variable, *SV*				
	Census Region	Census Division	Urban Area Size	MSA Size	Individual MSA
Model	0.0001 *(10.09)*	0.0001 *(7.97)*	0.0001 *(7.99)*	0.0001 *(6.79)*	0.0001 *(4.17)*
Main Effects					
TP	0.0001 *(249.64)*	0.0001 *(278.48)*	0.0001 *(256.85)*	0.0001 *(197.64)*	0.0001 *(203.31)*
HD	0.0001 *(23.53)*	0.0001 *(44.08)*	0.0001 *(27.59)*	0.0001 *(24.49)*	0.0001 *(48.05)*
SV	0.0246 *(3.22)*	0.2116 *(1.36)**	0.0274 *(2.58)*	0.1452 *(1.66)**	0.0001 *(3.27)*
Interaction Effects					
*SV*TP*	0.6614 *(0.69)**	0.3499 *(1.10)**	0.0442 *(1.92)*	0.1121 *(1.59)**	0.0918 *(1.32)**
*TP*HD*	0.0001 *(7.59)*	0.0001 *(8.99)*	0.0001 *(6.72)*	0.0001 *(5.21)*	0.0001 *(5.44)*
*HD*SV*	0.0310 *(1.46)*	0.1453 *(1.14)*	0.4481 *(1.01)**	0.0937 *(1.23)**	0.0425 *(1.16)*
Notes:	• A separate ANOVA was conducted for each spatial variable. • The figures indicate the probability of Type I error for each of the effects • The figures in the parenthesis indicate the F value for the indicated source of variance. • * indicates that the effect is not significant at α = 5 percent • *TP* - Trip Purpose • *HD* - Hour of Day • *SV* - Spatial Variable (Census Region, Census Division etc)				

Procedure for Determining Start Mode Percentages

These findings led to the following recommended procedure for determining the percentages of cold starts:

- Operating modes at trip starts may be derived by time-of-day and trip purpose. When the analysis by trip purpose or time-of-day are unimportant, appropriate composite values for start mode percentages may be derived for all trip purposes for the entire day.
- Whenever possible, the cold and hot start percentages may be derived from the NPTS data for the metropolitan statistical area in question.
- It is possible that for many MSA's there are not enough observations in some of the cells, such as work-related trips at night. When the percentages for some cells are missing and are required for analysis purpose, average trip starts for the urban area size may be derived and substituted for the required trip starts.
- When observations for individual MSAs are inadequate, the start modes derived based on the urban area size (Tables 5 through 10) may be used.

TABLE 5 Operating Modes at Trip Origins (Urban Area Size: 50,000 to 199,999)

Time Period	Percent HBW Trips in		Percent HBO Trips in		Percent NHB Trips in	
	Cold Start	Hot Start	Cold Start	Hot Start	Cold Start	Hot Start
12 AM to 1 AM	93.8 *(15)*	6.3 *(1)*	68.4 *(26)*	31.6 *(12)*	72.7 *(8)*	27.3 *(3)*
1 AM to 2 AM	62.5 *(5)*	37.5 *(3)*	68.8 *(11)*	31.3 *(5)*	50.0 *(2)*	50.0 *(2)*
2 AM to 3 AM	100.0 *(12)*	. *(-)*	66.7 *(8)*	33.3 *(4)*	80.0 *(4)*	20.0 *(1)*
3 AM to 4 AM	94.1 *(16)*	5.9 *(1)*	66.7 *(2)*	33.3 *(1)*	33.3 *(1)*	66.7 *(2)*
4 AM to 5 AM	100.0 *(19)*	. *(-)*	80.0 *(4)*	20.0 *(1)*	. *(-)*	. *(-)*
5 AM to 6 AM	93.4 *(57)*	6.6 *(4)*	85.7 *(6)*	14.3 *(1)*	100.0 *(2)*	. *(-)*
6 AM to 7 AM	90.1 *(182)*	9.9 *(20)*	72.1 *(49)*	27.9 *(19)*	. *(-)*	100.0 *(6)*
7 AM to 8 AM	86.0 *(282)*	14.0 *(46)*	62.9 *(149)*	37.1 *(88)*	18.8 *(9)*	81.3 *(39)*
8 AM to 9 AM	81.4 *(144)*	18.6 *(33)*	60.5 *(173)*	39.5 *(113)*	18.2 *(10)*	81.8 *(45)*
9 AM to 10 AM	83.8 *(67)*	16.3 *(13)*	67.5 *(187)*	32.5 *(90)*	37.2 *(35)*	62.8 *(59)*
10 AM to 11 AM	74.6 *(47)*	25.4 *(16)*	59.8 *(226)*	40.2 *(152)*	23.7 *(31)*	76.3 *(100)*
11 AM to 12 PM	70.3 *(45)*	29.7 *(19)*	54.7 *(222)*	45.3 *(184)*	40.3 *(75)*	59.7 *(111)*
12 PM to 1 PM	63.4 *(59)*	36.6 *(34)*	58.4 *(239)*	41.6 *(170)*	43.0 *(122)*	57.0 *(162)*
1 PM to 2 PM	56.9 *(41)*	43.1 *(31)*	49.4 *(195)*	50.6 *(200)*	43.3 *(97)*	56.7 *(127)*
2 PM to 3 PM	68.0 *(66)*	32.0 *(31)*	50.0 *(211)*	50.0 *(211)*	45.5 *(95)*	54.5 *(114)*
3 PM to 4 PM	77.2 *(156)*	22.8 *(46)*	43.2 *(171)*	56.8 *(225)*	43.0 *(105)*	57.0 *(139)*
4 PM to 5 PM	71.9 *(184)*	28.1 *(72)*	46.1 *(213)*	53.9 *(249)*	49.4 *(118)*	50.6 *(121)*
5 PM to 6 PM	71.2 *(173)*	28.8 *(70)*	43.0 *(203)*	57.0 *(269)*	53.0 *(116)*	47.0 *(103)*
6 PM to 7 PM	69.5 *(89)*	30.5 *(39)*	49.9 *(252)*	50.1 *(253)*	40.2 *(68)*	59.8 *(101)*
7 PM to 8 PM	80.3 *(53)*	19.7 *(13)*	49.9 *(214)*	50.1 *(215)*	41.7 *(53)*	58.3 *(74)*
8 PM to 9 PM	82.1 *(32)*	17.9 *(7)*	51.5 *(176)*	48.5 *(166)*	47.5 *(38)*	52.5 *(42)*
9 PM to 10 PM	77.8 *(42)*	22.2 *(12)*	48.9 *(115)*	51.1 *(120)*	57.4 *(39)*	42.6 *(29)*
10 PM to 11 PM	75.9 *(41)*	24.1 *(13)*	58.6 *(85)*	41.4 *(60)*	51.4 *(18)*	48.6 *(17)*
11 PM to 12 AM	83.7 *(36)*	16.3 *(7)*	64.0 *(55)*	36.0 *(31)*	61.5 *(16)*	38.5 *(10)*
Average Daily	77.8 *(1863)*	22.2 *(531)*	52.9 *(3192)*	47.1 *(2839)*	43.0 *(1062)*	57.0 *(1407)*
Notes:	*Figures in parentheses are number of observations in the cell*					

TABLE 6 Operating Modes at Trip Origins (Urban Area Size: 200,000 to 499,999)

Time Period	Percent HBW Trips		Percent HBO Trips		Percent NHB Trips	
	Cold Starts	Hot Starts	Cold Starts	Hot Starts	Cold Starts	Hot Starts
12 AM to 1 AM	77.8 (7)	22.2 (2)	76.2 (16)	23.8 (5)	76.9 (10)	23.1 (3)
1 AM to 2 AM	100.0 (6)	. (-)	84.6 (11)	15.4 (2)	50.0 (3)	50.0 (3)
2 AM to 3 AM	100.0 (6)	. (-)	57.1 (4)	42.9 (3)	50.0 (3)	50.0 (3)
3 AM to 4 AM	100.0 (1)	. (-)	55.6 (5)	44.4 (4)	50.0 (1)	50.0 (1)
4 AM to 5 AM	94.1 (16)	5.9 (1)	100.0 (7)	. (-)	50.0 (1)	50.0 (1)
5 AM to 6 AM	89.7 (35)	10.3 (4)	85.7 (6)	14.3 (1)	. (-)	. (-)
6 AM to 7 AM	92.7 (115)	7.3 (9)	72.4 (21)	27.6 (8)	25.0 (2)	75.0 (6)
7 AM to 8 AM	86.0 (191)	14.0 (31)	67.5 (110)	32.5 (53)	13.0 (3)	87.0 (20)
8 AM to 9 AM	80.8 (101)	19.2 (24)	57.8 (96)	42.2 (70)	36.4 (12)	63.6 (21)
9 AM to 10 AM	88.9 (40)	11.1 (5)	54.9 (101)	45.1 (83)	28.3 (13)	71.7 (33)
10 AM to 11 AM	76.3 (29)	23.7 (9)	59.6 (115)	40.4 (78)	42.5 (31)	57.5 (42)
11 AM to 12 PM	65.5 (19)	34.5 (10)	58.7 (108)	41.3 (76)	32.8 (44)	67.2 (90)
12 PM to 1 PM	63.4 (26)	36.6 (15)	51.6 (128)	48.4 (120)	46.8 (65)	53.2 (74)
1 PM to 2 PM	59.5 (22)	40.5 (15)	50.7 (115)	49.3 (112)	37.0 (47)	63.0 (80)
2 PM to 3 PM	78.3 (47)	21.7 (13)	50.6 (129)	49.4 (126)	46.9 (61)	53.1 (69)
3 PM to 4 PM	69.1 (67)	30.9 (30)	52.3 (138)	47.7 (126)	46.5 (72)	53.5 (83)
4 PM to 5 PM	70.4 (107)	29.6 (45)	45.1 (124)	54.9 (151)	39.5 (62)	60.5 (95)
5 PM to 6 PM	75.3 (143)	24.7 (47)	41.3 (109)	58.7 (155)	50.7 (74)	49.3 (72)
6 PM to 7 PM	71.0 (71)	29.0 (29)	50.5 (143)	49.5 (140)	35.0 (35)	65.0 (65)
7 PM to 8 PM	82.9 (29)	17.1 (6)	50.8 (124)	49.2 (120)	30.0 (21)	70.0 (49)
8 PM to 9 PM	74.2 (23)	25.8 (8)	57.9 (114)	42.1 (83)	40.0 (22)	60.0 (33)
9 PM to 10 PM	81.3 (26)	18.8 (6)	59.3 (86)	40.7 (59)	43.6 (17)	56.4 (22)
10 PM to 11 PM	75.8 (25)	24.2 (8)	52.8 (47)	47.2 (42)	50.0 (13)	50.0 (13)
11 PM to 12 AM	88.0 (22)	12.0 (3)	60.7 (34)	39.3 (22)	42.1 (8)	57.9 (11)
Average Daily	78.6 (1174)	21.4 (320)	53.6 (1891)	46.4 (1639)	41.1 (620)	58.9 (889)
Note:	*Figures in parentheses are number of observations in the cell*					

TABLE 7 Operating Modes at Trip Origins (Urban Area Size: 500,000 to 999,999)

Time Period	Percent HBW Trips		Percent HBO Trips		Percent NHB Trips	
	Cold Starts	Hot Starts	Cold Starts	Hot Starts	Cold Starts	Hot Starts
12 AM to 1 AM	80.6 (25)	19.4 (6)	67.4 (29)	32.6 (14)	88.2 (15)	11.8 (2)
1 AM to 2 AM	68.4 (13)	31.6 (6)	70.0 (28)	30.0 (12)	62.5 (5)	37.5 (3)
2 AM to 3 AM	100.0 (9)	. (-)	68.2 (15)	31.8 (7)	83.3 (5)	16.7 (1)
3 AM to 4 AM	91.7 (11)	8.3 (1)	57.1 (4)	42.9 (3)	. (-)	100.0 (1)
4 AM to 5 AM	81.0 (17)	19.0 (4)	90.0 (9)	10.0 (1)	60.0 (3)	40.0 (2)
5 AM to 6 AM	91.9 (57)	8.1 (5)	71.4 (10)	28.6 (4)	. (-)	100.0 (1)
6 AM to 7 AM	94.9 (260)	5.1 (14)	81.1 (43)	18.9 (10)	20.0 (1)	80.0 (4)
7 AM to 8 AM	85.6 (393)	14.4 (66)	65.3 (162)	34.7 (86)	26.2 (11)	73.8 (31)
8 AM to 9 AM	80.4 (193)	19.6 (47)	60.3 (188)	39.7 (124)	22.2 (14)	77.8 (49)
9 AM to 10 AM	80.6 (75)	19.4 (18)	60.3 (226)	39.7 (149)	31.3 (30)	68.8 (66)
10 AM to 11 AM	84.0 (42)	16.0 (8)	61.0 (211)	39.0 (135)	37.8 (48)	62.2 (79)
11 AM to 12 PM	64.9 (37)	35.1 (20)	58.8 (221)	41.2 (155)	42.9 (93)	57.1 (124)
12 PM to 1 PM	61.8 (63)	38.2 (39)	56.1 (242)	43.9 (189)	45.3 (124)	54.7 (150)
1 PM to 2 PM	60.3 (47)	39.7 (31)	55.1 (218)	44.9 (178)	44.0 (107)	56.0 (136)
2 PM to 3 PM	77.6 (76)	22.4 (22)	50.3 (240)	49.7 (237)	35.8 (78)	64.2 (140)
3 PM to 4 PM	79.4 (170)	20.6 (44)	46.6 (221)	53.4 (253)	49.4 (119)	50.6 (122)
4 PM to 5 PM	76.1 (258)	23.9 (81)	44.1 (217)	55.9 (275)	51.4 (144)	48.6 (136)
5 PM to 6 PM	75.4 (258)	24.6 (84)	44.8 (222)	55.2 (274)	48.1 (140)	51.9 (151)
6 PM to 7 PM	74.1 (140)	25.9 (49)	50.8 (271)	49.2 (262)	40.2 (70)	59.8 (104)
7 PM to 8 PM	71.8 (61)	28.2 (24)	51.5 (290)	48.5 (273)	37.0 (57)	63.0 (97)
8 PM to 9 PM	78.7 (48)	21.3 (13)	51.9 (202)	48.1 (187)	45.8 (55)	54.2 (65)
9 PM to 10 PM	85.5 (59)	14.5 (10)	57.3 (168)	42.7 (125)	49.3 (35)	50.7 (36)
10 PM to 11 PM	75.9 (41)	24.1 (13)	71.5 (118)	28.5 (47)	66.7 (20)	33.3 (10)
11 PM to 12 AM	88.9 (48)	11.1 (6)	63.1 (65)	36.9 (38)	79.2 (19)	20.8 (5)
Average Daily	79.7 (2401)	20.3 (611)	54.4 (3620)	45.6 (3038)	44.1 (1193)	55.9 (1515)
Notes:	*Figures in parentheses are number of observations in the cell*					

- When none of these analyses is feasible, nationwide averages in Table 2 may be used for the time period in question.

The use of these tables is illustrated by deriving operating modes at trip origins for Charlotte, North Carolina, for a morning peak period (7:00 a.m. to 9:00 a.m.) and a 24-hr period. Because the city has a population of about 500,000 in the urbanized area, it is appropriate to use the figures presented in Table 7.

HBW Trips

–Number. of cold start trips between 7:00 a.m. and 9:00 a.m.: 393 + 193 = 586
–Number. of hot start trips between 7:00 a.m. and 9:00 a.m.: 66 + 47 = 113
–Total number of trips between 7:00 a.m. and 9:00 a.m.: 586 + 113 = 699
–Percentage of cold starts between 7:00 a.m. and 9:00 a.m.: 100(586/699) = 83.8
–Percentage of hot starts between 7:00 a.m. and 9:00 a.m.: 100(113/699) = 16.2
–Percentage of cold starts for the 24-hr period: 79.7
–Percentage of hot starts for the 24-hr period: 20.3

HBO Trips

–No. of cold start trips between 7:00 a.m. and 9:00 a.m.: 162 + 188 = 350
–No. of hot start trips between 7:00 a.m. and 9:00 a.m.: 86 + 124 = 210
–Total number of trips between 7:00 a.m. and 9:00 a.m.: 350 + 210 = 560
–Percentage of cold starts between 7:00 a.m. and 9:00 a.m.: 100(350/560) = 62.5
–Percentage of hot starts between 7:00 a.m. and 9:00 a.m.: 100(210/560) = 37.5
–Percentage of cold starts for the 24-hr period: 54.4
–Percentage of hot starts for the 24-hr period: 45.6

NHB Trips

–No. of cold start trips between 7:00 a.m. and 9:00 a.m.: 11 + 14 = 25
–No. of hot start trips between 7:00 a.m. and 9:00 a.m.: 31 + 49 = 80
–Total number of trips between 7:00 a.m. and 9:00 a.m.: 25 + 80 = 125
–Percentage of cold starts between 7:00 a.m. and 9:00 a.m.: 100(25/125) = 23.8
–Percentage of hot starts between 7:00 a.m. and 9:00 a.m.: 100(80/125) = 76.2
–Percentage of cold starts for the 24-hr period: 44.1
–Percentage of hot starts for the 24-hr period: 54.9

Tables 5 through 10 may be used when the results of an NPTS data analysis for an individual MSA indicate inadequate observations.

TABLE 8 Operating Modes at Trip Origins (Urban Area Size: 1,000,000 or More; no Subway/Rail)

Time Period	Percent HBW Trips		Percent HBO Trips		Percent NHB Trips	
	Cold Starts	Hot Starts	Cold Starts	Hot Starts	Hot Starts	
12 AM to 1 AM	96.8 *(30)*	3.2 *(1)*	68.4 *(39)*	31.6 *(18)*	42.9 *(9)*	57.1 *(12)*
1 AM to 2 AM	88.5 *(23)*	11.5 *(3)*	71.8 *(28)*	28.2 *(11)*	90.0 *(9)*	10.0 *(1)*
2 AM to 3 AM	90.5 *(19)*	9.5 *(2)*	63.0 *(17)*	37.0 *(10)*	71.4 *(5)*	28.6 *(2)*
3 AM to 4 AM	93.3 *(14)*	6.7 *(1)*	83.3 *(5)*	16.7 *(1)*	100.0 *(2)*	. *(-)*
4 AM to 5 AM	90.5 *(38)*	9.5 *(4)*	87.5 *(7)*	12.5 *(1)*	. *(-)*	. *(-)*
5 AM to 6 AM	94.2 *(130)*	5.8 *(8)*	80.0 *(20)*	20.0 *(5)*	100.0 *(1)*	. *(-)*
6 AM to 7 AM	94.6 *(313)*	5.4 *(18)*	67.2 *(80)*	32.8 *(39)*	23.5 *(4)*	76.5 *(13)*
7 AM to 8 AM	85.9 *(519)*	14.1 *(85)*	61.0 *(221)*	39.0 *(141)*	19.5 *(8)*	80.5 *(33)*
8 AM to 9 AM	79.7 *(279)*	20.3 *(71)*	59.6 *(267)*	40.4 *(181)*	13.0 *(12)*	87.0 *(80)*
9 AM to 10 AM	75.6 *(118)*	24.4 *(38)*	62.4 *(279)*	37.6 *(168)*	24.4 *(32)*	75.6 *(99)*
10 AM to 11 AM	75.6 *(65)*	24.4 *(21)*	60.2 *(344)*	39.8 *(227)*	24.5 *(58)*	75.5 *(179)*
11 AM to 12 PM	73.5 *(61)*	26.5 *(22)*	58.4 *(309)*	41.6 *(220)*	39.9 *(129)*	60.1 *(194)*
12 PM to 1 PM	66.2 *(88)*	33.8 *(45)*	55.5 *(287)*	44.5 *(230)*	40.3 *(183)*	59.7 *(271)*
1 PM to 2 PM	70.8 *(80)*	29.2 *(33)*	55.9 *(312)*	44.1 *(246)*	46.2 *(160)*	53.8 *(186)*
2 PM to 3 PM	71.5 *(138)*	28.5 *(55)*	51.3 *(307)*	48.7 *(291)*	42.2 *(143)*	57.8 *(196)*
3 PM to 4 PM	79.6 *(215)*	20.4 *(55)*	45.7 *(341)*	54.3 *(405)*	50.3 *(177)*	49.7 *(175)*
4 PM to 5 PM	79.1 *(317)*	20.9 *(84)*	44.4 *(279)*	55.6 *(349)*	53.0 *(184)*	47.0 *(163)*
5 PM to 6 PM	78.6 *(382)*	21.4 *(104)*	45.2 *(330)*	54.8 *(400)*	50.3 *(199)*	49.7 *(197)*
6 PM to 7 PM	69.6 *(190)*	30.4 *(83)*	51.8 *(392)*	48.2 *(365)*	44.9 *(137)*	55.1 *(168)*
7 PM to 8 PM	73.8 *(107)*	26.2 *(38)*	49.1 *(347)*	50.9 *(360)*	41.7 *(100)*	58.3 *(140)*
8 PM to 9 PM	78.7 *(74)*	21.3 *(20)*	50.5 *(278)*	49.5 *(273)*	45.5 *(70)*	54.5 *(84)*
9 PM to 10 PM	72.4 *(63)*	27.6 *(24)*	50.5 *(220)*	49.5 *(216)*	55.9 *(71)*	44.1 *(56)*
10 PM to 11 PM	78.8 *(63)*	21.3 *(17)*	60.9 *(142)*	39.1 *(91)*	62.5 *(35)*	37.5 *(21)*
11 PM to 12 AM	88.5 *(54)*	11.5 *(7)*	64.5 *(100)*	35.5 *(55)*	63.0 *(34)*	37.0 *(20)*
Average Daily	80.1 *(3380)*	19.9 *(839)*	53.5 *(4951)*	46.5 *(4303)*	43.5 *(1762)*	56.5 *(2290)*
Notes:	*Figures in parenthesesare number of observations in the cell*					

TABLE 9 Operating Modes at Trip Origins (Urban Area Size: 1,000,000 or More; with Subway/Rail)

