Usefulness of Existing Travel Data Sets for Improved VMT Forecasting

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The ability to forecast vehicle miles of travel (VMT) has implications for policy planning in areas of transportation facility investment, energy use, and air quality. The use of existing data sets to develop improved methods for forecasting national VMT is discussed. These data sets include the 1977 Highway Statistics, the 1977 Nationwide Personal Transportation Survey, the 1976 Highway Inventory and Performance Study, the 1977 Regional Transportation Energy Conservation Data Book, and the 1977 Truck Inventory and Use Survey. Separate models are developed for personal and commercial VMT. A cross-sectional, as opposed to time-series, modeling approach has been used to extract maximum locational and behavioral information from available data for incorporation into the forecasting methodology. Personal VMT models incorporate population growth and geographic redistribution, changes in household composition and vehicle ownership, work-force participation, and driver licensing. Commercial VMT models reflect separate treatment of intrastate and interstate truck VMT, keyed to state-level economic and spatial determinants, as well as network bridging factors. Since all modeling objectives could not be realized within a given data set, data factoring and pivot-point modeling techniques were required. A major failing is the inability to satisfactorily incorporate fuel-price or travel-time determinants directly in models. The strengths and weaknesses of the data in relation to modeling objectives are discussed along with special procedures used in data handling.

This paper describes the use of current travel data sets for the purpose of developing improved methods of long-range forecasting of vehicle miles of travel (VMT). Ability to predict future levels of VMT has important implications for energy consumption, transportation system investment, air quality, and related policy concerns. Although no shortage of VMT forecasts exists, all have some serious limitations for policy planning purposes (1). Most forecasts are based on extrapolations of past trends through time-series models, which tend to be limited in specification and are most accurate for short-term forecasts. The project discussed here was initiated for the purpose of linking VMT production more closely to the actual determinants of travel rather than association with parallel trends. These determinants include demographic trends such as population growth and redistribution, household composition, income and other economic conditions, technology, geography, and the price and availability of fuel. It is also essential that commercial and personal VMT be separated. These expectations require a different approach in modeling VMT and place a special emphasis on the availability and quality of the source data. Experience with and problems encountered in the use of available VMT data sets are the focus of this paper.

PERSONAL VMT

One major reason for undertaking development of a new VMT forecasting methodology at this time was the recent availability of the 1977 Nationwide Personal Transportation Study (NPTS) (2). With up-to-date, detailed reporting of information on the characteristics of households and their travel, NPTS was seen as the nucleus of new forecasting methods tied to the key determinants in personal travel behavior. However, vigorous examination and testing of NPTS over a several-month period in alternative modeling approaches indicated that NPTS alone could not satisfy many of the major requirements expected of a forecasting methodology.

A serious constraint presented by NPTS was the lack of geographic identification of the national survey sample. To protect privacy, the residential location of respondents was available only through a generic standard metropolitan statistical area (SMSA) size or urban size group measure. Because a major goal of the proposed modeling system was to capture interregional variations in VMT, and because the level of VMT in a region is tied to land use and population growth and redistribution, it was clear that the modeling strategy and data requirements for personal VMT would have to be extended beyond NPTS.

Pivot-point analysis was conceived as an approach for incorporating factors not available in NPTS. The planned technique was to consist of three modules, each incorporating a different body of VMT determinants and formulated from a unique data set with these characteristics. The modules were to be linked through the dependent variable, daily VMT per capita.

The general approach is shown in Figure 1. Under the plan, the first module would focus on the relations between VMT and geography. Module 1 consists of a matrix depicting, jointly, population, total daily VMT, and a daily VMT per capita rate for regional and urban size cross-groupings of the nation. By establishing a base-year rate of VMT production keyed to geographic regions of the country, module 1 also serves as the first-stage forecasting model for estimating regional effects. Presuming the base-year VMT per capita rate to be reflective of VMT behavior generally in a given subregion, first-level forecasts are obtained by introducing population growth and redistribution in the year 2000 to the module 1 matrix. A first-level approximation of year 2000 VMT is obtained simply through population adjustment in conjunction with the base-year per capita rate. Module 1 is not concerned with changes in the structure of the rate itself.

The structure of the daily VMT per capita rate was to be determined by modules 2 and 3. Module 2 was intended to quantify region-level differences in the VMT per capita rate, keyed to economic, transportation system, and land use factors. Module 3 would reflect differences in the VMT per capita rate attributable to so-called behavioral factors, encompassing individual and household characteristics and modal-choice criteria.