Time Period	Percent HBW Trips		Percent HBO Trips		Percent NHB Trips	
	Cold Starts	Hot Starts	Cold Starts	Hot Starts	Cold Starts	Hot Starts
12 AM to 1 AM	93.5 *(29)*	6.5 *(2)*	75.5 *(71)*	24.5 *(23)*	82.4 *(14)*	17.6 *(3)*
1 AM to 2 AM	80.0 *(12)*	20.0 *(3)*	77.3 *(34)*	22.7 *(10)*	75.0 *(12)*	25.0 *(4)*
2 AM to 3 AM	100.0 *(11)*	. *(-)*	80.8 *(21)*	19.2 *(5)*	87.5 *(14)*	12.5 *(2)*
3 AM to 4 AM	78.9 *(15)*	21.1 *(4)*	73.9 *(17)*	26.1 *(6)*	83.3 *(5)*	16.7 *(1)*
4 AM to 5 AM	97.4 *(38)*	2.6 *(1)*	100.0 *(4)*	. *(-)*	100.0 *(2)*	. . *(-)*
5 AM to 6 AM	93.3 *(112)*	6.7 *(8)*	90.5 *(19)*	9.5 *(2)*	50.0 *(1)*	50.0 *(1)*
6 AM to 7 AM	92.8 *(336)*	7.2 *(26)*	75.9 *(63)*	24.1 *(20)*	50.0 *(2)*	50.0 *(2)*
7 AM to 8 AM	89.5 *(619)*	10.5 *(73)*	73.0 *(230)*	27.0 *(85)*	30.3 *(10)*	69.7 *(23)*
8 AM to 9 AM	82.5 *(428)*	17.5 *(91)*	56.6 *(304)*	43.4 *(233)*	21.8 *(19)*	78.2 *(68)*
9 AM to 10 AM	80.6 *(175)*	19.4 *(42)*	59.0 *(351)*	41.0 *(244)*	24.8 *(37)*	75.2 *(112)*
10 AM to 11 AM	76.9 *(83)*	23.1 *(25)*	64.4 *(407)*	35.6 *(225)*	23.6 *(56)*	76.4 *(181)*
11 AM to 12 PM	64.4 *(58)*	35.6 *(32)*	57.9 *(394)*	42.1 *(287)*	40.3 *(129)*	59.7 *(191)*
12 PM to 1 PM	56.6 *(69)*	43.4 *(53)*	58.2 *(452)*	41.8 *(324)*	43.7 *(226)*	56.3 *(291)*
1 PM to 2 PM	60.2 *(77)*	39.8 *(51)*	54.3 *(365)*	45.7 *(307)*	42.7 *(163)*	57.3 *(219)*
2 PM to 3 PM	75.3 *(116)*	24.7 *(38)*	54.4 *(403)*	45.6 *(338)*	45.7 *(179)*	54.3 *(213)*
3 PM to 4 PM	82.6 *(281)*	17.4 *(59)*	45.7 *(405)*	54.3 *(481)*	52.3 *(225)*	47.7 *(205)*
4 PM to 5 PM	79.5 *(373)*	20.5 *(96)*	46.3 *(358)*	53.7 *(416)*	54.9 *(226)*	45.1 *(186)*
5 PM to 6 PM	76.6 *(452)*	23.4 *(138)*	43.2 *(376)*	56.8 *(494)*	60.5 *(228)*	39.5 *(149)*
6 PM to 7 PM	78.6 *(264)*	21.4 *(72)*	50.9 *(442)*	49.1 *(426)*	48.6 *(139)*	51.4 *(147)*
7 PM to 8 PM	71.9 *(110)*	28.1 *(43)*	54.6 *(429)*	45.4 *(357)*	46.5 *(113)*	53.5 *(130)*
8 PM to 9 PM	85.7 *(96)*	14.3 *(16)*	50.8 *(330)*	49.2 *(320)*	41.2 *(73)*	58.8 *(104)*
9 PM to 10 PM	81.9 *(77)*	18.1 *(17)*	59.8 *(319)*	40.2 *(214)*	53.4 *(70)*	46.6 *(61)*
10 PM to 11 PM	89.7 *(70)*	10.3 *(8)*	61.3 *(195)*	38.7 *(123)*	68.8 *(44)*	31.3 *(20)*
11 PM to 12 AM	86.9 *(73)*	13.1 *(11)*	66.0 *(138)*	34.0 *(71)*	63.2 *(36)*	36.8 *(21)*
Average Daily	81.4 *(3974)*	18.6 *(909)*	55.0 *(6127)*	45.0 *(5011)*	46.6 *(2023)*	553.6 *(2334)*
Notes:	*Figures in parentheses are number of observations in the cell*					

When trip purposes are unknown or when a resolution by trip purpose is unnecessary, the cell frequencies may be aggregated across all trip purposes by each start mode within the analysis period. If the analysis period for a given urban area size contains no observations in a cell corresponding to a particular trip purpose, the start modes for this cell can be obtained from the nationwide averages listed in Table 2.

CONCLUSIONS

A methodology for deriving start mode fractions at trip origins is presented. This methodology may be applied to derive start modes for individual MSAs where personal travel data that can identify trip chains are available. These start modes may be used for a variety of mobile source emission modeling problems. Potential uses for these fractions include the following:

- As direct inputs to the mobile source emission models based on actual starts, such as the EMFAC model;
- As determinants of the number of vehicle trips in cold and hot starts in a trip exchange matrix used for traffic assignment and simulation studies; and
- As determinants of the VMT weighted transient and stabilized operating mode fractions used as inputs to emission rate estimation models, such as the MOBILE model.

The analysis methods used in this research to derive start mode fractions may be used for personal travel data sources other than the NPTS data source. Where available, local data are preferred to NPTS data. When such data are unavailable or individual analysis is infeasible, appropriate figures presented in several tables of this paper may be used.

The most important element lacking in the results presented in this paper is the effect of commercial trips. Intuitively, most commercial trips, such as truck trips and pickup and delivery trips, will be in the hot start mode. Therefore, the results presented may be biased toward a higher number of cold starts. It is advised that, based on sample surveys or any other available data source, appropriate adjustment factors showed be derived to account for commercial travel. The home-based trips, however, are expected to represent only personal travel and hence do not require any adjustment.

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TABLE 10 Operating Modes at Trip Origins (not in Urbanized Area)

Time Period	Percent HBW Trips		Percent HBO Trips		Percent NHB Trips	
	Cold Starts	Hot Starts	Cold Starts	Hot Starts	Cold Starts	Hot Starts
12 AM to 1 AM	83.1 *(64)*	16.9 *(13)*	67.7 *(63)*	32.3 *(30)*	75.7 *(28)*	24.3 *(9)*
1 AM to 2 AM	100.0 *(29)*	. *(-)*	60.4 *(29)*	39.6 *(19)*	83.3 *(10)*	16.7 *(2)*
2 AM to 3 AM	85.2 *(23)*	14.8 *(4)*	83.3 *(20)*	16.7 *(4)*	77.8 *(7)*	22.2 *(2)*
3 AM to 4 AM	94.7 *(36)*	5.3 *(2)*	52.6 *(10)*	47.4 *(9)*	100.0 *(8)*	. *(-)*
4 AM to 5 AM	94.1 *(80)*	5.9 *(5)*	76.9 *(20)*	23.1 *(6)*	100.0 *(6)*	. *(-)*
5 AM to 6 AM	94.3 *(312)*	5.7 *(19)*	77.3 *(58)*	22.7 *(17)*	46.2 *(6)*	53.8 *(7)*
6 AM to 7 AM	90.0 *(843)*	10.0 *(94)*	73.3 *(159)*	26.7 *(58)*	28.2 *(11)*	71.8 *(28)*
7 AM to 8 AM	85.3 *(1115)*	14.7 *(192)*	60.8 *(550)*	39.2 *(354)*	21.6 *(29)*	78.4 *(105)*
8 AM to 9 AM	78.8 *(521)*	21.2 *(140)*	59.3 *(611)*	40.7 *(419)*	23.2 *(55)*	76.8 *(182)*
9 AM to 10 AM	74.3 *(197)*	25.7 *(68)*	60.5 *(743)*	39.5 *(485)*	25.7 *(83)*	74.3 *(240)*
10 AM to 11 AM	65.0 *(115)*	35.0 *(62)*	58.3 *(772)*	41.7 *(552)*	32.9 *(171)*	67.1 *(349)*
11 AM to 12 PM	66.1 *(119)*	33.9 *(61)*	57.4 *(697)*	42.6 *(518)*	38.9 *(296)*	61.1 *(464)*
12 PM to 1 PM	54.1 *(185)*	45.9 *(157)*	49.7 *(761)*	50.3 *(771)*	44.6 *(445)*	55.4 *(552)*
1 PM to 2 PM	63.8 *(196)*	36.2 *(111)*	53.4 *(683)*	46.6 *(597)*	35.4 *(279)*	64.6 *(509)*
2 PM to 3 PM	73.7 *(263)*	26.3 *(94)*	53.9 *(716)*	46.1 *(613)*	39.7 *(296)*	60.3 *(449)*
3 PM to 4 PM	75.5 *(548)*	24.5 *(178)*	46.7 *(797)*	53.3 *(911)*	46.4 *(447)*	53.6 *(517)*
4 PM to 5 PM	73.2 *(676)*	26.8 *(247)*	45.0 *(742)*	55.0 *(906)*	48.0 *(446)*	52.0 *(484)*
5 PM to 6 PM	73.9 *(785)*	26.1 *(277)*	44.6 *(817)*	55.4 *(1013)*	44.7 *(390)*	55.3 *(482)*
6 PM to 7 PM	72.9 *(382)*	27.1 *(142)*	46.1 *(857)*	53.9 *(1001)*	35.2 *(200)*	64.8 *(368)*
7 PM to 8 PM	73.1 *(204)*	26.9 *(75)*	50.1 *(778)*	49.9 *(776)*	38.7 *(188)*	61.3 *(298)*
8 PM to 9 PM	75.1 *(145)*	24.9 *(48)*	48.0 *(602)*	52.0 *(652)*	39.1 *(118)*	60.9 *(184)*
9 PM to 10 PM	79.0 *(147)*	21.0 *(39)*	54.2 *(480)*	45.8 *(405)*	50.4 *(113)*	49.6 *(111)*
10 PM to 11 PM	84.5 *(158)*	15.5 *(29)*	57.8 *(305)*	42.2 *(223)*	65.1 *(69)*	34.9 *(37)*
11 PM to 12 AM	80.2 *(105)*	19.8 *(26)*	59.2 *(155)*	40.8 *(107)*	72.8 *(59)*	27.2 *(22)*
Average Daily	77.7 *(7248)*	22.3 *(2083)*	52.2 *(11425)*	47.8 *(10446)*	41.0 *(3760)*	59.0 *(5401)*
Notes:	*Figures in parentheses are number of observations in each cell*					

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Alternative Operating Mode Fractions to Federal Test Procedure Mode Mix for Mobile Source Emissions Modeling

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An emission inventory is a key component of an air quality control program. The emission rates of carbon monoxide and hydrocarbons are sensitive to the variations in the inputs related to cold transient, hot transient, and hot stabilized operating mode fractions. Therefore it is important to provide realistic values for these parameters while modeling emissions using air quality models such as the MOBILE model. The objective of the research presented is to derive aggregate operating mode fractions as alternatives to the federal test procedure (FTP) mode mix on the basis of a detailed analysis of personal travel data. The data source used for the analysis of personal travel information is the 1990 Nationwide Personal Travel Survey. Issues related to data quality, screening, and aggregation are discussed. After determining of the percentages of start mode as cold starts and hot starts, the percentages of vehicle miles of travel (VMT) operating in different modes are derived by trip purpose and for different time periods. The VMT weighted operating mode fractions derived from these start mode fractions indicated a significant difference from the FTP operating mode mix. It is observed that the FTP operating mode mix generally underestimates the portion of travel in cold transient mode. Also, it is observed that the percentage of VMT in cold transient mode decreases with the increase in the size of the urban area.

Corridor-level and area-wide air quality studies require accurate information on the emissions of several pollutants with high spatial and temporal resolution so that the causes of air pollution can be understood and effective plans developed for future air quality improvement (*1*). Emission inventories for mobile sources are prepared mainly using computerized air quality models, such as MOBILE and, in some cases, EMFAC, which is mostly used in California. Embedded in these air quality models are several look-up tables, mathematical relationships, and analytical techniques that were developed through laboratory and empirical studies. The computer models estimate emission rates by using these embedded techniques and relationships with a given set of variables and parameters as inputs. Included among these inputs is information on operating modes of engines in the traffic stream.

The engine operating mode of a vehicle, which primarily refers to the operating temperature of the combustion chamber and catalytic converter if it exists, has a significant effect on emissions. Operating mode fractions of vehicles in transient and stabilized modes are among the key inputs to modeling vehicular emissions. The emission rates of carbon monoxide (CO) and hydrocarbons (HC) are sensitive to the variations in the inputs related to operating mode fractions. CO and HC emissions are the highest in the cold transient mode, when fuel mixtures are rich and catalytic converters are too cold to function effectively. Depending on the ambient temperature, CO and HC emissions can be twice as high during the cold start mode as during hot stable operation.

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Therefore it is important to provide realistic values for the parameters related to operating mode fractions for emissions modeling using air quality models such as the MOBILE model. However, practitioners have traditionally been using an operating mode mix based on the federal test procedure (FTP), which is used to test emissions for new vehicles. The FTP mode mix was derived in the early 1970s based on a test driving cycle that may not be a true representation of the general driving patterns of the population. The purpose of this paper is to demonstrate an alternative approach to deriving operating mode fractions based on the analysis of one of the most widely used travel survey data bases, the Nationwide Personal Travel Survey (NPTS) data base.

The state of the practice in emission modeling with respect to operating mode fractions inputs is discussed in the next section. A brief discussion on the analysis of the NPTS data base is presented in the following section, which is followed by sections on trip length analysis and start mode analysis. The section on vehicle miles of travel (VMT) analysis explains the procedure used to derive alternative operating mode fractions to FTP mix and also compares the numbers derived from the NPTS data with the FTP values.

STATE OF THE PRACTICE

The Environmental Protection Agency (EPA) historically has defined a cold start to be any start that occurs 4 hrs or later following the end of the preceding trip for noncatalyst-equipped vehicles and 1 hr or later following the end of the preceding trip for catalyst-equipped vehicles. Hot starts are those starts that occur less than 4 hr after the end of the preceding trip for noncatalyst-equipped vehicles and less than 1 hr after the end of the preceding trip for catalyst-equipped vehicles (*2*). The time between the end of a trip and the engine restart for the following trip is called the cold-soak, or simply the soak, period.

Before attaining the hot stabilized operating mode, a vehicle will operate in a cold transient mode or hot transient mode, depending on the actual starting mode. The rate of emissions for stabilized mode is both uniform and significantly lower than the rate for any transient mode, especially the cold transient mode. The FTP is based on the assumption that in about 505 sec since the start of the engine, a vehicle's mode changes from a transient mode to hot stabilized mode.

The FTP involves determining the emissions of carbon monoxide, hydrocarbons, oxides of nitrogen, and carbon dioxide produced by a test vehicle during its operation through a standard driving schedule. Testing is performed on stationary vehicles using a dynamometer to simulate actual highway driving. The driving schedule, referred to as the EPA Urban Dynamometer Driving Schedule (UDDS), consists of three phases: cold transient, hot stabilized, and hot transient. On the basis of travel characteristics and conditions used for the FTP drive cycle, EPA derived operating mode fractions in the three phases of the UDDS.

In the absence of reliable field data or empirical studies of operating modes of vehicles, traditionally emission inventory studies have adopted an operating mode fraction mix specified in the MOBILE 5A user's manual, which were derived from the FTP drive cycle (*2*). The mode mix indicates that 20.6 percent and 27.3 of the vehicles in the fleet represent cold and hot transient modes of operation, respectively, and the remaining 52.1 percent of the vehicles are in hot stabilized modes of operation.

These operating mode fractions are being widely used in several corridor-level and area-wide emission studies at different levels of precision. The user manual states that EPA will accept for state implementation planning related modeling, the use of FTP operating mode values, except for small-scale scenarios where their use would clearly be inappropriate.

The research community and the practitioners have serious reservations in adopting the FTP operating mode mix for all cases. Ideally, the operating mode fraction values should be developed for varying situations. For example, these may be stratified by functional class of highways (freeways/expressways, principal arterials, etc.) and the geographic locations being modeled. (CBD, fringe, suburban, etc.). This concern is expressed in the following statement in the user guide to MOBILE 5A model (*2*).

> In the absence of supporting data for values other than those listed above (FTP mode mix), EPA believes that the values reflecting the conditions are appropriate in many cases. This is particularly true when the emission factors being modeled are intended to represent a broad geographic area (Metropolitan Statistical Area, entire state) and/or a wide time period (days, months).

Adding to this limitation, McIlvaine (*3*) states

> The FTP operating mode mix is only representative of conditions similar to those under which it was developed. These conditions include an urban setting (like Los Angeles), an average trip length of approximately 7.5 miles, and an average of 4.7 trips per day per vehicle. While the FTP was developed from a morning urban commute over a range of facility types, the FTP operating mode mix is not necessarily representative of the operating mode mix that occurs during a given hour, on a specific roadway facility type, and particularly not in non-urban areas.

One way to resolve the limitations associated with FTP's numbers is to use field observations and measurements. An accurate determination of the operating mode of a vehicle engine requires measurements of the engine temperature, and such measurements are difficult to implement on vehicles on roads under normal traffic conditions.

A study was done in New Jersey to determine the percentage of hot and cold transient trips for New Jersey roads (*4*). With the permission of the drivers, engine oil and coolant temperatures were measured, and engine run time estimates were obtained from the driver. The collected data were analyzed to determine the percentages of hot start, cold start, and hot stabilized modes of operation in the traffic.

There is also an indirect approach of estimating the operating modes of vehicles traveling on a roadway. This approach uses the travel time from a trip origin as an indicator of the operating mode. The travel time from trip origin can be estimated either by interviewing drivers (as in the case of New Jersey study) or by modeling. The interview technique is difficult to implement. Therefore, the modeling approach is more feasible.

Some studies have adopted the indirect modeling approach of estimating the operating mode of vehicles traveling on different road segments. Ellis et al. (*5*) attempted to develop procedures for estimating combined cold and hot transient operating fractions for light-duty vehicles from transportation planning data. Origin-destination survey data were used to determine area-wide operating mode fractions by trip purpose and by time-of-day.

An EPA study (*6*) focused on determining the percentages of vehicles operating in the cold transient mode for different functional classes of roads in two selected cities: Pittsburgh, Pennsylvania, and Providence, Rhode Island. This study estimated the percentage of VMT in the cold transient mode for the morning commuting hours, mid-day period, evening commuting hours, and early morning off-peak period for each of the 60 traffic streams analyzed. One important finding of the study indicates that the actual percentages of vehicles operating in the cold start mode are different from the percentages assumed in the FTP. The studies by Ellis et al. and EPA were conducted in the late 1970s. These studies were mostly localized and did not cover all classes of roads.

Another important issue related to the modeling approach for determining operating modes is the proportion of vehicles starting in cold and hot modes at trip origins. Several studies have assumed and recommended start modes for different trip purposes based on judgment. For example, 90 percent of home-based work (HBW) trips in the south Jersey area were assumed to have started as cold starts (*7*). The justification for this was based on the assumption that before the beginning of the trip, the engine would have been shut off for several hours, at work and at home.

When modeling emissions for different times of day, it is important to know these starting modes at the beginning of trips by time-of-day. Very few studies attempted to derive start modes at trip origins that would then be used to derive operating mode fractions on roadway facilities. Ellis et al. (*5*) and Venigalla et al., in another paper in this Record, have performed this analysis. Several limitations of the study by Ellis et al. were addressed in the study by Venigalla.

The network assignment techniques used by Venigalla (*7*) and COMSIS (*8*) required as input a detailed transportation network, trip matrices by purpose, and other transportation planning data appropriate to traffic assignment. When such planning data are unavailable or when the available resources are very limited, which renders the assignment analysis infeasible, an alternative to the FTP mode mix is desirable. The objective of the research presented in this paper is to derive aggregate operating mode fractions as an alternative to the FTP mode mix based on a detailed analysis of personal travel data. The data source used to analyze personal travel information is the Nationwide Personal Travel Survey (NPTS). The scope of the research presented in this paper, however, is limited to deriving aggregate operating mode fractions without specific detail on facility class and location.

ANALYSIS OF NPTS DATA

To compute the operating mode mix, it is important to have information on the travel characteristics, such as the travel time and trip length as well as the start modes at the trip origins. For deriving the start modes at trip origins, data pertaining to cold soak period and vehicle type are needed. Origin-destination data collected for comprehensive urban transportation planning purposes usually contain this information. However, these data sources are localized, tend to be outdated, and are some times inadequate for determining start modes.

A periodic survey on personal travel, NPTS, which is available for public use through the U.S. Department of Transportation, was examined for this purpose. The NPTS compiles national data on the nature and characteristics of personal travel. It addresses a broad range of travel in the United States, providing data on all personal trips for all purposes and by all modes of transportation (*9*).

For the 1990 NPTS, information on all trips made during a designated 24-hr period, called travel-day, was collected from a national household sample. Additional details were collected for trips of that were 120 km (75 mi) or longer and taken during the preceding 14-day period, or travel period, which included the 24-hr travel day. The information collected for each trip includes the purpose, mode, trip length, day-of-week, time-of-day, vehicle used, vehicle occupancy, and other information. For detailed information on this data source and other details, such as the sampling methods, data collection, and screening, the reader may consult the user's guide to the NPTS data base.

Available information in the 1990 NPTS data base pertinent to this study includes data on all trips that were made during a designated 24-hr period, including the time the trip began, the length of the trip, the mode of transportation, the purpose of the trip, and the vehicle used (if the travel was in a household vehicle). The data base contains information on 41,178 vehicles that were used for 149,546 trips taken during a 24-hr period.

The analysis of NPTS data for determining the operating modes at trip origins involved the following distinctive steps:

- Identify relevant variables in the data base,
- Identify vehicles with catalytic converters,
- Determine the cold-soak period for each trip,
- Screen data,
- Associate each trip end (origin and destination point) with a start mode (cold start or hot start) and an operating mode (transient or stabilized), and
- Analyze trip duration, operating modes at trip ends, percentage of VMT in different operating modes.

The four most important variables used to identify each chain of trips in the data base are the unique household identification number, the identification (within the same household) of the vehicle with which the trips were made, start time, and length of each trip. Variables such as the census region, the census division, the metropolitan statistical area (MSA), the size of the urban area, and the trip purpose were also used as stratification variables for this study.

Even though the NPTS data contain several items of information about the vehicles used for each of the travel-day trips, it is not obvious whether a vehicle is equipped with a catalytic converter. Because the emission standards from 1975 require using catalytic converters, all 1975 and later model vehicles were assumed to be equipped with catalytic converters (*7*). Because of a lack of sufficient information, it was assumed that about 25 percent of the vehicles manufactured and sold before 1975 were equipped with the converters. Vehicles with model year before 1975 were randomly identified as catalytic-converter equipped or noncatalytic-converter equipped in the proportion 25:75, respectively. Because the total number of vehicles with model years before 1975 was less than 8 percent of the total vehicles (41,178) in the data base, the possibility of errors occurring in the overall analysis as a result of this assumption is minimal. This procedure identifies 2191 (5.3 percent) vehicles in the data base as noncatalytic-converter equipped and 38,987 (94.7 percent) vehicles as catalytic-converter equipped.

The NPTS travel-day data file contains information on the characteristics of all the trips made by the respondents during the travel day (from 4:00 a.m. on the travel day to 3:59 a.m. the following day). Included among the available data items in this file are the time at which a trip started and the length of that trip (in minutes). This information was recorded for the chain of all trips made using each vehicle in the household.

By sorting and arranging the data base in a particular order, it was possible to identify the chain of trips made by each household vehicle. The time gap between the end time and the begin time of two successive trips, coupled with the characteristics of the vehicle used for that trip (i.e., catalytic-converter equipped or not), was used to determine the cold-soak period before each trip in a chain started. Following the determination of the cold soak period for each trip, each trip start is identified as a cold start or hot start according to the EPA's definitions.

Several consistency checks were performed to screen the data base so that only the error-free chains of trips would be used in the analysis. Chains of trips with information gaps and questionable data items were discarded. At the final stage of screening, there were 105,903 total trips in the data base that were eligible for final analysis. After the screening, the geographical distribution of the trips was found to be almost identical to that of the original data base.

Frequencies were obtained, by trip purpose and hour of day, for cold and hot start modes at the beginning of the trips. The analyses were conducted for all the trips in the data base, which means that the results should represent nationwide average values. The results of this analysis are presented in more detail in the work by Venigalla et al. in another paper in this Record. The results of this analysis indicated that the percentage of trips starting in cold mode decreases as the day progresses, a trend that would be expected.

An analysis of variance for the cold start percentages indicated that the time of day and the trip purpose significantly influence the variation in the percentage of cold starts. Among the geographic classification variables, individual MSAs exhibit different cold and hot start percentages, followed by the size of the urban area as the next best classification variable. These start modes based on NPTS data were used to derive the aggregate operating mode fractions presented in the next section.

TRIP LENGTH ANALYSIS

Regardless of the start mode at trip origin, the duration of an average trip indicates the operating modes on a road network. For example, when the average trip length associated with cold starts is less than 505 sec, the indication will be that most of these cold start trips end as cold transient trips. After the start mode is determined for each trip, the operating mode in which the trip ended was determined from the trip length analysis. Adopting the FTP transient mode duration of 8 min (closest approximation to 505 sec because the data indicate travel time only in increments of 1 min), the operating mode at the end of each trip was determined. As an example of this analysis, if the trip started in cold mode and ended before

8 min, the end of the trip was considered to be in a cold transient mode. The NPTS data were analyzed for trip duration (minutes) and length (miles).

When data on all trips are included, it was observed that the average trip duration and length were quite high [approximately 17 min and 16 km (10 mi)]. A few long trips [some as long as 1760 km (1,100 mi)] were found to be introducing a bias toward higher than usual average travel time and trip length estimates. To eliminate this bias, only the 48-km (30-mi) portion of these long trips was considered urban travel. In other words, the maximum length of the trips for the analysis was 48 km (30 mi).

Figures 1 and 2 illustrate the results of the trip length analysis. Travel time analysis (Figure 1) indicates a trend that would characterize the responses on travel time as approximations to the nearest 5-min intervals. Therefore, the results of any travel time analysis based on this data base should be used with caution, and adjustments are needed to counter the rounding of errors. The respondents do not appear to have rounded the trip length to the nearest 8-km (5-mi) interval as they did in the case of travel time responses (Figure 2). It can be seen that about 34 percent of all the trips have a duration of 8 to 9 min. This means that at least 34 percent of the trips would end in a cold or hot transient operating mode, depending on the operating mode at trip origin. It can be seen that an average trip is approximately 10.56 km (6.6 mi) long and is expected to last for about 13.5 min. The median (50th percentile) travel time and trip length are about 10 min and 7.2 km (4.5 mi), respectively.

ANALYSIS FOR VEHICLE MILES OF TRAVEL

As mentioned earlier, a key input to modeling the mobile source emissions using the MOBILE model is the percentage of VMT accumulated in each operating mode for each type of emission control equipment (or simply operating mode fractions). Whether a cold start or a hot start, each trip would operate in a transient mode for some length of time (defined as 505 sec per FTP) before operating in a hot stable mode. The distance traveled during the transient modes of operation can be assumed to be a portion of the total distance traveled, prorated for 8 min. For the remaining distance, the trip will be in a hot stabilized mode.

VMT Distribution in Different Modes

To study the distribution of the percentage of VMT operating in different modes, a VMT analysis was performed for different times of day and for different trip purposes. The trip-purpose categories used were HBW, trips, home-based other (HBO), trips and non–home-based (NHB) trips. Data pertaining to highway functional class used for NPTS trips are limited in the NPTS data base; hence, no attempts were made to classify the VMT by highway functional class or highway location. The percentages of VMT operating in each operating mode, stratified by trip purpose and hour of day, are presented in Table 1. (These numbers were derived for catalyst-equipped vehicles only.) The percentages of VMT numbers in cold transient, hot transient, and hot stabilized modes of operation in Table 1 are plotted in Figures 3 and 4, respectively.

The percentage of VMT operating in transient mode (Table 1 and Figure 3) indicates the following:

- Percentage of VMT operating in cold transient mode is higher during late hours in the night and early hours of the day,
- Peak for this operating mode occurs between 6:00 a.m. and 9:00 a.m.,
- NHB trips operate with low proportions of cold transient VMT between 6:00 a.m. and 9:00 a.m. The share of VMT in a cold transient mode due to NHB trips increases as the day progresses,
- In general, HBW trips have higher VMT operating in cold transient mode than the HBO trips.
- Percentage of VMT in hot transient mode is, in general, lower when compared with VMT operating in cold transient or hot stabilized modes,
- With the exception of NHB trips, hot transient mode VMT is lower in the morning hours and steadily increases as the day progresses,
- NHB trips exhibit higher percentages of hot transient VMT than home-based trips.

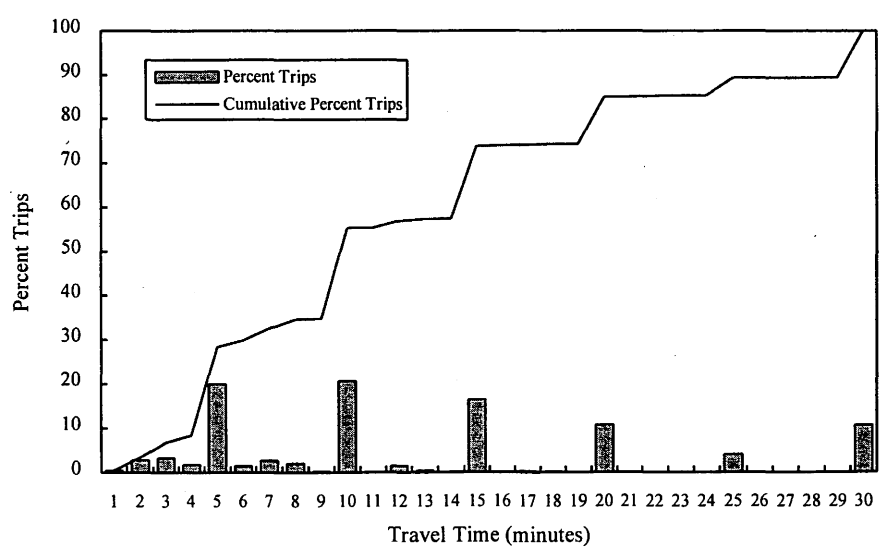

FIGURE 1 Distribution of trip duration for all trips.

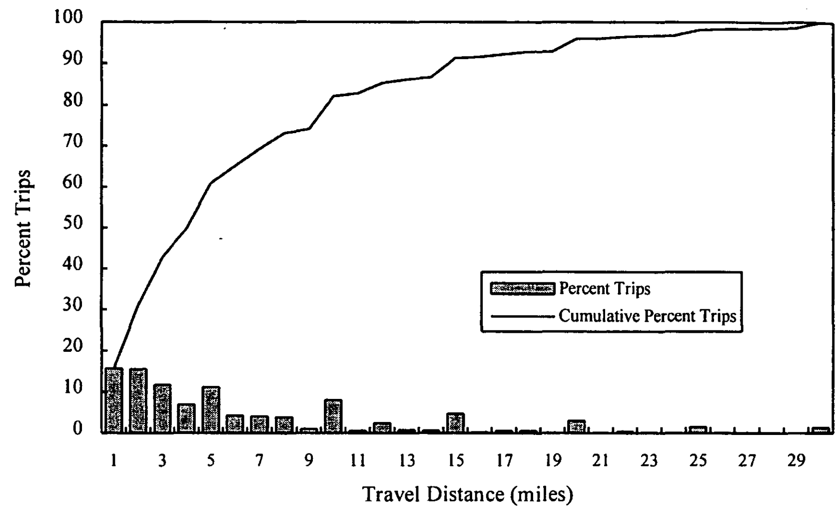

FIGURE 2 Trip length distribution of all trips (1 mi–1.61 km).

TABLE 1 Percentage of VMT Operating in Different Modes

Time Period	Home Based Work Trips			Home Based Other Trips		
	Cold Transient	Hot Transient	Hot Stabilized	Cold Transient	Hot Transient	Hot Stabilized
12 AM to 1 AM	41.1	3.7	55.3	36.5	14.3	49.2
1 AM to 2 AM	36.5	6.9	56.5	37.3	10.7	52.1
2 AM to 3 AM	46.6	1.0	52.3	36.6	13.3	50.1
3 AM to 4 AM	38.7	4.5	56.9	32.7	13.8	53.5
4 AM to 5 AM	42.0	3.7	54.3	49.1	5.2	45.7
5 AM to 6 AM	36.6	2.5	61.0	35.3	9.8	54.9
6 AM to 7 AM	36.2	2.5	61.3	38.0	11.4	50.6
7 AM to 8 AM	35.7	4.9	59.3	37.3	17.2	45.5
8 AM to 9 AM	36.0	7.6	56.4	35.9	21.3	42.8
9 AM to 10 AM	39.1	8.8	52.1	36.3	20.1	43.6
10 AM to 11 AM	37.4	9.2	53.4	35.7	20.1	44.2
11 AM to 12 PM	36.1	13.7	50.2	33.7	20.7	45.7
12 PM to 1 PM	33.4	16.5	50.1	31.4	21.0	47.5
1 PM to 2 PM	32.8	17.2	50.0	29.7	23.6	46.7
2 PM to 3 PM	35.2	10.8	54.0	29.5	24.1	46.4
3 PM to 4 PM	34.3	6.9	58.8	26.1	25.7	48.2
4 PM to 5 PM	34.1	8.0	57.9	25.0	27.3	47.6
5 PM to 6 PM	32.6	8.4	59.0	24.7	27.1	48.2
6 PM to 7 PM	33.7	9.6	56.7	29.0	24.1	46.9
7 PM to 8 PM	35.4	8.9	55.7	29.0	24.6	46.4
8 PM to 9 PM	37.8	6.6	55.6	28.6	23.6	47.8
9 PM to 10 PM	38.2	6.5	55.2	30.4	20.2	49.4
10 PM to 11 PM	37.5	6.8	55.7	30.4	15.7	53.9
11 PM to 12 AM	39.2	6.2	54.7	31.5	16.5	52.0
24 Hour Period	35.4	7.4	57.3	30.0	22.8	47.2

(continued on next page)

TABLE 1 *(continued)*

Time Period	Non Home Based Trips			All Purpose Trips		
	Cold Transient	Hot Transient	Hot Stabilized	Cold Transient	Hot Transient	Hot Stabilized
12 AM to 1 AM	37.0	11.2	51.8	38.0	10.4	51.6
1 AM to 2 AM	35.3	9.4	55.3	36.7	9.4	53.9
2 AM to 3 AM	37.4	9.1	53.5	40.5	8.0	51.5
3 AM to 4 AM	39.5	11.7	48.8	37.0	8.1	54.8
4 AM to 5 AM	44.3	16.2	39.5	43.0	4.3	52.7
5 AM to 6 AM	20.4	17.2	62.4	36.3	3.2	60.4
6 AM to 7 AM	10.0	46.8	43.1	36.0	4.3	59.7
7 AM to 8 AM	15.2	36.9	47.9	35.3	8.7	55.9
8 AM to 9 AM	11.0	45.7	43.3	34.1	15.4	50.5
9 AM to 10 AM	17.0	38.8	44.1	34.1	20.0	45.9
10 AM to 11 AM	17.9	38.2	43.9	32.0	22.4	45.5
11 AM to 12 PM	24.1	31.0	44.9	31.1	22.9	46.0
12 PM to 1 PM	25.9	29.9	44.2	29.9	23.4	46.8
1 PM to 2 PM	26.8	29.6	43.6	29.2	24.6	46.2
2 PM to 3 PM	25.3	26.1	48.5	29.3	22.3	48.4
3 PM to 4 PM	26.6	22.7	50.6	28.5	19.6	51.8
4 PM to 5 PM	27.1	21.6	51.3	28.8	19.0	52.2
5 PM to 6 PM	27.8	20.3	51.9	28.4	18.5	53.1
6 PM to 7 PM	23.7	27.6	48.8	29.2	20.9	49.9
7 PM to 8 PM	24.0	29.7	46.3	29.0	23.0	47.9
8 PM to 9 PM	26.3	28.0	45.7	29.5	22.0	48.5
9 PM to 10 PM	29.7	24.6	45.7	31.6	18.6	49.8
10 PM to 11 PM	34.7	17.8	47.5	32.7	13.8	53.5
11 PM to 12 AM	32.7	16.8	50.5	33.8	13.6	52.6
24 Hour Period	25.2	27.2	47.6	31.2	18.7	50.1

The percentage of VMT operating in hot stabilized mode (Table 1 and Figure 4) indicate the following:

- In general, VMT operating in hot stabilized mode are higher than that in the transient modes.
- During morning hours, the share of hot stabilized VMT in the total VMT is higher and decreases as the day progresses.
- Variation in the share of hot stabilized VMT is similar for home-based and NHB trips.

FTP Driving Cycle Versus NPTS Travel Patterns

The results of the VMT analysis for operating mode fractions are summarized in Table 2. It can be seen that average VMT per vehicle operating in transient modes (cold or hot) varies narrowly between 4.8 and 5.6 km (3 and 3.5 mi). The average VMT operating in hot stabilized mode is much higher for catalyst- and noncatalyst-equipped vehicles. Cold transient mode of operation accounts for 31 percent of the catalyst vehicles. The contribution by the hot transient mode (18.5 percent) of operation toward the total VMT is much lower than the FTP value of 27.3 percent for catalyst-equipped vehicles. The disagreement could be due to two reasons.

First, the composition of the catalyst and noncatalyst vehicles has changed dramatically since the FTP driving cycle was introduced in the early 1970s. The 1990 NPTS data indicated that about 95 percent of the vehicles surveyed could be catalyst equipped. By definition, with a cold-soak period of 1 hr or more, catalyst vehicles will start in the cold mode. It may be recalled that the cold-soak period for a noncatalyst vehicle is 4 hrs or more for a vehicle to start in cold mode. Therefore, the increase in catalyst vehicles in the overall vehicle composition would reduce the soak time required for cold starts. As a result, fewer engine starts are in hot start mode when compared with the vehicle composition in early 1970s.

Second, the NPTS data analysis indicated that the distance traveled following a hot start is significantly less when compared with the distance traveled following a cold start. These factors eventually contribute to the reduction of the VMT in the hot transient mode of operation.

This hypothesis is also supported by the fact that the VMT mode mix by noncatalyst vehicles (cold transient, 21.6 percent; hot transient, 28.8 percent; and hot stabilized, 49.6 percent) closely resem-

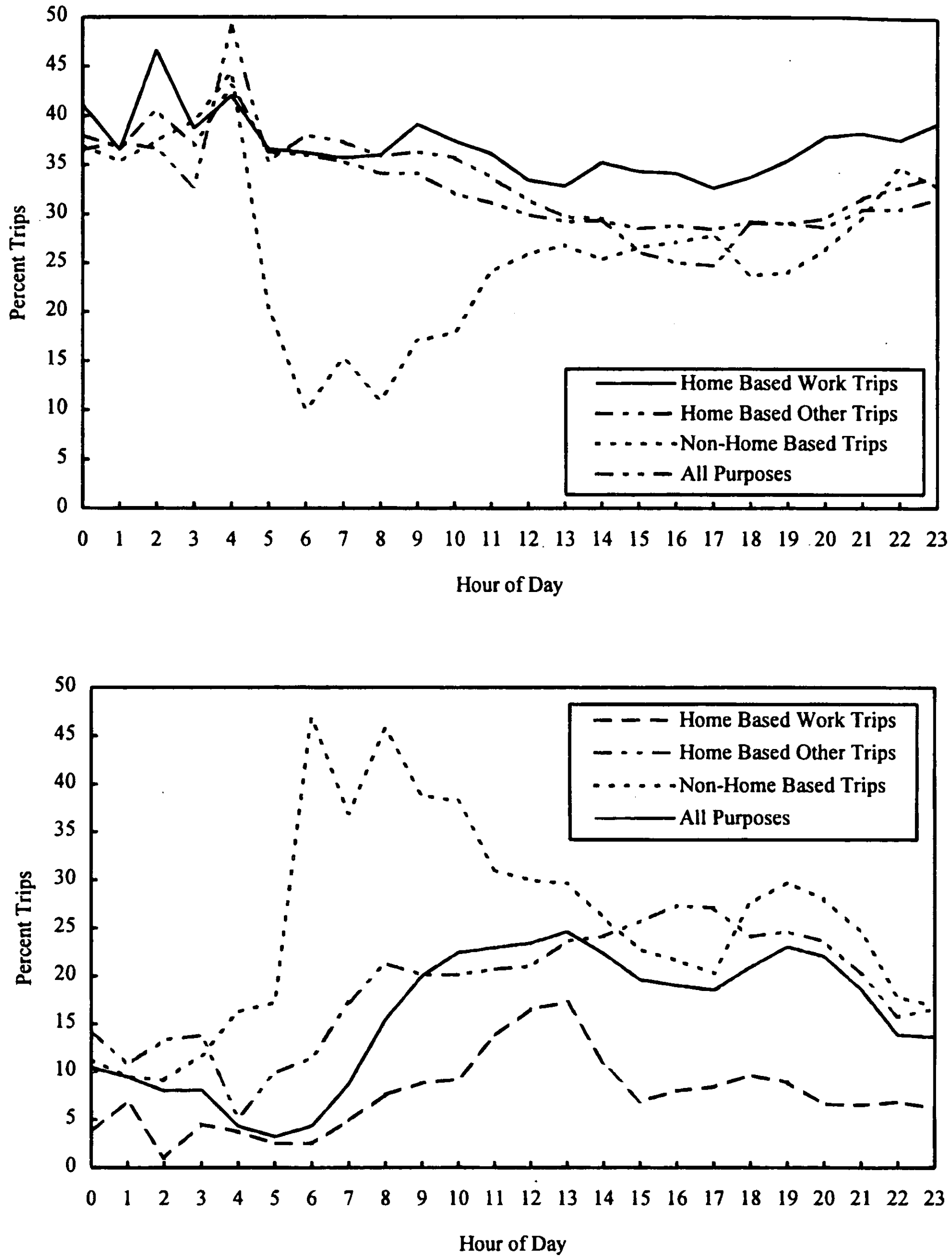

FIGURE 3 Distribution of transient mode VMT: (*top*) cold transient VMT; (*bottom*) hot transient VMT.

bles the FTP operating mode mix (cold transient, 20.6 percent; hot transient, 27.3 percent; and hot stabilized, 52.1 percent). As would be expected, in the morning peak period, cold starts are significantly higher than the cold starts for an average day (34.5 percent vs. 31.2 percent).

For a 24-hr period, total transient mode VMT are 49.9 percent, which is comparable to the FTP transient mode VMT of 47.9 percent. Most of the total VMT (over 50 percent) from the NPTS study, and over 52 percent for the FTP driving cycle), however, operates in hot stabilized mode. Because emission rates are sensitive to the share of VMT operating in cold transient mode, these findings could have a significant impact on overall emission estimation studies. Specifically, the mode fractions derived from the NPTS analysis may result in higher emission rates for CO and HC. However, it should be noted that these numbers are also sensitive to the length of the trip because the fraction of VMT in each operating mode was derived from a prorated basis of the total length of the trip.