Data sources for the three modules are shown in Figure 2. Module 1 was to be constructed primarily from state-level VMT data taken from Federal Highway Administration (FHWA) Highway Statistics (3), net of commercial VMT, and urban size group breakdowns were to be accomplished through 1976 Highway Inventory and Performance Study (HIPS) data (4). Module 2 would be constructed from joint use of HIPS and 1972 National Transportation Study data (5). Module 3 was to be fashioned entirely from the 1977 NPTS data.

Each of these data sets was found to have its own special limitations. Because of its widespread use, Highway Statistics was used as the controlling source of VMT data for the overall effort. Many have questioned the accuracy and usefulness of the Highway Statistics VMT data because of the indirect and nonstandardized manner in which they are compiled by the states (1,6). However, this was less of an issue here than the difficulty encountered in

attempting to separate personal from commercial VMT. In Table VM-2 (3), Highway Statistics offers total VMT only (personal plus commercial) at the state level. A procedure for separation was developed that uses information from the 1977 Truck Inventory and Use Survey (TIUS) (7). TIUS presents detailed information on truck use for each state. However, TIUS itself must first be modified to represent actual VMT occurring within the state. In addition, it is necessary to separate personal (chiefly light) truck use from commercial truck use in TIUS. These procedures are described more fully later in this paper, in the discussion of the methodology for commercial VMT.

The breakdown of state-level personal VMT into urban size classes was accomplished through the 1976 HIPS data. HIPS compiled data on VMT production for individual urban areas by state, for each area with more than 50 000 population, for aggregates of urban areas with populations between 5000 and 25 000 and 25 000 and 50 000, and for all rural areas. These data are more accurate than the Highway Statistics data, since they are derived from actual traffic counts and credible sampling procedures, but they are also limited to combined personal and commercial travel. To accomplish a personal-commercial split, the 1972 National Transportation Survey, which had such information, was used (even though it is based on 1972 levels). To summarize the sequence of data preparation tasks for module 1, primary state-level VMT was obtained from 1977 Highway Statistics and then reduced to personal VMT only (including automobile, personal truck, motorcycle, and bus) by using the 1977 TIUS. This VMT was subsequently distributed to urban size groups within the state by using 1976 HIPS VMT data as a distribution function after modification to personal VMT only through use of the 1972 National Transportation Survey.

To forecast with module 1, future VMT is estimated at the regional level and then totaled for the nation. This procedure is shown in Figure 3 for a typical region. Region-level population forecasts are applied to per capita VMT rates in the base-year matrix to obtain a primary estimate of total VMT for the region. When OBERS Series E (8) population projections were applied to module 1 in this manner, the result was an estimated increase in daily VMT from 3527.5 million to 4281.5 million, or 21.4 percent, for the nation compared with a population growth rate of only 20.1 percent. The higher rate of growth in VMT in relation to population is attributable to the net redistribution of population into regions with higher rates of VMT production. This was a desired capability of the methodology. However, the capability to forecast urban and rural migration patterns within regions was not realized, since demographic forecasts of these trends are not available. Hence, module 1 is sensitive only to interregional growth differentials and does not capture the effects of the increasing urbanization of areas that experience rapid growth, which would affect density and the nation's effective rate of VMT production.

In module 2, the goal was to develop a family of econometric models representing economic activity and land use patterns in the individual regions. Data for this module were taken from the 1976 HIPS survey, the 1972 National Transportation Survey, and the census [by use of the 1977 City and County Data Book (9)]. Data on economic conditions, population, land area, and transportation facility investment were compiled for 306 urban areas and 50 rural areas. After considerable work, the effort to develop regional models was abandoned because models with plausible coefficients and predictive power could not be obtained. Analysis of the unsuccessful effort suggests that difficulty in obtaining a pure measure of personal VMT from the base data sets was a major contributing factor. As described earlier, the more recent 1976 HIPS data have the strength of being a fairly accurate measure of VMT due to the use of actual VMT data obtained from sampling

Figure 1. Modular approach for forecasting personal VMT.