Table 3 compares the trip characteristics and the operating modes of FTP driving cycle with the results from the NPTS data analysis. There are some noteworthy differences between the characteristics of FTP trips and the trips recorded for NPTS. An average NPTS trip is shorter than an FTP trip [10.56 versus 12 km (6.6 mi versus 7.5 mi) per vehicle trip for an average daily trip]. However, the number of cold and hot starts per household for an average day is comparable to the FTP driving cycle starts. According to NPTS data, on an average day, the number of cold and hot starts for a household is

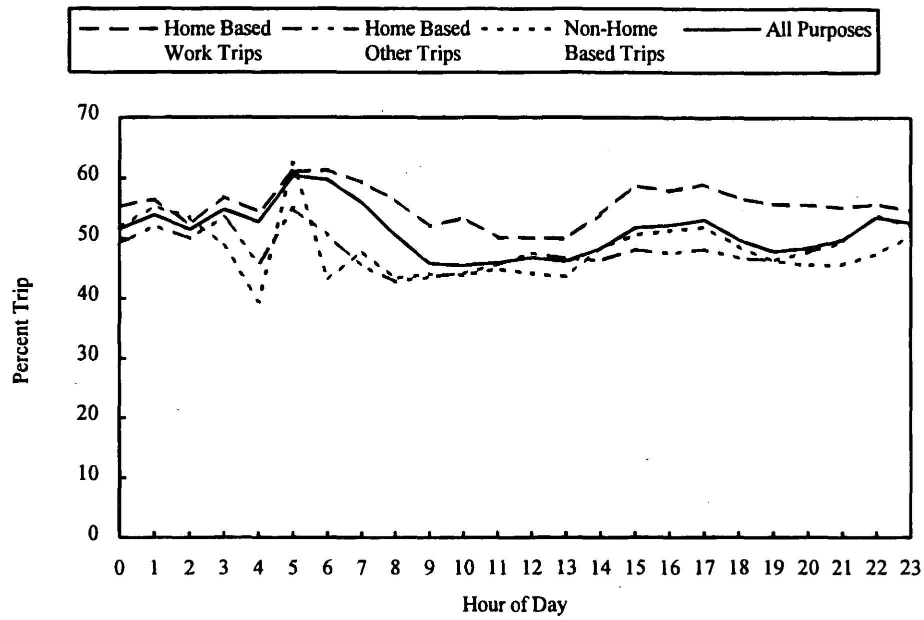

FIGURE 4 Distribution of hot stabilized mode VMT.

similar, 3.6 and 3.7, respectively. The data also indicate that, on a starts-per-vehicle basis, there are more hot starts than cold starts for an average day.

The FTP cycle, therefore, appears to be underestimating the cold transient mode VMT and overestimating the hot transient mode VMT. Also, FTP considers a longer trip duration (22.9 min) than the NPTS trip duration (13.5 min). It would appear that as the proportion of cold transient mode trips increases, the emissions would also increase. However, it is difficult to visualize the effect of these differences on the emission rates, which will be modeled using the MOBILE model. The relative significance of these differences can be analyzed by conducting a detailed sensitivity analysis of the emission factor model with FTP operating mode fractions and the NPTS operating mode fractions.

As mentioned earlier, an analysis of variance test indicated that the cold start fractions are different for individual MSAs. At a more aggregate level, the size of the urban area is found to explain variation in the start mode fractions. The geographic variation in transient and stabilized operating modes was also examined at an aggregate level for various urban areas based on the NPTS data. These numbers, presented in Table 4, do not indicate a clear trend. However, in general, the share of transient mode VMT is lower in larger urban areas. Because total VMT in larger urban areas are relatively higher, it would be natural to expect more stabilized mode VMT than the transient mode trips in these areas.

The use of the results presented in Table 4 can be demonstrated with a simple example. To conduct an areawide emission inventory analysis using MOBILE 5, if the urban area population is 300,000, an analyst will use cold transient, hot transient, and stabilized mode fractions of 35.9 percent, 23.7 percent, and 40.4 percent, respectively. The mode fractions for noncatalyst vehicles, however, can be used as specified by the FTP mode mix.

TABLE 2 VMT Accumulated in Each Operating Mode—NPTS Data

	Catalyst Equipped Vehicles[1]		Non-Catalyst Equipped Vehicles[2]		All types of vehicles	
Operating Mode	Mean VMT[3]	Percent VMT	Mean VMT[3]	Percent VMT	Mean VMT[3]	Percent VMT
Cold Transient	3.47	31.0	3.28	21.6	3.47	31.2
Hot Transient	3.00	18.5	3.11	28.8	3.00	18.7
Hot Stabilized	5.10	50.5	4.93	49.6	5.10	50.1

Notes:
[1]*98.02 percent of total VMT is represented by catalyst equipped vehicles.*
[2]*1.98 percent of total VMT is represented by non-catalyst vehicles*
[3]*Average vehicle miles traveled in the indicated operating mode per vehicle*

TABLE 3 FTP Driving Cycle Versus NPTS Data

Trip Characteristic	FTP (Av. Daily)	NPTS Data 7 - 9 AM	NPTS Data Daily
Number of trips made by household	n.a.	1.8	6.3
Number of trips made by each vehicle	4.7	1.5	4.5
Average trip length (miles/veh trip)	7.5	6.8	6.6
Average trip duration (min/veh trip)	22.9	14.0	13.5
Vehicle miles (for analysis period)	35.25	10.2	29.7
Number of cold starts (per household)	n.a.	1.3	3.6
Number of cold starts (per vehicle)	2	1.1	2.6
Number of hot starts (per household)	n.a.	1.8	3.7
Number of hot starts (per vehicles)	2.7	1.7	3.1
Cold transient travel (% of total VMT)	20.6[1]	34.5	31.2
Hot transient travel (% of total VMT)	27.3[1]	13.7	18.7
Hot stabilized travel (% of total VMT)	52.1[1]	51.8	50.1

n.a. - data not available for analysis or the characteristic is not applicable
[1] based on morning commute.

CONCLUSIONS AND RECOMMENDATIONS

The operating mode mix based on the FTP is only representative of the FTP drive cycle and does not necessarily apply to other conditions. Therefore, use of these operating mode fractions for deriving emission rates using the MOBILE model can produce incorrect results. An analysis of the NPTS data base indicates that, in most cases, the average VMT fraction of cold starts is more then 30 percent instead of the 20.6 percent as derived from the FTP drive cycle. Depending on the ambient temperature, this could yield a 20 to 40 percent increase in predicted CO and HC emissions using the MOBILE 5A model. Furthermore, during certain times of day, the cold transient mode travel may exceed 40 percent of the total VMT (Table 1). The greater the error in estimating the transient mode travel, especially the cold transient travel, the greater the error will be in emission estimate.

The methodology to deriving operating mode fractions presented in this paper as an alternative to the FTP mode mix is a step toward improving the inputs to emission estimation models. The numbers presented in Table 4 may be used in areawide emission inventory studies using the MOBILE model. The results of the methodology provide a basis for estimating vehicle operating mode mix for different times of day, by trip purpose and urban area size. However, for high-resolution emission inventory studies, it would be appropriate to derive operating mode fractions at even finer resolution, such as by functional class of roadways and geographic location.

It should be noted that the NPTS data do not contain information on the commercial trips. Correction factors are needed to modify the operating mode fractions presented in this paper to account for the commercial travel in the traffic flow. Also, it would be academically interesting to study the sensitivity of the emission estimation models to various sets of operating mode fractions presented in this paper. Such a study would likely draw attention to the degree of underestimation of CO and HC emissions when using the FTP operating mode fractions.

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TABLE 4 Operating Mode Fractions for Urbanized Areas (Daily)

Urban Area Population	Percent VMT in: Cold Transient Mode	Hot Transient Mode	Hot Stabilized Mode
50,000-199,999	32.9	21.9	45.2
200,000-499,999	35.9	23.7	40.4
500,000-999,999	31.0	18.6	50.4
Over 1,000,000 (No Subway)	29.8	18.1	52.1
Over 1,000,000 (With Subway)	30.0	18.8	50.5
Nationwide	31.2	18.7	50.1
FTP	20.6	27.3	52.1

Note: The urban area categories are according to the NPTS classification

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Driving Pattern Variability and Impacts on Vehicle Carbon Monoxide Emissions

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An analysis of instrumented vehicle data revealed significant differences in operating mode profiles for vehicle operations in Atlanta, Georgia; Baltimore, Maryland; and Spokane, Washington. Differences in such operating mode characteristics as acceleration rates and cruise speed distributions are important in the development of new emissions models because certain vehicle and engine operating modes are proving to be significant sources of elevated emissions rates. Although not conclusive, these data indicate that the variations in operating mode fractions across cities may be related to differences in road network characteristics. A simple predictive model, based on three operating parameters (vehicle speed, engine speed, and manifold absolute pressure) was developed from data collected from eight instrumented General Motors 3.1-L vehicles and is capable of predicting elevated carbon monoxide (CO) emission rates for various vehicle and engine activities. These emission results do not apply to hydrocarbons (HC) or oxides of nitrogen (NO_x), which behave differently. The modeling technique discussed has been developed exclusively for CO. The model is used to estimate the relative CO emission differences associated with the differences in operating profiles noted from city to city (and potentially from driver to driver). This modeling approach appears capable of adequately distinguishing the CO emission effects associated with variations in engine and vehicle operations for individual vehicle makes and models. However, it should be noted that the large variability in vehicle-to-vehicle CO emission response to changes in operating modes that has been noted in ongoing studies indicates that a model based on vehicle speed and acceleration profiles alone may not provide sufficient CO emission rate predictive capabilities for the fleet.

Mobile emissions are known to be a significant source of air pollution in U.S. cities, typically accounting for more than 50 percent of the ground-level ozone and 70 to 90 percent of the carbon monoxide (CO) (*1*). It is because of this role in air pollution that federal legislation has focused on stringent motor vehicle emission standards and to a limited extent on the implementation of transportation control measures (TCMs) to control the levels of pollutants that originate from mobile sources. With over 100 metropolitan areas in violation of ozone standards and 60 in violation of CO standards (*1*), there is a significant challenge facing the United States in attaining and maintaining ambient air quality standards.

Of great importance in meeting this challenge is the development and validation of a model that can accurately estimate changes in pollutant emission rates associated with changes in transportation network, vehicle, and driver characteristics. Although existing emissions models have been in use for many years (with improvements made in each new generation of model release), these models still have serious deficiencies (*2,3*) that prevent their use in accurately assessing emission rates at the corridor level (i.e., for transportation system links). Ongoing research continues to add to an understanding of the basic phenomena associated with emissions occurring from components of the vehicle fleet. For example, several remote sensing studies have shown that a small proportion of the fleet, known as "super-emitters," may be responsible for a large proportion of the excess emissions (*4,5*). The public perception is that these super-emitters are either poorly maintained or very old vehicles. However, recent studies have shown that new, properly maintained vehicles can become high emitters under certain operating conditions, such as high load conditions (*6,7,8*). Hence, a small fraction of each vehicle's activity may be responsible for super-emissions, or a large fraction of that vehicle's daily emissions (*9*). New models must be capable of addressing the effects of both the presence of super-emitters in the fleet and the occurrence of super-emissions events associated with various vehicle operating modes.

Inherent in all the existing emissions models, and in most of the new models being developed, is the assumption that there is an average driver, or at least that the variations in driver to driver behavior is insignificant in the production of emissions from the vehicle. Average values for vehicle miles traveled and speed are used, resulting in the loss of variation inherent from vehicle to vehicle and driver to driver. Much of the research related to developing new test driver cycles (which may replace or supplement the federal test procedure cycle) for emission rates assumes typical driving in urban areas (*10*). However, if the engine mode of operation is going to become an important element of new models, there is clearly a need to better understand how driver behavior can affect the frequency of these modes. For example, given the same vehicle, are older drivers likely to drive more conservatively than younger drivers, entering into engine enrichment modes less often? Is there evidence to suggest that driving patterns are indeed different from one city to another?

This paper examines instrumented vehicle data sets from Baltimore, Maryland; Spokane, Washington; and Atlanta, Georgia, to assess first the variation in driver behavior from one city to another and to assess the potential impact this variation might have on CO emissions estimation. After the sources and limitations of the data used in this study are laid out, this paper examines the differences in the frequency of activity that leads to high CO emissions among the three urban areas. Then, two methods for estimating CO emissions as a function of vehicle and engine operating modes are presented and used to assess the potential impacts that different driving patterns may have on CO emissions estimation.

INSTRUMENTED VEHICLE DATA

A 1992 study in Spokane, Washington; Baltimore, Maryland; and Atlanta, Georgia; instrumented approximately 350 vehicles with a

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device that recorded data for three parameters: vehicle speed in meters per second, engine speed in revolutions per minute (RPM), and manifold absolute pressure (MAP) in kilopascals (kPa). The three-parameter data set yielded 213 vehicles for which valid data were recorded on all channels. In Baltimore and Spokane, a six-parameter data base contained data from 79 vehicles for the following measures: vehicle speed in meters per second, engine speed in RPM, throttle position in percentages, and one of three measures of air flow, engine coolant temperature, and the output of a wide-range oxygen sensor that monitored exhaust gas composition (i.e., air-to-fuel ratio). The six-parameter data set yielded 46 vehicles with valid data on all channels. Both studies recorded each parameter once per second, and each device continuously recorded the date and time of operation.

Each resulting data set was subject to strict quality control procedures. More than 15 error-detection measures were used to track the wide variety of anomalous conditions that could be part of any given data set. Many of the problems detected were transient and were corrected by substituting the erroneous value with an interpolated value. Only the vehicle records containing valid data on all recorded channels for the entire study period were used in this analysis.

To avoid the emissions modeling problems associated with elevated emissions rates during vehicle warm-up (*2*), the research team used data collected only from hot stabilized engines. Engines were assumed to have achieved hot stabilized combustion, and catalytic converters were assumed to have reached light-off temperatures by the time the engine temperature reached 70°C. Thus, the six-parameter data used in developing emission rate models excluded all data from operations when the engine coolant temperatures were lower than 70°C.

Each vehicle recorded data for approximately 1 week before the instruments were removed. In the three-parameter data set used in this study, Atlanta drivers recorded over 3.0 million sec of operation from 76 vehicles, Baltimore drivers recorded 2.5 million sec of operation from 68 vehicles, and Spokane drivers recorded 1.9 million sec of operation from 69 vehicles. The six-parameter data used in this study recorded 1.6 million sec of operation from 46 vehicles.

Driver Selection

Baltimore and Spokane drivers were solicited at centralized emissions inspection centers, with vehicles instrumented at the time of solicitation (*11*). Atlanta has no centralized emission inspection. Drivers were solicited at three driver's license stations; their vehicles were instrumented later at remote sites.

Data Limitations

The six-parameter data base was limited. The sample size was small and appears biased in important respects. For example

- Only fairly new vehicles (i.e., model years between 1989 and 1991) were instrumented,
- A limited number of engine types and sizes were included,
- Young drivers are poorly represented (only 1 of the 46 drivers was under the age of 25,
- Manual transmission vehicles were underrepresented, and
- High-performance vehicles were not included in the sample.

For the three-parameter data sets in all three cities, efforts were made to select a representative sample of drivers and vehicle types from the target population. For example, the three-parameter data set was not restricted to the type or age of vehicle instrumented. Potential driver bias has not yet been examined in the three-parameter data set. However, based on the preliminary analysis of the Atlanta data set, the three-parameter data set appears less likely to be biased than the six-parameter data set.

Both data sets are somewhat limited in their usefulness because geographic positioning data or accelerometer data were not collected for use in evaluating the impacts of grade on speed, acceleration, and throttle position. Furthermore, without positional information, the data could not be directly associated with the roadway classification upon which the vehicle was operating. Hence, if the noted speed was 56 km/hr (35 mph), it was not possible to determine directly whether the activity occurred on a congested freeway or a free-flowing arterial.

Despite the potential biases and shortcomings in the data sets, the six-parameter and three-parameter data sets from these three cities still represent a rich source of information on vehicle activity. The data serve as an excellent point of departure for preliminary discussions of the potential impacts of variations in driving patterns.

DATA ANALYSIS

Vehicle speed distributions for the three-parameter data set for each city are shown in Figure 1 and indicate the proportion of total driving time spent in each specific speed range. For example, approximately 15 percent of the total driving time in Spokane occurred in the 48 to 56 km/hr (30 to 35 mph) speed range, compared with only 8 and 6 percent in Baltimore and Atlanta, respectively. If it is assumed that the speed range from 25 to 40 mph (40 to 64 km/hr) represents driving that would occur primarily on arterial highways or congested freeways, Spokane has the highest percentage of such activity in the three cities studied. In addition, Spokane has the lowest percentage of activity above 60 mph. Atlanta drivers tended to drive much faster than their counterparts in the other two cities.

If drivers in the different cities operated on uncongested freeways, the shape of the high end of the speed distributions should be the same. Because they are different, it may be because (a) the drivers in the different cities do not drive on uncongested freeways, which means that they do not have freeways, they do not drive on their freeways, or that their freeways are not uncongested, or (b) the drivers in the different cities are driving differently on uncongested freeways, which means that the freeways may be physically different, causing different responses, or that the freeways are physically similar but that there is a behavior difference between drivers in various cities. Unfortunately, with the data collected, the reason cannot be determined.

If it is assumed that the largest fraction of vehicle activity occurs on arterial highways, this activity occurs in Spokane and Baltimore in the 40 to 64 km/hr (25 to 40 mph) speed range. In Atlanta, this fraction of activity occurs in the 56 to 80 km/hr (35 to 50 mph) speed range. In addition, there appears to be a less distinctive break between the arterial highway activity fraction and the freeway fraction in Atlanta. However, depending on congestion conditions, some of the data from congested freeways may overlap data from arterial operations.

These results are perhaps not surprising given the different terrain and road network characteristics of the three cities. Although

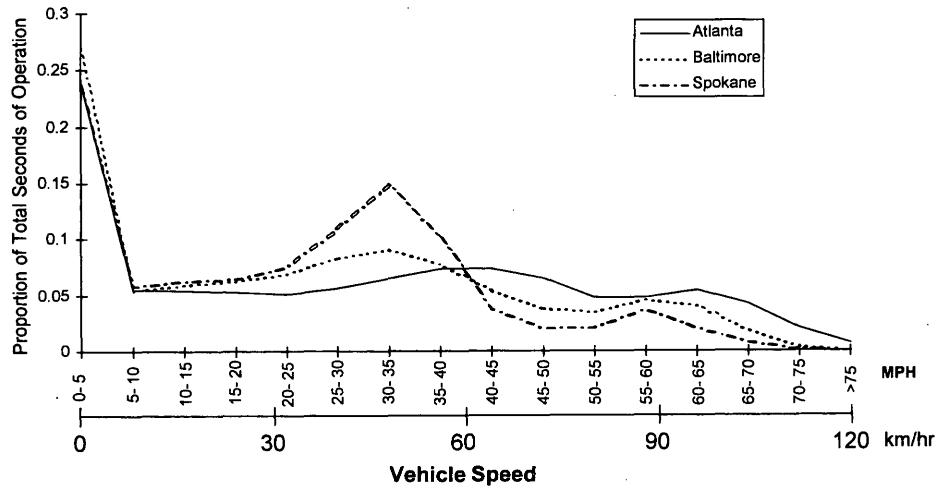

FIGURE 1 Vehicle speed distributions for three-parameter data sets. (Bin marked "5–10" refers to speeds ≥ 5 mph and < 10 mph.)

the Spokane metropolitan area includes an Interstate highway, the Interstate serves primarily as a bypass link and does not serve as a major transportation link for trips internal to Spokane. Baltimore is a more densely developed, older city than Atlanta and Spokane, with a freeway system that is more expansive than Spokane's but not as large as Atlanta's. The freeway system in Baltimore is augmented with a highly developed set of arterial highways that have traditionally served many of the internal Baltimore trips. Atlanta, on the other hand, has a newly expanded freeway system that many drivers use as the major means of reaching destinations in the Atlanta area. The freeway system is accessed by a large network of major arterial roads, many with high levels of capacity that experience high-speed activity.

Although the reasons for the noted differences are as yet unclear, the data in Figure 1 clearly indicate that there are substantial differences in vehicle speeds from one city to another. These differences are statistically significant and were substantiated through discriminant analysis, where a set of functions is derived that minimizes the variance within a group and maximizes the variance between groups (*12*). The discriminant analysis results are contained in Table 1. In this case, two functions were needed to classify each driver into the three groups. The proportion of total driving time in each of 16 speed bins for each driver was used to predict in which city the driver operated the vehicle.

If the speed profiles contained little information about the city in which a driver operated, a discriminant analysis would misclassify most of the drivers, with a success rate approaching that of chance assignment. In this case, the speed profiles worked well in determining in which city the driver operated, with a success rate of 79 percent. Atlanta drivers were most frequently correctly grouped, indicating that Atlanta drivers' speed profiles are more distinctive than those for Baltimore or Spokane. Also, no Atlanta driver was misclassified as Spokane drivers were. There is also some overlap between the driving patterns found in Baltimore and the other two cities.

TABLE 1 Results of Discriminant Analysis Based on Speed Profiles

Actual Group		Predicted Group Membership		
City	Cases	Baltimore	Atlanta	Spokane
Baltimore	68	51	10	7
		75.0%	14.7%	10.3%
Atlanta	76	13	63	0
		17.1%	82.9%	0.0%
Spokane	69	13	2	54
		18.8%	2.9%	78.3%

However, Figure 1 does not allow for observations about the style or aggressiveness of driver behavior (which could also be related to the characteristics of the road network). For the purposes of this paper, aggressive is defined to indicate higher acceleration rates. If each data set was segregated into subsets by driver according to the proportion of driving in arterial or highway modes, previous research indicates that the acceleration distributions would not be distinctly different for these subsets (*13*). That is, drivers who spend most of their driving time at freeway speeds are not more likely to drive more aggressively in any speed range than the drivers who spend most of their driving time at arterial speeds. However, one possible measure of driver aggressiveness is the distribution of acceleration across all speed ranges.

To examine the potential differences in acceleration profiles across cities, the standard deviation of the acceleration and deceleration values was calculated for 8 km/hr (5 mph) bins for each of the cities (Figure 2). A larger standard deviation implies a larger number of vehicles with greater acceleration or deceleration values, or both, in that speed group, a phenomenon of great interest in estimating emissions related to engine load or power enrichment. By this measure, Atlanta drivers were more aggressive in most speed ranges.

The acceleration profiles were also examined by using discriminant analysis, and the results are better than those obtained using only the speed profiles. The analysis grouped the drivers into their correct cities 85 percent of the time, with Atlanta drivers grouped properly 88 percent of the time.

The results of the discriminant analysis clearly show that the driving patterns are significantly different across the three cities. It may be that particular transportation network characteristics are the most important parameter. For example, higher levels of acceleration changes could be explained by a larger number of opportuni-

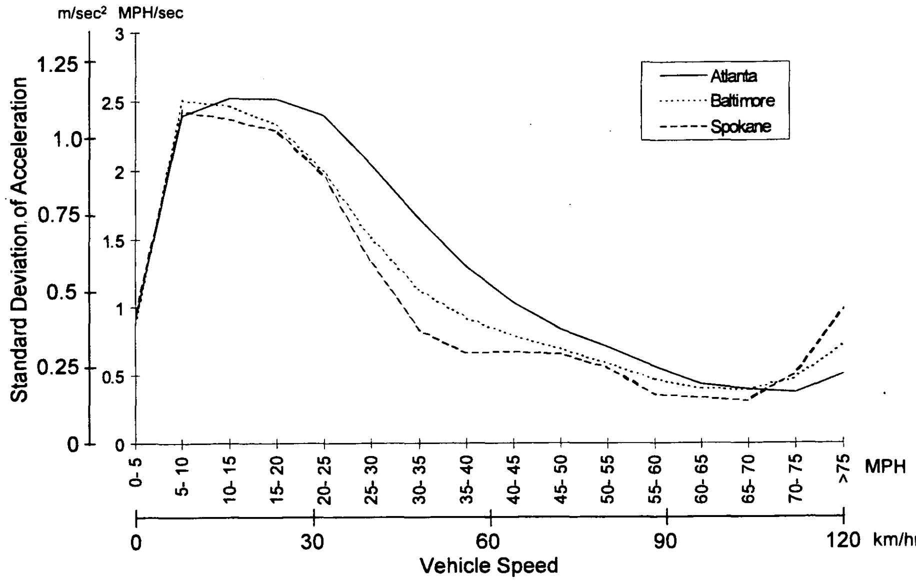

FIGURE 2 Standard deviation of acceleration distributions for three-parameter data sets. (Bin marked "5–10" refers to speeds ≥ 5 mph and < 10 mph.)

ties in a road network to accelerate or decelerate (e.g., stop signs or traffic signals). This could certainly be one explanation for the differences in the lower speed ranges (such traffic controls are not found on freeways). The greatest differences in acceleration standard deviations between Atlanta and the other two cities occur in the 24 to 72 km/hr (15 to 45 mph) speed ranges. This suggests that the greatest variation in acceleration behavior may occur on arterial highways (or congested freeways). One possible contributing factor is that the Atlanta arterial road network covers a much larger geographic area than that of the other two cities, often providing drivers with greater distances before signal interruptions. This may not only allow greater speeds but also account in part for the distinct differences in acceleration activity. Perhaps the transportation system characteristics have conditioned drivers to drive in the manner noted for each city. That is, drivers may simply respond to various infrastructure characteristics, such as lane width or presence of highway barriers, in terms of speed and acceleration profiles.

However, demographic differences or vehicle sample could also account for some of these characteristics. It may be that driver characteristics are responsible for the differences noted across the cities. Perhaps the age distribution or previous driving experiences play a role in modal profiles. Perhaps the vehicles themselves are an important explanatory variable or an interaction term with driver characteristics. It may even be that local law enforcement habits play a role in these differences. There are no clear reasons why such differences in vehicle activity occurred. But the Georgia Institute of Technology has undertaken additional studies to explain these differences. In future studies, vehicle characteristics, driver characteristics, and infrastructure characteristics will be controlled during data collection so that statistical analyses are more likely to reveal the factors that appear to affect these activity differences (*14*).

In summary, an examination of instrumented vehicle data sets from three U.S. cities indicated that there are significant differences among the cities in vehicle activity profiles. These differences may be caused by the characteristics of the road networks or the driving styles found in separate regions of the United States. The importance of this finding is that it suggests the existence of potentially substantial differences across cities in mobile emissions estimates, depending on the relative contribution of modal emissions to the overall emissions inventory. To examine the potential impacts of these activity differences, two simple predictive models for CO emissions, derived as functions of vehicle and engine parameters, were developed from the data collected during the six-parameter study. These models were then used to examine the relative CO emissions from the cities, given the different speed-acceleration distributions found in each city.

POTENTIAL EMISSIONS IMPACT OF DRIVER BEHAVIOR VARIABILITY

CO emissions can be estimated from variables contained in the six-parameter data set. By coupling the wide-range oxygen sensor (which detects the exhaust air-to-fuel ratio) reading with mass air flow and assumed catalytic converter efficiency, the CO emissions rate can be estimated. The development of this method was covered extensively in a previous work (*15*) and is not repeated here.

Using the methodology developed previously (*15*), two alternative engine-specific models were developed from the largest subset of the six-parameter data available, eight General Motors vehicles with 3.1-L engines that were equipped with MAP sensors. The eight vehicles in this subset made 350 trips, and emissions were modeled on a per-trip basis. Two different models were considered: a speed-acceleration model and a speed-MAP-RPM model. These parameters were chosen because the three-parameter data included these variables. These models could likely be improved if throttle position were also used as a predictive variable, because many engine control units base commanded enrichment logic on throttle position (as well as other factors not included in the model) and because throttle position is controlled directly by the driver.

The speed-acceleration model initially considered six zones of operation (Figure 3). The characteristics of the zones are

1. Speed and acceleration combinations within the bounds of the FTP test,
2. Speeds less than the maximum FTP speed of 92 km/hr (57 mph) and acceleration rates higher than the FTP maximum for any given speed,
3. Speeds less than the maximum FTP speed and deceleration rates higher than the FTP maximum for any given speed,
4. Speeds greater than the maximum FTP speed and acceleration rates greater than 0.45 m/sec^2 (1 mph/sec),
5. Speeds greater than the maximum FTP speed, acceleration rates less than 0.45 m/sec^2 (1 mph/sec), and deceleration rates less than 0.45 m/sec^2 (1 mph/sec),
6. Speeds greater than the maximum FTP speed of 92 km/hr (57 mph) and deceleration rates greater than 0.45 m/sec^2 (1 mph/sec).

Of these six zones, the two deceleration zones (Zones 3 and 6) were not found to be statistically significant. Zones 3 and 6 were merged with the FTP zone. The functional form of the regression equation is

$$\text{CO(g/sec)} = 0.050514 + 0.094067 * (\text{HI\_SPEED}) + 0.642077 * (\text{LO\_ACCEL}) + 0.823341 * (\text{HI\_ACCEL})$$

where

HI_SPEED = the proportion of each trip with speeds greater than 92 km/hr (57 mph) and acceleration rates less than 0.45 m/sec^2 (1 mph/sec) (Zone 5),
LO_ACCEL = the proportion of each trip with speeds less than 92 km/hr (57 mph) and accelerations greater than those found on the FTP (Zone 2), and
HI_ACCEL = the proportion of each trip with speeds greater 92 km/hr (57 mph) and accelerations greater than 0.45 m/sec^2 (1 mph/sec) (Zone 4).

The R^2 for this model is fairly poor at 0.29, with an F-statistic of 46.9 and a standard error of 0.035 g/sec.

The speed-MAP-RPM model is based on the concept that engine parameters govern commanded enrichment and will better predict modal emissions for a single engine type. When the CO emissions rate is plotted across MAP and RPM, four zones were defined to account for different engine modes. These four zones were defined arbitrarily as operations with

- MAP ≤ 70 kPa and RPM ≤ 3,500, corresponding to normal driving;
- MAP > 70 kPa and RPM ≤ 3,500, corresponding to high-load conditions, such as climbing a steep hill;
- MAP ≤ 70 kPa and RPM > 3,500, corresponding to a high-RPM, low-load condition, which rarely occurs; and
- MAP > 70 kPa and RPM > 3,500, corresponding to high-load conditions that are often associated with both commanded enrichment and high-mass air flows.

Each of these four zones was then examined for variance with respect to vehicle speed. With the exception of the rare high-RPM, low-load condition, the CO emission rates in each zone varied similarly with speed. Each zone showed the lowest emission rates when speed was less than 16 km/hr (10 mph). Emission rates then became speed-invariant to approximately 113 km/hr (70 mph). In light of this, each of the four engine zones was divided into three speed zones: less than 16 km/hr (10 mph), between 16 and 113 km/hr (10 and 70 mph), and greater than 113 km/hr (70 mph).

This model required fine tuning as well. The high-RPM, low-load zone had very little data and did not exhibit a clear relationship with vehicle speed; thus, the three zones were merged into a single zone. The high-load, zone with RPM less than 3,500 had insufficient data to support separate groups for moderate and high speeds, and these two zones were merged as well. No data points included activity at speeds less than 10 mph and with both high MAP and RPM.

The resulting regression equation displayed much better results than the model based only on speed and acceleration with an R^2 value of 0.56, an F-statistic of 62.8, and a standard error of 0.029 g/sec.

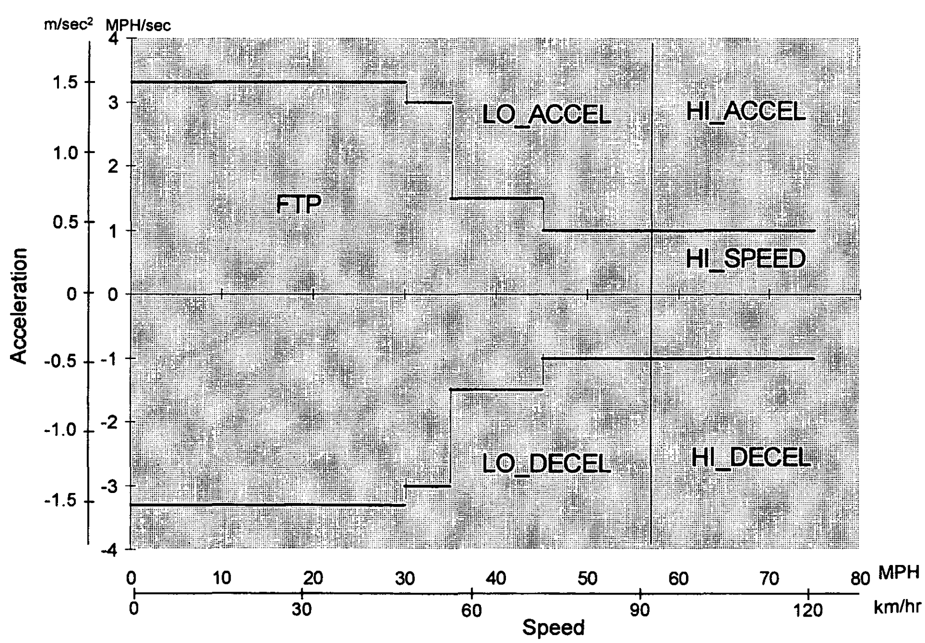

FIGURE 3 Zones used in development of speed-acceleration model.

The engine-based model clearly explains more of the variation in the CO emission rates of vehicles equipped with 3.1-L engines than does the speed-acceleration model. This is because the engine control unit (on-board computer) commands enrichment based largely on monitored engine parameters. A given speed-acceleration combination does not directly determine these engine parameters. (Note, however, that the linear acceleration variable, change in speed per change in time, used in the model did not include acceleration due to grade.)

Throttle position is another potentially significant variable because it is monitored by the on-board computer system and appears to be used by many vehicles in commanded enrichment algorithms. Preliminary analyses indicate that emission rate variation for specific vehicle makes and models can be comparably explained by a model based solely on RPM and throttle position. Because throttle position appears to be only partially correlated with engine load expressed as MAP (a Pierson correlation coefficient of roughly 0.75 for the six-parameter data examined), variation in throttle position may be in part due to the individual differences in how the driver uses the throttle to interface with the engine.

It is important to keep in mind, however, that other studies have indicated that the vehicle-to-vehicle variations in emissions response to various operating modes and loads (i.e., modes that may cause commanded enrichment) appear to be large (*9*). Hence, an engine-parameter model developed from single or limited engine types may be inappropriate when applied to other vehicles.

The speed-acceleration and speed-MAP-RPM models were then re-derived using the entire six-parameter data set. The three-parameter data set was not used because engine sizes were not recorded. In the case of the Spokane and Baltimore data, even the vehicle type was unknown. It is theoretically possible to derive engine size data from the vehicle identification number, but this was not attempted. In future analyses, it would be ideal to use some measure of differences among vehicles, particularly engine size, when extending this type of model. As expected, the models did not perform as well when they were derived from data collected for several vehicles with different engine types and control strategies taken together. In the case of the speed-acceleration model, the R^2 dropped from 0.29 to 0.17, with the standard error rising from 0.035 to 0.056 g/sec. The speed-MAP-RPM model did not suffer as severe a degradation, with the R^2 dropping from 0.56 to 0.37, which is a better fit than the speed-acceleration model was able to manage over a single vehicle type. However, the standard error is also fairly high at 0.050 g/sec. The proportion of each trip spent at low speeds and normal engine operation was taken as the regression constant because this region would usually correspond to idle and was found to be statistically insignificant. The regression equation, where the value of each variable is the proportion of each trip that fell into a given zone is

$$\begin{aligned}\text{CO(g/sec)} = {} & 0.029854 + 0.034631(\text{NOR\_MED}) \\ & + 0.196595(\text{NOR\_HI}) \\ & + 1.304044(\text{HI\_RPM}) \\ & + 0.029155(\text{HI\_MAP\_LO}) \\ & + 0.273061(\text{HI\_MAP\_MEDHI}) \\ & + 3.228802(\text{HI\_LOAD\_LOMED}) \\ & + 22.74787(\text{HI\_LOAD\_HI})\end{aligned}$$

where

NOR_MED = activity at speeds between 16 and 113 km/hr (10 and 70 mph) and normal engine parameters;
NOR_HI = normal engine parameters where speed > 113 km/hr (70 mph);
HI_RPM = all activity at high RPM and MAP < 70 kPa;
HI_MAP = activity at high MAP, but RPM < 3,500, with the speed divisions as above; and
HI_LOAD = activity where MAP and RPM are both high.

The smaller degradation of the engine model may be because any engine is likely to be in enrichment at high MAP and RPM, and to some degree at high MAP independent of RPM. However, the frequency of high-load activity for any vehicle will vary as a function of engine size and vehicle weight (i.e., load is associated with the power-to-weight ratio). Engine size appears from other studies to be an important causal variable (*9*), and engine size and vehicle weight were not used as explanatory variables in the derived models. That these variables are not included is a limitation in the derivation and application of these two models. Note, however, that engine size may not be a sufficient discriminant variable—the GM 3.1-L vehicles equipped with MAP sensors behaved differently from the GM 3.1-L engines equipped with LV8 sensors, and there were significant differences between these and the 3.0-L Ford.

It is important to note that the estimate of the CO emissions rate does not include measure of startup or cold-operation emissions because these data were not used in the analyses. In addition, as noted earlier, the six-parameter data base is limited to only a few engine types of a limited manufacture date range. Large engines, sports cars, manual transmissions, and young drivers are all under-represented in this data set. Any values obtained by extrapolation to the three-parameter data should not be considered an accurate estimate of overall CO emissions for a particular vehicle, only as a preliminary indication of emission rate differences associated with differences in vehicle activities. A much larger study would be necessary to obtain enough data to accurately predict the emissions rates for the general population. Applying the models developed using the six-parameter data to the three-parameter data sets is not ideal. The application was intended to explore only the capability of the three-parameter data to distinguish among different driving patterns and to see whether the differences in speed and acceleration behavior have a possible impact on emissions. As such, these models are taken as a common metric that should be used for comparative purposes only.

These models based on the six-parameter data produce interesting results when applied on a trip-by-trip basis to the three-parameter data sets. There were 4,354 trips recorded in Atlanta, 3,701 trips in Spokane, and 3,641 trips in Baltimore. The speed-acceleration model tended to predict a much smaller variability than the speed-MAP-RPM model (Figure 4). The speed-acceleration model yielded a median CO emissions rate (on a per-trip basis) of 0.078 g/sec for Atlanta drivers, 0.067 g/sec for Baltimore drivers, and 0.064 g/sec for Spokane drivers. The speed-MAP-RPM model yielded a median CO emissions rate of 0.102 g/sec for Atlanta drivers, 0.087 g/sec for Baltimore drivers, and 0.079 g/sec for Spokane drivers (Figure 5). These results are not surprising when compared with the overall behavior patterns found using speed and acceleration profiles. (Spokane drivers exhibited the lowest average speeds and the lowest acceleration rates, the Baltimore drivers were in the middle, and the Atlanta drivers exhibited the highest speeds and acceleration rates.) This trend is replicated in the results of these two models. Interestingly, the speed-acceleration model shows little difference between the median emissions rates of Spokane and Baltimore drivers, in contrast with the results of the speed-MAP-RPM

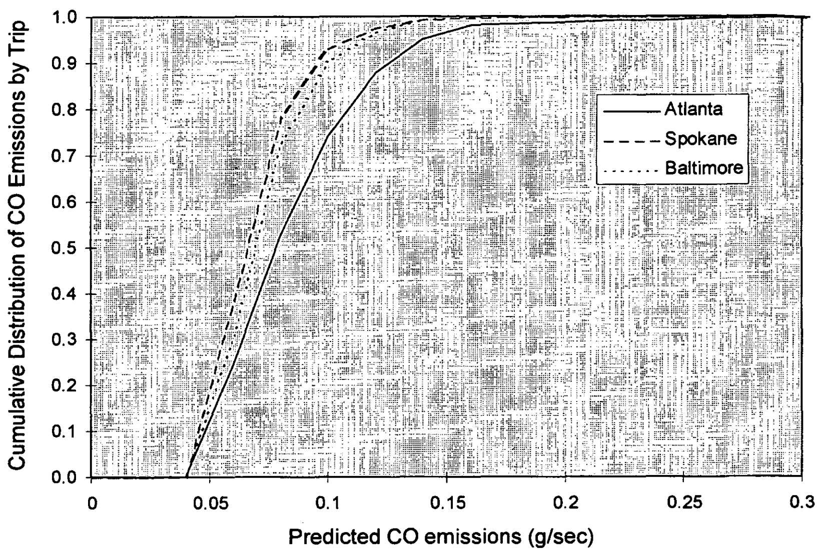

FIGURE 4 Cumulative distribution of predicted CO emissions by trip for speed-acceleration model.

model, which predicts larger differences between median emission rates in these cities.

At this time, it is unclear whether the relatively poor performance of the speed-acceleration model is due to inherent flaws in attempting to model emissions based solely on speed and acceleration, lack of control over the grade variable, or inadequate model specification (i.e., only four activity zones were used in this model), or whether poor performance is an artifact of the potential biases within this particular data set. Nevertheless, this initial work indicates that the speed-MAP-RPM model may provide greater sensitivity to changes in driving patterns.

One factor that has not yet been discussed is long-term modeling implications of speed-acceleration models versus speed-MAP-RPM models. When a CO emission rate model is developed, the challenge that remains is to quantify the activity that must be used in the modeling process. That is, if a speed-acceleration model is used, the vehicle activity on a transportation link must be quantified in terms of speed and acceleration profiles. If a speed-MAP-RPM model is used, the vehicle activity on a transportation link must be quantified in terms of speed, MAP, and RPM profile. This is clearly not a simple modeling issue. Whereas the identification of speed and acceleration profiles is fairly straightforward and likely to be independent of the vehicle subfleet characteristics operating on the link, the RPM and MAP profiles are totally dependent on the characteristics of that vehicle subfleet. Hence, the potentially higher explanatory power of engine-based models may be compromised if

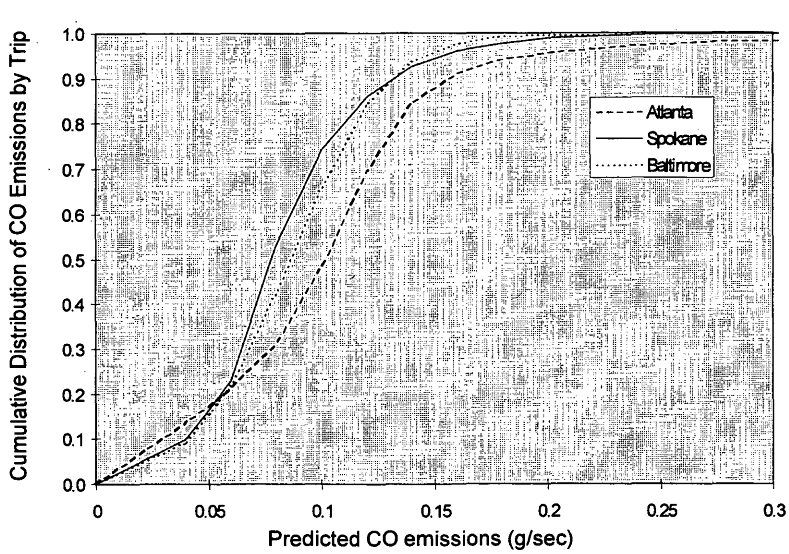

FIGURE 5 Cumulative distribution of predicted CO emissions by trip for speed-MAP-RPM model.

highly uncertain vehicle MAP and RPM distributions are linked with the emission rates. Clearly, in constructing long-term emissions models, a difficult balance must be reached.

CONCLUSIONS

Mobile source emissions are dependent on vehicle type, vehicle activity, and possibly transportation network or driver characteristics, or both. Important and statistically significant differences in vehicle activity profiles have been found among the three cities studied. It is unclear from this data set whether network characteristics explain these differences completely or whether other characteristics of these cities also play a role. A study looking for differences and similarities between drivers in cities with similar transportation networks would be necessary to test this hypothesis.

The differences noted in vehicle activity profiles suggest that emissions models must adequately incorporate these variations into the modeling regime if they are to be applied across a variety of metropolitan areas. An emissions model using engine operating parameters could provide a basis for newer, state-of-the-art transportation models where fleets of vehicles are modeled based on the characteristics of driving conditions and engine modal operations. These models can account for differences in driving habits and possibly point out locations on the transportation network (such as on-ramps) where high-emissions driving would occur. However, such an application requires accurate vehicle and engine operating profiles to be developed for the vehicle fleet for the emission rate algorithms to be applied. Note that these results should not be extrapolated to HC or NO_x.

A model that uses only the speed and acceleration distributions for a given roadway segment can be developed and applied. However, this approach initially appears to be much less sophisticated than the engine-based approach. It should be noted, however, that the model tested in this research used linear acceleration and did not account for grade effects. Once grade effects are included in net acceleration, the speed-acceleration model may provide significantly improved explanatory power. Also, the effects of grade may be more significant at higher speeds than at lower speeds. In addition, the speed-acceleration model developed used only four activity zones, and improvements in explanatory power may result from a more refined model. Although a model based only on speed and acceleration may not perform as well as an engine parameter model, the activity data are likely to be more easily and accurately measured and modeled. Hence, the approach may simply be more practical than an engine model.

Perhaps most important, this paper highlights the need for further research on variation in driving behavior. As emissions modeling research continues to develop new approaches on emissions prediction based on engine modal operation, the transportation community needs to know more about the characteristics of drivers that would cause these vehicle-and engine-operating distributions to occur. Driving patterns vary from one city to the next; hence, it is not enough to collect statistically valid vehicle data within a single city. At the very least, this would suggest that an important input variable for emissions models may be a driving behavior factor that represents the driving style and trip cycles found in that particular city, perhaps as a function of infrastructure, fleet characteristic, and demographics. Additional research is necessary to define better the different characteristics of this driving factor.

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Critical Analysis of Sketch-Planning Tools Used To Evaluate Benefits of Transportation Control Measures

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Two premier sketch-planning tools used to evaluate transportation control measures (TCMs)—the San Diego Association of Governments (SANDAG) TCM tools method and the Systems Applications International (SAI) method—are examined. A critical analysis and sensitivity analysis were performed on the SANDAG and SAI methods. Data collected for the El Paso, Texas, nonattainment area were used to evaluate the sensitivity results. The sensitivity analysis examined several variables in five TCMs: flextime, ridesharing, transit fare decrease, transit service increase, and parking management. Results of the sensitivity analysis showed that the tools are most sensitive to the TCM project descriptors and work-related variables. The report concludes that (a) recent work in the field has advanced the state of the practice and (b) although sketch-planning tools are gross estimating techniques, they are currently the best TCM analysis tools. Areas identified for improvement include (a) developing procedures for estimating TCM participation rates; (b) developing indirect trip effects and latent demand estimation procedures; (c) evaluating synergistic, additive, and negative effects of TCM programs; and (d) incorporating modal emission analysis.

Motor vehicles are an important part of modern society. Significant trends in automobile use have become apparent during the past 20 to 30 years. These trends are growth in vehicle miles of travel (VMT), number of licensed drivers, number of registered motor vehicles, and amount of fuel consumption. The combination of these trends has produced congestion in urban areas. The increase in congestion has brought mobile source emissions to the forefront of environmental concerns.

The main transportation-related pollutants are carbon monoxide (CO), hydrocarbons (HC), and nitrous oxides (NO_x). The Environmental Protection Agency (EPA) has reported that 78 million Americans live in the 41 metropolitan areas that exceed CO standards (*1*). The Clean Air Act Amendments of 1990 (CAAA) were enacted to reduce the extent of mobile source emissions in urban areas. These amendments specifically call for transportation control measures (TCMs) to reduce air pollution. TCMs are best defined by the California Clean Air Act Amendments of 1988 (*2*), which describe them as strategies that "reduce vehicle trips, vehicle use, vehicle miles traveled, vehicle idling, or traffic congestion for the purposes of reducing motor vehicle emissions."

Before TCMs can be used to reduce mobile source emissions in metropolitan areas, the type and extent of their implementation must be decided. These steps are part of the transportation air quality planning process, which has been used since the late 1970s in metropolitan areas throughout the United States. Several sketch-planning tools for TCM evaluation have been devised over the years. Most have built on past work, whereas others have strived to break new ground through their own methodologies. The two most current methodologies are the San Diego Association of Governments (SANDAG) methodology developed by Sierra Research, Inc., with support from JHK & Associates, and the Systems Applications International (SAI) methodology prepared for EPA.

Sketch-planning tools are used to predict the effects of engineering actions before they are implemented. The SANDAG and SAI methodologies best represent the state of the practice for sketch-planning tools to evaluate the potential benefits of TCM implementation.

This study had one primary objective and several secondary objectives. The primary objective was to analyze critically sketch-planning methods that evaluate the mobile source emission benefits of TCMs. This analysis examined each method's logic, data requirements, and results. The secondary objectives were to assess each methodology's sensitivity to specific data inputs, identify areas for improvement, and suggest possible solutions to enhance the current models.

The scope of the study was limited to the SANDAG and SAI methods. This study used data gathered from El Paso, Texas. El Paso is categorized as a serious ozone nonattainment area and a moderate CO nonattainment area.

LITERATURE REVIEW

Several TCM evaluation methods have been developed during the past 20 years. The first document on TCM analysis was NCHRP Report 263, published in the early 1980s. Little subsequent development occurred until the late 1980s. Since then, several new methods have been developed through California's leadership in air quality analysis. The Sacramento 1991 Air Quality Attainment Plan summarized the state of the practice, "There is currently no universally acceptable methodology for evaluating TCMs." (*3*)

The methods reviewed as part of this study were NCHRP Report 263, Air Quality Analysis Tools version 3 (AQAT-3), Turnbull method, Sacramento Metropolitan Air Quality Management District (SMAQMD), San Luis Obispo Air Pollution Control District (SLOAPCD), SANDAG TCM Tools, SAI, North Central Texas Council of Governments (NCTCOG), Houston-Galveston Area Council (HGAC), and the Texas Department of Transportation (TxDOT). The AQAT-3, SMAQMD, SLOAPCD, and SANDAG methods were developed in California.

Many of the California-based methods were not developed with out-of-state use in mind. Specifically, these methods incorporate

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California emission factor models that are not appropriate to use outside of California.

Older methods generally were concerned with determining the reduction in either trips or vehicles. Current methods investigate these changes as well as changes in VMT and speeds. Obtaining estimated changes in VMT and speeds is important when estimating the mobile source emission benefits from TCMs.

No method reviewed is capable of fundamental demand estimation. SANDAG and SAI are the only methods reviewed that evaluate the effects of latent demand and indirect trips on the total performance of a TCM. SAI estimates latent demand and indirect trip effects through social and economic parameters, which fall away from fundamental demand estimation. Other methods neither estimate these factors nor document that they are a concern. Induced demand through latent demand and indirect trips can negate some of the benefits gained from TCMs.

The basic mobile source emission components of a vehicle trip are start emissions, running emissions, hot soak emissions, and diurnal emissions. Very few methods reviewed accounted for start emissions. Start emissions are an important component of the vehicle trip because most vehicle emissions occur when the vehicle is started. A vehicle produces more emissions when it has been at rest for some time (cold start) than when it is started within a few minutes of the engine being turned off (hot start). The SANDAG and SAI methods account for all of the basic mobile source emission components. Other methods account for only some of the components.

The SANDAG and SAI methodologies are at the forefront of the sketch-planning methods to evaluate mobile source emission reductions from TCMs. These methods begin to evaluate the travel effects generated from latent demand and indirect trips caused by TCM implementation. They also begin to account for start fractions and emissions generated for the whole trip.

The SANDAG methodology has three modules: travel impacts, emission impacts, and cost-effectiveness. The method is designed to predict the effect of individual TCMs (*4*). The method includes 25 TCMs; user-defined TCMs can also be evaluated. These TCMs are

- Growth controls,
- Jobs and housing balance,
- Densification,
- Mixed use,
- Transit service increases,
- Park-and-ride lots,
- Bicycle improvements,
- Ridesharing,
- VMT tax,
- Pedestrian improvements,
- Traffic signal improvements,
- Employee Transit pass subsidy,
- Telecommuting,
- Flextime,
- Staggered work hours,
- Compressed work week,
- Delivery timing,
- Capacity increases,
- High-occupancy vehicle (HOV) lanes,
- Trip reduction ordinances,
- Parking management,
- Gas tax and cost increase,
- Motorist information, and
- Incident management and response.

The method was developed using LOTUS 1-2-3 and FORTRAN. The emission module uses two California emission factor models: EMFAC7 and BURDEN7C. The cost-effectiveness module uses output from the travel and emission modules and computes daily costs for pollutant mass removed.

The SAI methodology is EPA's most recent attempt to estimate the potential emission benefits from the implementation of TCMs. Its basic structure consists of two modules: travel effects and emission effects. The method provides analysis procedures for seven TCMs: telecommuting, flextime, compressed work week, ridesharing, transit improvements, HOV lanes, and parking management. The documentation of the methodology provides step-by-step instructions on how to estimate the effects on trips, VMT, and speeds from selected TCMs. The emission module can be used with any emission factor model. A limitation of this method is that no computer software is available to implement the method, and it would be very cumbersome to use with pencil and paper.

STUDY DESIGN

Conversion of SANDAG and SAI Methodologies to Spreadsheet

Both methods were programmed or imported, or both, into an available spreadsheet. The SAI method was programmed in its entirety. The SANDAG method was imported and modified to the available spreadsheet's standards. The SANDAG method was further modified so that emission estimates could be compared between the two methods.

The SANDAG method estimates emission reductions using the California-specific emission factor models (EMFAC7E and BURDEN7C). The SANDAG emission module could not be modified to allow MOBILE emission factors to be used. Thus, the SANDAG emission module could not be used to directly compare those results obtained from the SAI method. To overcome this problem, the SAI emission module was adapted for use with the SANDAG method's travel estimates to calculate a mobile source emission reduction.

Fourteen travel effect variables used in the SAI emission module were identified. The SANDAG method had equivalent variables for each of the 14 variables identified. This similarity made the use of the SAI emission module compatible with the SANDAG travel variables. Therefore, the two methods should produce comparable emission estimates given similar travel effects.

Description of Study Region

El Paso is located in west Texas and borders New Mexico and the Republic of Mexico. During the past decade, the city's population has increased steadily to a 1990 census population of 561,965, the fourth largest in Texas. The city is 4,000 ft above sea level and has several mountains around the perimeter of the central business district, forming an air basin. Because El Paso is classified as a serious ozone nonattainment area and a moderate CO nonattainment area, El Paso officials were interested in evaluating TCM options that could be used to reach attainment.

Data Collection

Data requirements for the two methods cover several areas: demographics, travel characteristics, and descriptors of the TCM. More than 100 variables were identified for evaluating TCMs with the SANDAG and SAI methods.

The data sources included TxDOT, the El Paso Metropolitan Planning Organization, Sun Metro (El Paso's transit authority), and the city of El Paso. Data collected from these sources accounted for approximately 60 percent of the baseline data required. The remaining data were collected by other means. For these data, suggested values developed in other regions of the United States were used, and other values were calculated from published sources. Peak-hour characteristics were estimated using peak-period modeling data based on the San Antonio 1990 travel survey. San Antonio was used to estimate El Paso's peak-period travel characteristics because the two cities are closer in size than other cities examined in the Texas travel survey study.

MOBILE5A Highway Vehicle Emission Factor Model

The MOBILE5A emission factor model was used in this analysis to calculate mobile source emission factors for the El Paso region. This version of MOBILE is the most current release from EPA. El Paso, like most nonattainment areas, is required to use mobile source emission factors developed from this model for evaluating mobile source emissions in the region. MOBILE data requirements include several control flags as well as additional input describing the region and scenarios. Control flags and additional data developed by the Texas Air Control Board (now the Texas Natural Resource Conservation Commission) were used in this study.

Sensitivity Analyses

Sensitivity analyses were performed on several of the methods' variables for two reasons: (a) to determine their impact on the methods and (b) to identify which variables are most critical to the estimation of travel and emission effects. These variables include several elasticities, user-specified values, and assumed data values used to evaluate five TCMs: flextime, ridesharing, transit fare decrease, transit service increase, and parking management. These TCMs were selected because El Paso officials showed interest in them.

Key travel results from the TCM evaluation (vehicle trip and VMT changes occurring in the peak and off-peak periods) were used in the sensitivity analysis. Emissions were not compared for two reasons: (a) the use of the SAI emission model in both spreadsheet models would not allow for a unique comparison between the two methods, and (b) emission estimates are calculated on the basis of the travel effects. The following equations were used to identify the methods' sensitivity to each variable:

$$\text{Sensitivity of Change in Vehicle Trips} = \frac{\Delta\ \text{Variable}}{\Delta\ \text{Vehicle Trips}}$$

$$\text{Sensitivity of Change in VMT} = \frac{\Delta\ \text{Variable}}{\Delta\ \text{VMT}}$$

These equations allow comparison between variables because each ratio has a common denominator. Variables were compared with other variables within a TCM and with the same variable in other TCMs. Each variable examined was changed by 10 percent of the baseline value where possible to simplify and standardize the analysis process across all variables.

The variables examined in the sensitivity analysis for each method were grouped according to defined categories: base travel variables, TCM scope descriptors, supplemental TCM descriptors, work-related variables, nonwork-related variables, and peak-period-related variables. Each of the categories is described as follows:

- Base travel variables are defined as those variables that describe the current condition of the region's transportation system. An example of the variables in this category is the fraction of trips made via shared mode.
- TCM project descriptors include scope descriptors and supplemental inputs used to determine the TCM's effectiveness. Scope descriptors are variables used to define the TCM's operation when implemented. Examples of scope descriptors are number of participants, frequency of participation, and average percentage of fare decrease. Examples of supplemental TCM descriptors are the new work trip length and elasticity of transit use with respect to cost.
- Work-related variables define characteristics of the work trips in the region. An example is the work trip generation rate for SOV users.
- Nonwork-related variables would include variables such as the fraction of nonwork trips during the peak period. Nonwork-related variables define the region's nonwork trip characteristics.
- Peak-period-related variables are variables about trip characteristics in the peak periods. An example is the fraction of the work (nonwork) trips during the peak period.

COMPARISON AND EVALUATION OF SANDAG AND SAI METHODOLOGIES

The comparison of the SANDAG and SAI methods covers several areas. The structure of each method is presented and reviewed. The outputs and data requirements of the two methods are also discussed. Unique and interesting areas in travel and emission change estimates are present. The discussion concludes with an evaluation of the methods' abilities to assess the benefits of TCM packages.

Method Structures

The SANDAG method can analyze a variety of TCMs. Its TCM selection covers a broad range of transportation actions that may be used in metropolitan areas to improve air quality.

The SANDAG method generally processes each TCM the same way, but there are exceptions. The travel module consists of four basic steps. The first step determines the changes in person trips. (For some TCMs, this step is omitted or included in the step that estimates vehicle trip changes.) The second step estimates changes in vehicle trips for the peak and off-peak periods. After the change in vehicle trips is determined, changes in VMT in the peak and off-peak periods are calculated from the trip changes. Finally, speed changes are determined for the peak and off-peak periods.

The SANDAG emission module is California specific and does not allow analysis for areas outside California. The regional limitation of this method is being corrected through FHWA funding and was expected to be available in fall 1994 for use throughout the nation. Documentation provided with the software did not clearly present the processes used to estimate mobile source emission reduction estimates.

The SAI method is consistent and straightforward. The method is limited in its selection of TCMs to analyze; however, a good base has been established in the documentation for future development of additional procedures to analyze additional TCMs.

The SAI travel module consists of nine steps. The first step is to calculate the number of person trips affected. Next, person trips are transformed into a reduction in vehicle trips based on the person trips affected. The change in vehicle trips is calculated for work and nonwork trips. The method then determines the indirect trip effects for each TCM for work and nonwork-related vehicle trips. Trip shifts out of the peak period and into the off-peak period are determined for TCMs associated with flextime and compressed work week programs. After these trip changes are determined, the method calculates the total vehicle trip changes associated with four trip categories: (a) work, peak; (b) work, off-peak; (c) nonwork, peak; and (d) nonwork, off-peak. This organization of trips provides a good accounting system of trips that occur in a region. Next, the reduction in VMT is calculated by the sum of VMT associated with vehicle trip reduction and changes in trip lengths. Finally, the change in regional speed is determined from changes in VMT, the initial VMT levels, and elasticities. Changes in emissions are estimated based on the results from travel changes.

The emission module consists of four steps. First, mobile source emission changes are calculated from vehicle trip changes. Second, mobile source emission changes associated with VMT changes are determined. Next, changes in mobile source emissions are calculated from fleet speed changes. Finally, the values from the previous steps are summed to yield a total mobile source emission change associated with a TCM.

Outputs

Reports of estimated mobile source emission changes are important because the objective of the CAAA is to influence mobile source emissions. Reports of travel changes are equally important because they are used to estimate mobile source emission changes.

The SANDAG and SAI methods both provide output in absolute terms. The SANDAG and SAI travel outputs are changes in vehicle trips, VMT, and regional speed (this is reported as a percentage of increase or decrease). The emission changes in the SAI method cover HC, CO, and NO_x. These pollutant reductions are reported in grams per day. The units of the emission output can be easily converted to other acceptable units (kilograms per day or tons per day). The SANDAG method provides emission change estimates for reactive organic gases, CO, NO_x and particulate matter. Before-and-after regional emission levels, as well as the percentage of reduction in emissions, are supplied to the user.

Data Requirements

Both methods have extensive data requirements. Three concerns with these data requirements are the user-supplied TCM participation rates, the use of defaults, and an inconsistency in the definition of work trips with traditional planning models.

User-Supplied TCM Participation Rates

Both methods require the TCM analyst to enter target participation rates; however, MPOs cannot confidently provide participation rates for TCMs. Therefore, the tools provide a means for testing "what if" scenarios for TCM participation and require the TCM analyst to design a program to reach the target participation rate.

Neither method covers the total TCM planning process by requiring the user to input target participation rates. The TCM planning process includes governmental or employer actions, traveler reactions, and transportation system changes. There are three steps in the TCM planning process: (a) estimate the number of travelers who will participate in the TCM, (b) estimate the change in travel demand resulting from this level of participation, and (c) estimate the change in traffic conditions resulting from this change in demand. The SANDAG and SAI sketch-planning tools require the TCM analyst to perform the first step (i.e., estimate TCM participation rates) and provide the results as input for the second step. The sketch-planning tools perform the second and third steps.

Use of Defaults

Defaults are used in many analysis tools as a means of managing the burdens of data collection. The same principle applies to these sketch-planning tools. Default values are generally used for elasticities and data that are difficult to obtain.

Both methods use elasticities to predict traveler behavior and travel characteristics. Elasticities for predicting traveler behavior estimate the travel responses to cost increases. Elasticities used to predict travel characteristics estimate the changes in travel speed with respect to volume. The TCM analyst should be aware that the speed-volume elasticity is not constant over a wide range of volumes as implied when using a single elasticity. The elasticity should be a reflection of the expected volume-to-capacity ratio on the transportation network.

Both methods stress that TCM analysts should develop regional data inputs to accurately model the effects of TCMs on the regional transportation system. The TCM analyst must understand that results can be substantially different if regional data are used in place of default data.

Inconsistent Work Trip Definition

There is a conflict in the work trip definition between sketch-planning tools and traditional planning models. In sketch-planning tools, a work trip is defined as a trip ABC, as shown in Figure 1, regardless of the number of intermediate stops. In traditional planning models, this trip is broken into components if there is an intermediate stop B between points A and C. The original trip would then become two distinct trips: AB and BC. These two trips cannot be reassembled once they are broken into its components. Users cannot obtain complete trip information in the study region once the trips have been segmented in the traditional planning models.

Travel Change Estimations

Vehicle trip reduction is estimated after the affected person trips are calculated. The SANDAG method determines changes in person and vehicle trips. In most instances, calculating the change in person trips is not a separate step in the analysis. It is, however, com-

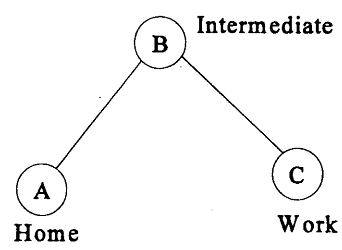

FIGURE 1 Work-Trip Schematic.

bined in the step that determines the reduction in the number of vehicle trips associated with a particular TCM. SAI has two distinct steps that determine reduction in person and vehicle trips.

The SANDAG vehicle trip changes are categorized in a different process from the SAI method. The SANDAG method first determines vehicle trip reduction for the peak and off-peak periods and then divides those trip reductions into work and nonwork trips. The SAI method categorizes vehicle trip changes by work and nonwork before splitting these categories into time periods (peak and off peak).

Indirect Trip Effects

Indirect trip effects refer to additional trips that occur when a commuter leaves a vehicle at home and another household member uses the vehicle for other purposes. These effects must be estimated to model the complete travel effects of a TCM.

The SAI method is the only method to estimate indirect vehicle trip effects. The method estimates vehicle trip increases related to work and nonwork travel based on several variables including the fraction of the population that does not own a vehicle and the work and nonwork trip generation rates for SOV users. The estimated increase in work and nonwork vehicle trips are combined with the overall trip changes to yield a net change in vehicle trips.

Latent Demand

Latent demand is the demand attracted to a roadway because of improved conditions. This phenomenon is not completely understood, and research is ongoing to determine its processes. SANDAG and SAI were the only methods reviewed that recognized latent demand as a factor that influences the overall effectiveness of a TCM. As a result from the lack of conclusive research on the attraction and effects of latent demand, both methods lack a quantitative completeness needed in this area.

SANDAG estimates the latent demand effects associated with TCMs differently from SAI. First, SANDAG does not evaluate latent demand effects for all TCMs. Where it is used, SANDAG requires the user to enter the increase in volume.

SAI is the first model to attempt to calculate latent demand. It does not, however, use its latent demand results in subsequent calculations to assess its impact on the transportation system.

Emission Change Estimations

The SANDAG and SAI methods include many mobile source emission components that are small contributors to total vehicle emissions. These components include running exhaust, start exhaust, and evaporative and diurnal emissions. Evaporative emissions in the SANDAG method cover running, hot soak, and diurnal breathing. The SAI method's evaporative emissions do not include diurnal breathing but do account for crankcase and refueling emissions.

A unique step in the SAI emission analysis is the estimation of emission changes from fleet speed changes. These emission changes are a result of decreased congestion and improved levels of service. CO is reduced more substantially in this step than are the other two pollutants (HC and NO_x) because a decrease in recurrent congestion decreases the amount of vehicle idling, which is a direct and major contributor to CO hot spots. The assumption for this step is that all vehicles are affected by the TCM, regardless of participation in the TCM. This assumption is made because the TCM will benefit the region by increasing the speed, affecting all drivers in the region. In many cases, a TCM project may experience additional mobile source emission benefits if the regional fleet speed is increased by only 1.61 or 3.2 km/hr (1 or 2 mph).

Neither method was able to incorporate modal emissions in their analysis. Modal emissions are currently being researched by EPA as a part of understanding the mobile source emission interrelationships within the acceleration, cruise, deceleration, and idle cycle. Numerous acceleration and deceleration cycles have been known to increase fuel consumption, which in turn leads to increased automotive emissions. Once results are available on this topic, modal emissions should be included in the SANDAG and SAI methods as part of the total emission analysis.

TCM Packages

Neither method has the complete ability to assess TCM packages. The methods can evaluate the additive effects of TCMs but cannot assess the synergistic and negative effects of TCM combinations. It is important to consider these effects when designing a TCM program. Individual TCM analysis within a package of TCMs may lead to a false conclusion about their combined effectiveness if these effects are not considered.

Many TCMs work with other TCMs to increase further the mobile source emission benefits from a TCM program. Conversely, many TCMs compete for the same traveler market. Analyzed separately, the TCM package may indeed exhibit sizable benefits, but once implemented, the program may not be cost effective because of competing TCM actions.

SENSITIVITY ANALYSIS OF SANDAG AND SAI METHODOLOGIES

A sensitivity analysis was performed on many variables for each of the TCMs studied to determine their effect on the estimated TCM's benefits. The sensitivity analysis was based on changes from base scenarios. In each sensitivity test, base scenario values were used in the TCM, except for the variable being tested. The variables were then categorized by type and the sensitivity for the variable category was summarized.

Qualitative sensitivity ratings were based on the percentage of changes between the set of variables examined within each TCM. If a variable exhibited a significantly higher percentage of change than other variables within the TCM, it was ranked as possessing a high sensitivity.

The relationship between sensitivity and data reliability is important to understand. Table 1 shows possible combinations of sensi-

TABLE 1 Potential Error in TCM Evaluation

	Sensitivity		
Reliability	High	Moderate	Low
High			MINIMUM
Moderate			
Low	MAXIMUM		

tivity and data reliability. The minimum potential error in TCM estimation lies in variables where the sensitivity is low and the data reliability is high. Potential error in TCM evaluation increases as the sensitivity increases and the reliability decreases.

The reliability of target TCM participation rates is a concern for the TCM analyst. Currently, there is no basis for selecting participation rates of TCMs. Thus, the sketch-planning tools act as a test bed for "what if" scenarios.

Tables 2 and 3 summarize the sensitivity analysis performed for this study. Several pages of tables document the complete sensitivity analysis in a TTI Research Report 1279-5 (*5*). Table 2 shows the average sensitivity results for the SANDAG and SAI methods. The sensitivity of vehicle trip and VMT changes to the variable categories is shown for the peak and off-peak periods, as well as a total average. Table 3 displays the qualitative assessment of the sensitivity results obtained from the results of individual TCM evaluations and the averages shown in Table 2. Three variable categories were not represented in the sensitivity analysis from the SANDAG method: work, nonwork, and peak period.

The variable categories yielding the highest sensitivity on the outputs are the TCM project descriptors (scope descriptors and supplemental descriptors). These are the most critical variables to estimate or enter. These variables define the extent of the TCM and which trips will be affected.

The word "estimate" is used in this discussion for cases in which TCM participation rates are input, because accurate values cannot be used in the analysis. TCM analysts must provide the sketch-planning tools with their best guess of TCM participation. TCM analysts may decide to test a range of participation, which would yield an estimated range of emission reduction.

Work-related and base travel variables were found to have a moderate sensitivity effect on the methods' results. This is a logical ranking considering that the focus of TCMs is on work-related travel. Very few TCMs are designed to affect travel for nonwork trips.

Nonwork-related and peak-period-related variables yielded moderate to low output sensitivities. Nonwork-related variables do not pose significant problems in TCM analysis because TCMs do not focus on affecting this travel type.

CONCLUSIONS

Recent work on sketch-planning tools has advanced the state of the practice. The two methods examined in this report are evidence of this progress. More work is being conducted on the analysis procedures for TCMs throughout the country. Many methods provide unique techniques in estimating both travel and emission effects. As work in this area progresses, standard analysis procedures may be developed and implemented.

TCM analysts must realize that sketch-planning tools are techniques for gross estimation of TCM benefits. Although these tools provide TCM analysts with only a first look at the potential benefits of TCMs, they are the best tools for analysis at this time. Network-based travel demand and traffic simulation models do not have the capability at this time to estimate benefits of a wide range of TCMs.

Several areas of the sketch-planning tools were identified for improvement. Data requirements could be improved by assisting

TABLE 2 Average Sensitivity Results for SANDAG and SAI Methods

		Vehicle Trips (%)			VMT (%)		
Method	Variable Category[a]	Peak	Off-Peak	Total	Peak	Off-Peak	Total
SANDAG	Base Travel	-0.00050	-0.00020	-0.00035	-0.00040	-0.00020	-0.00030
	TCM Scope Descriptors	-0.00646	-0.00793	-0.00720	-0.00604	-0.00545	-0.00574
	Supp. TCM Descriptors	-0.00024	-0.00021	-0.00023	-0.00023	-0.00016	-0.00019
	Work Related[b]						
	Non-Work Related[b]						
	Peak Period Related[b]						
SAI	Base Travel	0.00045	0.00023	0.00034	0.00047	0.00020	0.00034
	TCM Scope Descriptors	-0.03639	-0.01001	-0.02320	-0.03043	-0.01291	-0.02167
	Supp. TCM Descriptors	-0.00184	-0.00075	-0.00129	-0.00179	-0.00052	-0.00116
	Work Related	0.00054	0.00031	0.00042	0.00058	0.00026	0.00042
	Non-Work Related	0.00001	0.00014	0.00008	-0.00005	0.00010	0.00006
	Peak Period Related	-0.00013	0.00010	-0.00002	-0.00012	0.00006	-0.00003

[a] Average variable changes were 10%
[b] No variables tested with this designation

TABLE 3 Qualitative Sensitivity Results for SANDAG and SAI Methods

Method	Variable Category	Sensitivity		
		High	Moderate	Low/None
SANDAG	Base Travel		X	
	TCM Scope Descriptors	X		
	Supp. TCM Descriptors		X	
	Work Related[a]			
	Non-Work Related[a]			
	Peak Period Related[a]			
SAI	Base Travel Variables		X	
	TCM Scope Descriptors	X		
	Supp. TCM Descriptors		X	
	Work Related		X	
	Non-Work Related			X
	Peak Period Related			X

[a] No variables tested with this designation

analysts in (a) estimating TCM participation, (b) developing regional data for the model and not relying on defaults developed elsewhere, and (c) finding some consistency in the work trip definition between sketch-planning tools and traditional planning models. Travel change estimates may be improved by continuing to develop procedures to estimate the effects of indirect trips and latent demand. Mobile source emission changes estimated in the methods do not account for modal emissions. Once research is completed on modal emissions, efforts should be undertaken to include modal emissions in the sketch-planning tool analysis. TCM packages are unable to be evaluated with sketch-planning tools. These tools currently can only evaluate TCMs individually, thus not accounting for any synergistic, additive, or negative effects TCM actions may cause.

The sensitivity analysis showed that TCM project descriptors are the most sensitive when analyzing a TCM. Descriptors that define the scope of the TCM being evaluated are also extremely important to obtain accurate representations of regional benefits from a TCM. The base travel and work-related variables have a moderate sensitivity. Accurate data collection for the sketch-planning tools should focus on variables that define the base travel characteristics of the region as well as work-related variables. The work-related variables are more sensitive than nonwork- and peak–period-related variables.

RECOMMENDATIONS

Four recommendations were made based on the results of this study:

- Develop procedures for estimating TCM participation rates. The sketch-planning tools currently require the TCM analysts to enter target TCM participation rates. However, procedures do not exist to assist in defining the scope of TCM programs. Therefore, procedures designed to predict traveler reactions to TCM actions must be developed.
- Develop indirect trip effects and latent demand estimation procedures. The SAI method provides a good first attempt to quantify indirect trip effects and latent demand; however, the procedure should be refined and in the case of latent demand should be used in the analysis. Indirect trip effects and latent demand have a potential to counter the benefits from a TCM program. Therefore, research results from these areas should be incorporated into TCM analysis.
- Incorporate modal emission analysis. Modal emission analysis may provide insight on which TCMs can most effectively reduce these types of emissions. Fewer accelerations and decelerations made by a vehicle decrease fuel consumption and tailpipe emissions. Although work in this area is just beginning, an effort should be undertaken to determine if this type of analysis can be included in the sketch-planning tools.
- Evaluate synergistic, additive, and negative effects of TCM programs. TCM experts agree that single TCMs will not provide as great a benefit as a well-designed program of TCMs can deliver. Many TCMs do not have additive effects when implemented with other TCMs. For instance, an increase in carpools coupled with a transit fare decrease would detract riders from one of the two TCMs and would not effectively reduce overall emissions. Currently, the only way to assess the potential benefits of a TCM program is to analyze each TCM individually, which is inadequate.

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Statistical Assessment of Vehicular Carbon Monoxide Emission Prediction Algorithms

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Increased concern about the ability to accurately model and predict emissions from motor vehicles prompted this research. The ability of the mathematical algorithms contained in version 4 of the CALINE line source dispersion model (CALINE4) developed by Caltrans to accurately predict carbon monoxide (CO) emissions from a fleet of motor vehicles is assessed. The CALINE4 model contains algorithms that predict CO emissions from discrete modal events of idle, cruise, acceleration, and deceleration. A BASIC computer program is used to assess and compare the performance of the CALINE4 algorithms with those incorporated in version 7F of the EMFAC model (EMFAC7F), which is used and developed by the California Air Resources Board. The statistical assessment includes comparisons of mean prediction bias, Theil's U-Statistic, and the linear correlation coefficient. The analyses demonstrate that the currently used CALINE4 algorithms perform similarly to those contained in EMFAC7F, but when modified to use individual emission rates (instead of fleet average emission rates), the CALINE4 algorithms generally outperform the EMFAC7F algorithms. For short- to medium-term microscale model improvements, it is recommended that the CALINE4 model be revised to (a) incorporate individual emission rates into its emission estimation algorithms, (b) update its statistically derived model coefficients, and (c) update the modal activity algorithms to cover all modeling scenarios. For long-term modeling improvements, it is recommended that a more robust modal model be estimated based on second-by-second data and additional causal variables, and true vehicle simulation models be used to estimate vehicle activity.

The Clean Air Act (CAA) requires metropolitan regions in nonattainment with National Ambient Air Quality Standards (NAAQS) for carbon monoxide (CO) to demonstrate timely reductions in regional CO emission inventories and zero increases in CO hot spots for project level air quality impact analyses (*1*). When regional and local planners are faced with making transportation growth and investment decisions, they are constrained to select only those projects that will decrease CO emission inventories and the severity and number of CO hot spots. Because these decisions often involve millions and sometimes billions of local, state, and federal dollars, there is a need for planners to conduct accurate, precise, and meaningful analyses. Accurate and precise estimates of CO inventories and CO hot spot impacts require statistically and theoretically robust CO estimation algorithms. The model California is using to estimate CO emission inventories is EMFAC7F-BURDEN, developed by the California Air Resources Board (CARB). A project-level CO impact analysis model commonly used in California is CALINE4, developed by the California Department of Transportation (Caltrans).

There are important differences between EMFAC and CALINE. First, CALINE is primarily a pollutant dispersion model used to estimate the CO impacts of transportation projects—it is intended for microscale applications. EMFAC, on the other hand, is an emission inventory model (when coupled with BURDEN and regional motor vehicle activity data) and estimates inventories of CO, nitrogen oxides (NO_x), and hydrocarbons (HC). In practice, EMFAC and CALINE emissions predictions are never directly compared because they operate under entirely different frameworks. The common thread between these two models, and the central focus of this paper, is that the EMFAC and CALINE models contain mathematical algorithms that predict CO emissions given vehicle activity estimates.

This paper examines how well these algorithms predict CO emissions. There are two motivations for this research. First, concern over the ability of CARB's EMFAC7F emissions model to estimate accurately modal emission inventories from motor vehicles (*2,3,4,5,6*) has prompted the need to statistically quantify the performance of the mathematical algorithms. In addition, the CO emission prediction algorithms contained in the CALINE4 model use modal correction factors, which correct the baseline emission rate employed in EMFAC (or MOBILE) based on estimates of acceleration, deceleration, cruise, and idle activity. This is in contrast to the EMFAC model algorithms, which use speed correction factors to correct baseline emission rates based on average speed estimates.

Second, the CO-emission prediction algorithms that are embedded in the CALINE4 model and that are used when the intersection option portion of the model is selected have never been statistically verified using real emissions data. Because Caltrans uses these models to perform project-level CO emission analyses, Caltrans staff wanted to verify the CO emission prediction algorithms by comparing their predictions to those predicted by the EMFAC model—expecting that the CO-emission predictions between models would be consistent.

This paper presents the results of a technical and statistical assessment of the ability of the CALINE4 and EMFAC7F mathematical algorithms to adequately predict measured CO emission rates from motor vehicles tested on numerous laboratory testing cycles. The algorithms are dissected to determine where prediction errors are likely to originate and how the algorithms could be improved. The statistical assessment uses measures of performance such as mean prediction bias, Theil's U-Statistic, and the linear correlation coefficient to compare predicted CO emissions with measured CO emissions. These performance tests use the CO emission test results from 14 standardized testing cycles (*2*). To aid in the analyses, a BASIC computer program was developed to reproduce the internal algorithms for both the CALINE4 and EMFAC7F models (*7*).

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DESCRIPTION OF STANDARDIZED TESTING CYCLES USED TO ASSESS CALINE4 AND EMFAC7F

Summary statistics on the standardized testing cycles contained in the speed correction factor (SCF) data set are shown in Table 1. The table shows some of the pertinent characteristics unique to each the cycle, such as the distance of the test cycle and the duration of the cycle. The table also depicts modal attributes of each cycle. For example, almost half of Low Speed Test Cycle #3 is spent with vehicles in the idle mode of operation. The age of the vehicles tested on these cycles ranged from 1977 model years to 1990 model years. About half of the cycles have emission results for 464 vehicle tests, while a couple of the tests (High Speed Test Cycles #1 and #2) have only 25 vehicle test results. These emissions test results represent the current data set used by CARB and the Environmental Protection Agency (EPA) to develop their emission factor models, EMFAC7F and MOBILE5A respectively. The data are currently the most comprehensive and quality-controlled U.S. emissions data available over a variety of testing cycles.

The modal activity data shown in the table represent the percentage of time the total cycle spent in a particular mode of operation. For example, 21 percent of the 505 sec of the Federal Test Procedure (FTP) Bag 1 is spent with the vehicles accelerating. Acceleration (A) conditions are defined as increases in velocity (V) over two consecutive seconds of operation and can last any number of seconds. Derivation of deceleration ($-A$), idle ($A = 0$, $V = 0$), and cruise operations ($A = 0$, $V \neq 0$) are derived in a similar straightforward manner.

The 14 test cycles shown in the table represent unique profiles of modal activity. Each cycle was developed to approximate driving behavior under different conditions. For example, the New York City cycle approximates driving in New York City, which is characterized by a low mean speed (11.4 km/hr) and a lot of modal activity. The FTP Bags 1 through 3 are important fundamental components of the MOBILE and EMFAC emissions models. In the EMFAC7F model, for example, FTP Bag 2 test results are used as the base emission rate, which are then "speed corrected" to derive emissions at average speeds other than 16 mph (the FTP Bag 2 cycle average speed). FTP Bags 1 and 3 contain emission contributions from cold and hot starts, respectively, and FTP Bag 2 contains hot stabilized emissions only. The importance of these test cycles is evident later in the paper.

THEORETICAL BASIS OF EMISSION PREDICTION ALGORITHMS

CALINE4 Line Source Dispersion Model

The CALINE4 line source dispersion model has been developed over many years by Caltrans. The CALINE4 line model estimates CO, NO_x, and suspended particulate concentrations. It uses the Gaussian diffusion equation to distribute air pollution over and along modeled roadways (*8*). EPA has approved the model as a tool to assess impacts from CO hot spots. The model is used primarily for local project analyses in areas where its use was established before July 1993. The model contains algorithms that estimate CO emission contributions from modal events of idle, acceleration, deceleration, and cruise, and therefore contains a modal emissions model component. This modal emission model component is used only when the intersection link option is used when running the CALINE4 model; otherwise for main line sections, MOBILE- or EMFAC-derived average emission rates are used.

CALINE4 has undergone three revisions since the original version in 1972, and it uses the Gaussian dispersion equation to distribute estimated emissions along a roadway. When the intersection link option is used, CO emissions are estimated on a modal basis; that is, equations or algorithms are used to predict CO emissions from each modal event (idle, cruise, acceleration, and deceleration). Information required to derive the modal events are intersection specific and require information about acceleration and deceleration times (from link endpoint to intersection stopline), minimum and maximum idle times, traffic volumes, and the number of vehicles delayed. The program uses these inputs to generate the modal activity occurring at an intersection (*8*). When the intersection option is not chosen, CO emission predictions are based on the speed-corrected baseline emission rates provided by EMFAC or MOBILE (*8*).

TABLE 1 Summary Statistics on Standardized Testing Cycles Used in Analyses

CYCLE NAME	TIME (sec)	DIST. (km)	MEAN SPEED (kph)	% IDLE	% ACCEL.	% DECEL.	% CRUISE
Federal Test Procedure - Bag 1	505	6.65	41.2	19.6	21.0	20.4	39.0
Federal Test Procedure - Bag 2	866	7.15	25.8	18.6	25.3	19.3	36.8
Federal Test Procedure - Bag 3	505	6.65	41.2	19.6	21.0	20.4	39.0
Highway Fuel Economy Test	765	19.00	77.7	0.7	14.1	11.8	73.4
High Speed Test Cycle # 1	474	10.98	72.5	1.1	13.3	9.9	75.7
High Speed Test Cycle # 2	480	12.59	82.1	1.0	13.8	10.4	74.8
High Speed Test Cycle # 3	486	14.44	93.0	1.0	14.2	10.9	73.9
High Speed Test Cycle # 4	492	16.32	103.7	1.0	15.3	11.4	72.3
Low Speed Test Cycle #1	624	1.30	6.5	36.5	24.2	25.6	13.7
Low Speed Test Cycle #2	637	1.18	5.9	38.8	23.4	24.3	13.5
Low Speed Test Cycle #3	616	0.96	3.9	47.7	16.2	17.9	18.2
New York City Cycle	598	2.18	11.4	34.9	23.9	24.2	17.0
Speed Cycle 12	349	2.17	19.4	27.2	26.1	24.1	22.6
Speed Cycle 36	996	18.37	57.7	6.5	19.0	16.0	58.5

The latest version of the algorithms used in the CALINE4 model is similar to those in the Colorado Department of Highways (CDOH) model released in 1980. The data used to estimate the CDOH models were derived from 37 discrete modes driven by 1,020 light-duty vehicles ranging from 1957 model year to 1971 model year (*9*). A subset of 62 vehicles representing California cars for model years 1975 and 1976 was used to estimate the coefficients employed in the CALINE4 algorithms (*8*). In the Caltrans and CDOH model development efforts, the modal acceleration speed (AS) product demonstrated good explanatory power for CO emissions estimation. Consequently, the AS product, defined as the product of the average acceleration and average speed for the acceleration event, is one of the explanatory variables used in the CALINE4 model (*8*). For a more detailed description of the CALINE4 model, see the work by Benson (*8*).

The CALINE4 modal emission algorithms can be written as

$$TE_{ik} = EI_{ik} + EA_{ik} + EC_{ik} + ED_{ik} \tag{1}$$

where

TE_{ik} = total CO emission estimate for vehicle i on cycle k in grams,
EI_{ik} = CO emissions from idle events for vehicle i on cycle k in grams,
EA_{ik} = CO emissions from acceleration events for vehicle i on cycle k in grams,
EC_{ik} = CO emissions from cruise events for vehicle i on cycle k in grams, and
ED_{ik} = CO emissions from deceleration events for vehicle i on cycle k in grams.

The emission contributions from the discrete modal events can be defined as

$$EI_{ik} = (IR_{[g/sec]}) * (t_{i[sec]}) \tag{2}$$

where IR is measured idle emission rate and t_i is time spent in the idle operating mode.

$$EA_{ik} = [(FTPB2_{[g/min]}) * (C1) * EXP\ (C2 * AS)] * t_{a\,[sec]} * 1_{[min]}/60_{[sec]} \tag{3}$$

where

$FTPB2$ = measured emission rate on FTP Bag 2,
Coefficients $C1$ = 0.75 and $C2$ = 0.0454 for acceleration condition 1,
Coefficients $C1$ = 0.027 and $C2$ = 0.098 for acceleration condition 2,
Acceleration condition 1 is for vehicles starting at rest and accelerating up to 45 mph (72.42 km/hr),
Acceleration condition 2 is for vehicles starting at 15 mph (24.14 km/hr) or greater and accelerating up to 60 mph (96.56 km/hr),
AS = acceleration speed product based on average speed and average acceleration rate of the accel mode in mi²/hr²/sec, and
t_a = time spent in the acceleration mode.

$$EC_{ik} = (FTPB2_{[g/min]}) * [(0.494 + 0.000227 * S_{[km/hr]})^2] * (t_{c\,[sec]} * 1_{[min]}/60_{[sec]}) \tag{4}$$

where

$FTPB2$ = measured emission rate on FTP Bag 2,
t_c = time spent in the cruise event, and
S = average speed of the vehicle in the modal event in mph.

$$ED_{ik} = (IR_{[g/sec]}) * (t_{d[sec]}) * 1.5 \tag{5}$$

where IR is measured idle emission rate and t_d is time spent in the deceleration operating mode.

It is critical to note that the FTP Bag 2 emission rate and the IDLE emission rate used in the CALINE4 model program are estimated average values for the on-road fleet of motor vehicles. The CALINE4 algorithms do not contain emission factors that differentiate between technology groups or model year. The result is that the CALINE4 modal emission prediction algorithms predict equivalent modal contributions of emissions for all modeled vehicles, the average emission rate over a given driving segment. In other words, a 1980 Cadillac Seville is predicted to emit the same as a 1993 Geo Metro, the Seville's emissions being underpredicted and the Metro's emissions being overpredicted using the fleet mean value.

EMFAC7F—California Regional Emissions Model

The EMFAC7F emissions model developed by CARB operates differently from CALINE4. Instead of taking a modal approach, EMFAC7F uses average operating speed and fuel delivery technology and model year as explanatory variables in the model. For each of four technology group classifications based on fuel delivery technology and model year, EMFAC7F predicts a modal emission ratio, based on the ratio of emissions on the FTP to emissions at other cycle average speeds. The resultant ratios are called SCFs and are used to estimate emissions at speeds other than 16 mph (at 16 mph measured emissions are predicted). For a complete description of the operating characteristics and analyses of the recent EMFAC7F model, see the work by Guensler (*2*).

The regression form of the EMFAC7F model for predicting CO emissions can be written as

$$TE_{mn} = \{BAG2_n * [EXP\ (\mathbf{B1}_n * SADJ1) + (\mathbf{B2}_n * SADJ2) + (\mathbf{B3}_n * SADJ3) + (\mathbf{B4}_n * SADJ4)]\} + \text{error} \tag{6}$$

where

TE_{mn} = total CO emissions for vehicle m from technology group n,
$BAG2_n$ = average measured Bag 2 result for technology group n vehicles,
$SADJ1$ = (16 − average prediction speed),
$SADJ2$ = (16 − average prediction speed)²,
$SADJ3$ = (16 − average prediction speed)³,
$SADJ4$ = (16 − average prediction speed)⁴,
$\mathbf{B1}_n, \ldots, \mathbf{B4}_n$ = least squares estimated coefficients, and
error = the disturbance term.

As noted previously, four models are estimated based on CARB-defined technology groups. The technology groups are shown in Table 2.

Also, somewhat similar to CALINE4, EMFAC7F derives an average emission factor, in grams per mile, for an entire fleet of on-road vehicles. This average emission factor will result in over-

TABLE 2 Technology Groups Used in EMFAC7F SCF Model

CARB Technology Group	Model Year	Fuel Delivery Technology
1	1985 or earlier	Carbureted and Throttle Body Injection
2	1985 or earlier	Port Fuel Injection
3	1986 or later	Carbureted and Throttle Body Injection
4	1986 or later	Port Fuel Injection

prediction of emissions for "clean" vehicles and under-prediction of emissions for "dirty" vehicles.

CARB's model has been criticized for statistical and theoretical reasons. Among the statistical criticisms are non-normal error distributions, high multicollinearity among the explanatory variables, biased parameter estimates, and wide confidence intervals around the SCF curves (*2*). The theoretical criticisms are primarily concerned with the exclusion of causal explanatory variables, a nonrepresentative sample fleet of vehicles, and nonrepresentativeness of driving cycles as compared with real driving behavior.

MODEL PERFORMANCE EVALUATION

This research compares the ability of CALINE4 and EMFAC7F co-emission prediction algorithms to adequately predict measured emissions from a standardized and large data set. Using the SCF data base as the validation data set, the ability of both models to accurately predict measured emissions obtained from vehicles under numerous testing cycles is assessed. EMFAC7F has a slight advantage over CALINE4 because its emission algorithms were estimated using the SCF data set, while the CALINE4 model algorithms were estimated using a subset of the CDOH data set discussed earlier.

In practice, the CALINE4 and EMFAC7F model algorithms operate using fleet average FTP Bag 2 and idle rates (the CALINE4 user inputs values derived from EMFAC7F or MOBILE). In other words, the emission input data are aggregate data for a fleet of vehicles. For the analyses presented here, aggregate Bag 2 and idle rates were obtained by computing the average values for these variables for all vehicles contained in the SCF data set.

Using individual vehicle Bag 2 and idle rates, on the other hand, represents a significant modification to the way in which the model algorithms are used. Using individual vehicle test results, or disaggregate data, the model algorithms are allowed to capture the effect of algorithm prediction differences between vehicles, a degree of prediction flexibility not possible when aggregate data are used. Disaggregate analyses are performed here to investigate algorithm improvement possibilities.

Comparison of Mean Predicted Emissions

A desirable emission prediction algorithm will not be biased in its prediction of CO emissions. One indicator of bias in a model is the difference between true average emissions and estimated average emissions. Ideally, the mean value of the predicted emissions should be the same as the mean value of actual emissions. This is especially true when considering the current application of CALINE4 and EMFAC7F, which operate using average fleet emission rates. A great discrepancy in means over a large sample suggests that the model is consistently over- or underpredicting the actual emissions and that model predictions are biased.

To quantify biases for the CALINE4 and EMFAC model algorithms, estimated emissions were summed over a test cycle and then averaged according to the number of vehicles in the test cycle. As an example, the predicted emission estimates for vehicles tested on High Speed Cycle #2 are summed and then divided by 25 vehicles to compute the average emission estimate. The average emission estimate is then compared with the average observed emission result for the vehicles tested on that cycle to determine the mean bias. The formula for mean bias is given by

$$MPB_j = \left(\sum_i Y_{ij} - \sum_i \Psi_{ij}\right)/n_j \tag{7}$$

where

MPB_j = mean prediction bias on all vehicles on cycle j,
$\sum_i$ = summation over i vehicles,
Y_{ij} = predicted emissions for vehicle i on cycle j in grams,
Ψ_{ij} = observed emissions for vehicle i on cycle j in grams, and
n_j = number of vehicles tested on cycle j.

The mean prediction bias for the CALINE4 and EMFAC emission prediction algorithms is shown in Table 3. The table shows both the aggregate and the disaggregate model assessments. Disaggregate refers to the use of individual vehicle Bag 2 emission rates in model emission prediction algorithms, and aggregate refers to the use of average fleet Bag 2 emission rates, which is consistent with the manner in which the model algorithms are used in practice.

Note that EMFAC7F CO-emission prediction algorithms generally outperform the CALINE4 algorithms when mean prediction bias comparisons are studied. This suggests that when average fleet emission rates (aggregate) are used, EMFAC7F algorithms in general perform better than CALINE4 algorithms. (Recall, however, that model results are never compared in practice because of their distinctly different purposes.) The difference is not drastic, however, and the CALINE4 model algorithms have less prediction bias on several cycles. Furthermore, EMFAC7F CO-emission prediction algorithms have smaller biases for disaggregate model analyses. These findings are not surprising, because the coefficients embedded in the CALINE4 model were estimated using an older fleet of vehicles, whereas EMFAC7F coefficients were estimated using the SCF data base vehicle test results. Because the comparison provides an unfair advantage to the EMFAC7F model, whether the modal components embedded in the CALINE4 model are performing well cannot be adequately assessed. It can be speculated, however, that given the comparisons depicted in the table, if the coefficients in the CALINE4 emission model were updated using the SCF data base vehicles, CALINE4 would likely outperform EMFAC7F.

CALINE4 and EMFAC7F model algorithms generally underpredict CO on the low-speed test cycles. CALINE4 underpredicts on the two highest high-speed cycles and overpredicts on the two lowest high-speed cycles. EMFAC7F tends to overpredict on all high-

TABLE 3 Comparison of Mean Model Prediction Bias (in grams)

Cycle	Mean Aggregate CO[a]	MPB Dis-aggregate CALINE4	MPB Dis-aggregate EMFAC7F	MPB Aggregate CALINE4	MPB Aggregate EMFAC7F
Highway Fuel Economy Test	51.40	-6.2	-3.3	-6.2	**-2.9**
High Speed Test Cycle # 1	4.24	**2.4**	3.9	**2.4**	4.0
High Speed Test Cycle # 2	4.55	**3.9**	5.4	4.0	5.4
High Speed Test Cycle # 3	11.60	-2.4	**2.2**	-2.3	2.3
High Speed Test Cycle # 4	38.26	-25.3	**12.1**	-25.3	13.7
Low Speed Test Cycle #1	24.99	-9.5	-3.2	-9.9	**-3.0**
Low Speed Test Cycle #2	24.47	-9.8	-2.5	-10.3	**-2.4**
Low Speed Test Cycle #3	22.34	-8.6	-3.3	-8.8	**-3.2**
New York City Cycle	29.20	-0.9	**0.3**	-2.0	0.8
Speed Correction Factor 12	16.65	**0.0**	-0.3	**0.0**	-0.2
Speed Correction Factor 36	63.68	**2.3**	4.6	3.0	2.4

Bold = Smallest absolute mean bias in emission estimate in Dis-aggregate or Aggregate comparison
[a] Mean aggregate CO determined by computing the arithmetic mean of Bag 2 test results of vehicles in SCF data base

speed cycles. It is important to note that model algorithms are not performing consistently across testing cycles with varying characteristics. This suggests that there still may be cycle-related variables not included in model algorithms that may help to explain these emission variations.

Theil's U-Statistic Comparisons

A proposed measure of model performance that is not subject to the scaling problems of the previous measure is Theil's U-Statistic (*10,11*). Theil's U-Statistic is related to R-Square but is not bounded by 0 and 1. Large numbers of U reflect poor fit to the data, and small values of U indicate good fit. The U-Statistic formula is given by

$$U_j = \{[(1/n_j) \textstyle\sum_i(\Psi_{ij} - Y_{ij})2] / [(1/n_j) \textstyle\sum_i(\Psi_{ij}) 2]\}^{0.5} \quad (8)$$

where

U_j = Theil's U-Statistic for all vehicles on cycle j,
$\sum_i$ = summation over i vehicles on cycle j,
Y_{ij} = predicted emissions for vehicle i on cycle j in grams,
Ψ_{ij} = observed emissions for vehicle i on cycle j in grams, and
n_j = number of vehicles tested on cycle j.

Theil's U-Statistic results are shown in Table 4. The table shows that, for disaggregate comparisons, Theil's U is consistently smaller for CALINE4 than for EMFAC7F. Under aggregate model applications, however, the emission prediction algorithms in the EMFAC7F model are superior. These results suggest that the CALINE4 model works well when the values input for IDLE and FTP Bag 2 are allowed to vary simultaneously with vehicles but, when constrained to fleet average values, it is no better than EMFAC7F. In fact, because algorithm coefficients for CALINE4 were derived from a much older fleet, the EMFAC7F model performs better under contemporary model applications.

Linear Correlation Coefficient Comparisons

As a final useful statistical comparison of the two models, the linear correlation coefficient is used (*12,13*). The linear correlation coefficient reflects the degree of probability that a linear relationship exists between observed and predicted emissions. If a model can predict observed emissions well, then the linear correlation is expected to be high, whereas if a model predicts poorly, the linear correlation coefficient will be low. The formula for the correlation coefficient is given by

$$r_j = \textstyle\sum_i[\Psi_{ij} - Y_j(\text{ave})][Y_{ij} - Y_j(\text{ave})] / \{\textstyle\sum_i[\Psi_{ij} - Y_j(\text{ave})]2 \times \textstyle\sum_i[Y_{ij} - Y_j(\text{ave})]2\}^{0.5} \quad (9)$$

where

r_j = correlation coefficient between observed and predicted emissions for i vehicles on cycle j,
$\sum_i$ = summation over i vehicles on cycle j,
Ψ_{ij} = observed emissions for vehicle i on cycle j in grams,
$Y_j(\text{ave})$ = average observed emissions for all vehicles on cycle j in grams, and
Y_{ij} = predicted emissions for vehicle i on cycle j in grams.

The correlation coefficients for the two emission prediction algorithms are compared in Table 5. The table shows that CALINE4 model algorithms generally outperform EMFAC model algorithms for disaggregate comparisons. Comparisons are not valid under aggregate conditions because the CALINE4 model predicts a constant value; thus the computation of the correlation coefficient yields 0. That the correlation coefficient varies over cycles with characteristically different modal activity suggests that a large proportion of modal activity is not explained by CALINE4's modal algorithms. This finding is magnified when it is considered that a great deal of observed modal activity is not represented in any of the test cycles contained in the SCF data set. For example, the greatest acceleration rate contained in the SCF data set is 3.3 mph/sec, whereas accelerations as high as 8.0 mph/sec have been observed in real world driving.

DISCUSSION OF RESULTS

This research effort has identified modeling deficiencies inherent in the algorithms contained in the CALINE4 and EMFAC7F emissions models. The CALINE4 model is used primarily for project-level analyses and is intended for microscale emission impact

TABLE 4 Comparison of Theil's U-Statistic (in grams)

Cycle Name	Dis-aggregate CALINE4 (Grams)	Dis-aggregate EMFAC7F (Grams)	Aggregate CALINE4 (Grams)	Aggregate EMFAC7F (Grams)
Highway Fuel Economy Test	0.605	**0.537**	0.967	0.966
High Speed Test Cycle # 1	1.107	1.524	**0.760**	0.968
High Speed Test Cycle # 2	1.524	1.930	**0.922**	1.125
High Speed Test Cycle # 3	0.799	0.935	0.752	**0.720**
High Speed Test Cycle # 4	**0.921**	1.054	0.940	0.936
Low Speed Test Cycle # 1	**0.689**	1.019	0.930	0.911
Low Speed Test Cycle # 2	**0.655**	0.964	0.943	0.923
Low Speed Test Cycle # 3	**0.702**	1.035	0.942	0.922
New York City Cycle	**0.389**	0.549	0.919	0.917
Speed Correction Factor 12	**0.413**	0.424	0.932	0.933
Speed Correction Factor 36	**0.533**	0.554	0.952	0.950

Bold = Smallest U-Statistic in emission estimate

assessment. It is often used to determine worst-case CO impact assessments of transportation projects. The CALINE4 model, furthermore, is not used for emission inventory purposes.

EMFAC7F, on the other hand, is primarily used for performing regional analyses. Used with transportation network models (UTPS type models), EMFAC7F estimates CO emission rates applied to activity in the air basin. Although both models are used to satisfy air quality modeling requirements stipulated in the Clean Air Act, their purposes are different. This distinction is important when considering recommendations for improving the models and technical improvements.

Several important deficiencies in the current modeling methodologies were illustrated, including the impact of errors in predicting mean emission rates on regional inventories, the use of fleet averages instead of individual vehicle emission rates, and the lack of causal variables in model formulations.

Statistical comparisons between the two models' algorithms included comparisons of mean prediction bias, Theil's U-Statistic, and the linear correlation coefficients between predicted and observed emissions. The assessment looked at both the aggregate model algorithms using average fleet emission rates and a disaggregate version of the algorithms using individual vehicle emission rates.

When making across-the-board comparisons between aggregate EMFAC7F and CALINE4 algorithms, it can be seen that EMFAC7F performs slightly better on almost all performance measures. This is not surprising, however, because the data set used to compare algorithms was also used to estimate the EMFAC7F algorithms, and the CALINE4 algorithms were estimated using a much older and smaller data set. Considering emissions algorithms using disaggregate data, however, CALINE4 algorithms predict emission rates better than do EMFAC7F algorithms. This difference is attributable to the inclusion of the idle variable in the CALINE4 model,

TABLE 5 Comparison of Correlation Coefficients (*r*)

Cycle Name	r Dis-aggregate CALINE4 (Grams)	r Dis-aggregate EMFAC7F (Grams)	r Aggregate CALINE4 (Grams) [a]	r Aggregate EMFAC7F (Grams) [b]
Highway Fuel Economy Test	0.792	**0.835**	0	0.006
High Speed Test Cycle # 1	**0.843**	0.836	0	0.126
High Speed Test Cycle # 2	**0.786**	0.774	0	0.028
High Speed Test Cycle # 3	0.310	**0.361**	0	0.328
High Speed Test Cycle # 4	0.201	**0.266**	0	0.149
Low Speed Test Cycle # 1	**0.702**	0.635	0	0.128
Low Speed Test Cycle # 2	**0.734**	0.634	0	0.141
Low Speed Test Cycle # 3	**0.684**	0.515	0	0.161
New York City Cycle	**0.911**	0.878	0	0.092
Speed Correction Factor 12	0.900	**0.913**	0	0.102
Speed Correction Factor 36	**0.832**	0.828	0	0.068

Bold = Greatest correlation coefficient between observed and predicted emissions

[a] The correlation coefficient for the CALINE4 model is 0 since the prediction uses the constant FTP Bag2 fleet average rate, the constant fleet average idle rate, and coefficients that are determined by cycle modal characteristics. The result is no variation in emissions predictions within a cycle (see Washington, Guensler, and Sperling, 1994).

[b] The correlation coefficient for EMFAC7F is non-zero since different within-cycle predictions result from the differences brought about by different vehicle technology groupings and their associated unique model coefficients.

which varies independently of the FTP Bag 2 emission rate and therefore captures more of the variation in emissions performance between vehicles.

The use of individual vehicle emission test results in the model algorithms brings about drastic improvements in overall performance of both models' algorithms. This improvement can be seen in Tables 3, 4, and 5, where theoretical modifications using disaggregate data result in greatly improved statistical performance over models using aggregate data. This improvement is attributable to the algorithms' ability to predict the wide fluctuation in emissions between clean and dirty vehicles, largely reflected in their FTP Bag 2 emission test results.

CALINE4 emission prediction algorithm performance is perhaps more impressive when it is noted the EMFAC7F model algorithms were estimated using the SCF data base, but CALINE4's algorithms were estimated using a much older and smaller data set. Both statistical and practical factors were taken into account, and the improved CALINE4 algorithms represent a more powerful approach for estimating CO emissions for individual vehicles, provided that the algorithms are based on comprehensive testing of a representative sample fleet. Note, however, that the CALINE4 modal model still does not capture the effect of different modal activity reflected in the different testing cycles, as evidenced by the vast differences in correlation coefficients across cycles. This suggests the transportation air quality modeling community still needs an improved modal model.

CONCLUSIONS AND RECOMMENDATIONS

To put the research findings presented in this paper to effective and productive use, the transportation community must consider the current regulatory framework. The transportation community must also consider the current direction that complementary modeling efforts are taking and how simultaneous modifications will benefit future air quality analyses. Finally, the findings must be considered with respect to both short- and long-term solutions to current air quality analyses problems.

Research/Modeling Arena

In the short to medium term, the next CALINE4 model revision effort should include an upgrade to its modal emission algorithms. Among its improvements should be the addition of individual vehicle Bag 2 and idle emission rates and the recalculation of the modal model coefficients.

Incorporating individual vehicle Bag 2 and idle rates into model algorithms would require several steps. As an example of how this could be done, consider the following. A sample of tested vehicles (e.g., an expanded SCF data set) would need to be broken down into subsamples by emitter class. For example, four or five subsamples could separate vehicles by emission results on testing cycles, with classes of ultra-high emitters, high-emitters, normal emitters, low emitters, and ultra-low emitters. These subsamples of vehicles would constitute the sample bins from which local vehicle fleets could be approximated. Support files would be included with the CALINE4 software containing local or regional fleet characteristics necessary for subroutine calls from the main program. The subroutine would randomly sample vehicles from the five bins of emitters in the correct proportion to represent the local or regional fleet. These support files constituting the five bins would contain individual vehicle Bag 2 and idle test data (and additional variables needed in the model).

To obtain local or regional fleet characteristics, local or state DMV and BAR records could be used to determine critical determinants of the vehicle fleet composition. The end user could then select default fleet characteristics (a dirty vehicle fleet for worst-case analyses) or enter local or regional fleet characteristics for more accurate analyses. This formulation would require careful classification of emitter subsamples listed in the previous step. This improvement to CALINE would avoid, to the extent possible, miscomputation of average fleet FTP Bag 2 rates and subsequent emission impacts.

The coefficients contained in the CALINE4 model's algorithms were estimated using an older and smaller data set. These coefficients could be verified against a new data set (i.e., the SCF data set) to see whether they still characterize emissions behavior of these vehicles. Using mathematical search procedures, the coefficients could be simultaneously adjusted to minimize the mean squared prediction error and therefore optimize modal algorithms to the current vehicle fleet. Of course, there still remain questions of how representative the SCF data base is of the current vehicle fleet and whether the functional form of the CALINE4 model is the best available modal model formulation. There is reason to believe that improving the coefficients could improve the robustness of CALINE4's explanatory power, providing better estimates of CO emissions from modal events. With updated model coefficients, the modal model could be reassessed to determine whether it captures the emissions variations associated with the range of modal activities.

The CALINE4 modal model algorithms should be used during all assessments, not just those incorporated with intersections (assuming coefficients have been updated and prediction improvements follow). Because average emission outputs from current EMFAC7F and MOBILE models are questionable, their use will increase the uncertainty associated with cruise-related emissions on roadway segments. The cruise emission factor incorporated in the CALINE4 model is likely to yield more accurate results than the method now used, although this should be verified.

In the long term, CALINE's vehicle activity algorithm's should be upgraded to use traffic simulation algorithms for all vehicle activity estimation (not just intersections). In addition, a new, more robust modal model derived from second-by-second emissions data should be used. These upgrades, in addition to the dispersion component of CALINE4, would allow a more accurate assessment of project-level CO emission impacts under worst-case conditions.

Any new model development effort should explore the impact and role of high-emitters in the vehicle fleet. Research of this nature would involve random testing from vehicle fleets in various regions. Factors such as tampering rates, average condition of vehicles, average age of vehicles, accrued mileage, and types of vehicles will likely play a large role in the results. These influential factors are likely to help characterize a local or regional fleet of vehicles and help determine the discrepancies between a regional fleet and the fleet used to estimate models now in use. Research currently under way is assessing the differences between the true vehicle fleet and the fleet used to estimate regional emissions models (Smith et al., unpublished draft research report, Institute of Transportation Studies, University of California at Davis).

Finally, new model development efforts should include outputs that provide uncertainty bounds associated with predictions. Although providing more information to decision makers will make their task more difficult, it will aid in more effective policy decisions. It will also provide policy makers the information with which to devise more sensitive and reasonable policies, which explicitly account for technical uncertainty. Monte Carlo techniques could be used in this sort of model development effort to estimate confidence bounds around predicted values (*14*), or repeated random sampling and model runs to develop long-run average impacts with a measure of confidence could also be used. In either case, the technical uncertainty currently associated with emission impact assessment should be quantified and provided as part of standard assessment outputs.

Policy/Regulatory Arena

For there to be an incentive to develop more robust project-level impact models, regulators must demonstrate that they are willing to commit resources to develop improved models, commit resources to run models, maintain in-house expertise, and approve model improvement efforts for future conformity analyses. Although there is motivation for new model development from a theoretical and academic standpoint, new models are of no use to practitioners if they are not allowed to use them. Regulatory agencies such as CARB and EPA should be urged to remain flexible, yet rigorous, when considering new models for the extremely timely and difficult air quality analyses now predominant in nonattainment regions throughout the United States.

In addition, many of the benefits and methodologies developed for improved project-level modeling are likely to benefit regional modeling improvements as well. Regional models are perhaps in more critical need of improved emission estimation procedures than are project-level models, and therefore a model development effort should keep both modeling arenas in mind.

As a final and critical note, the link between evolving transportation activity models (microsimulation and regional) and evolving air quality models (local impact and regional) must be considered. Currently, the outputs from transportation activity models are seriously deficient for inputs into air quality models and have contributed to emission estimation uncertainties (*2,15*). The link between these two models is absolutely critical to the accurate assessment of emission inventories. If an overall improvement to local and regional air quality models is not accompanied by parallel improvements in transportation activity and simulation models, then few accuracy and precision gains in air quality analyses will be realized. The evolution of these models is likely to take an interesting and exciting path.

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