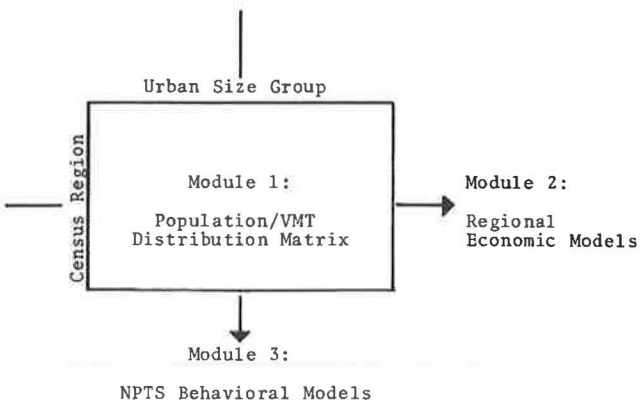


Figure 2. Source data for personal VMT model.

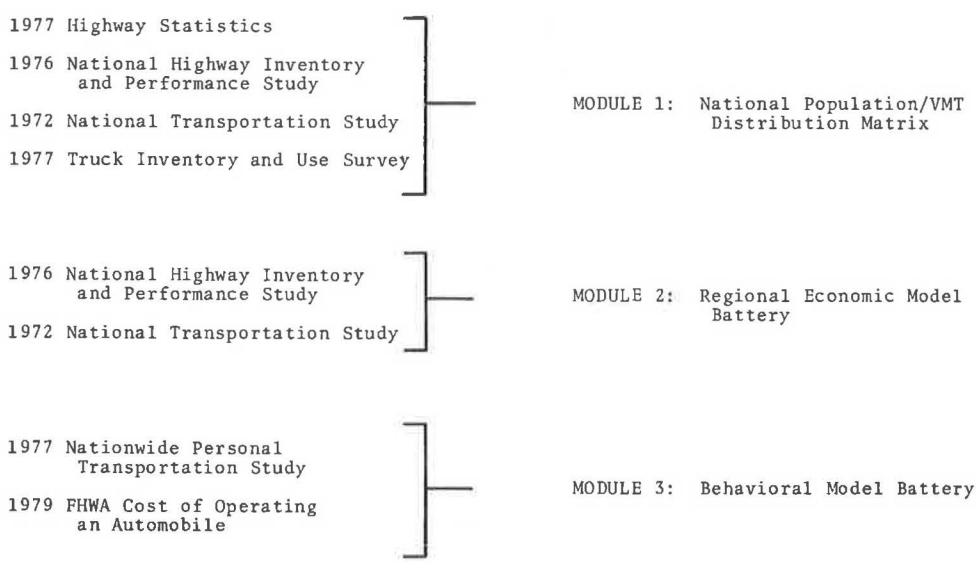
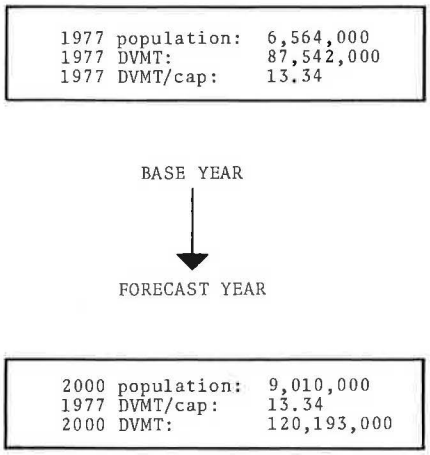


Figure 3. Module 1 forecasting procedure.



methods. However, HIPS does not distinguish personal from commercial VMT, and the use of the 1972 National Transportation Survey data to accomplish this split through factoring was not sufficiently precise for use of the estimate in an econometric model. The two data sets were simply not similar enough in terms of urban-area definition, VMT definition, and point in time for their joint use to be effective.

Module 3 was to comprise a battery of individual-level behavioral models built from the recent 1977 NPTS survey data. The goal of module 3 was to capture the relation between individual VMT and the factors that most directly affect the individual's travel decision making. These factors are listed below:

1. Characteristics of the individual, such as age, sex, possession of a driver's license, and employment status;
2. Characteristics of the individual's household, such as income, vehicle ownership, and household composition (number of members, adults, workers, drivers, etc.);
3. Travel-related considerations, such as time and cost of travel and availability of alternatives;
4. Purpose of travel, nominally work and nonwork;
5. Location of travel, i.e., local versus intercity; and
6. Residence location, approximated by urban size class.

The input data for the models were based on a 20 percent random sample of individuals from the NPTS data base. For each sample individual, a measure of individual daily VMT was constructed from trip information in the survey's 24-h travel log. All trips made by the sample individual were identified, and the individual's share of VMT computed as total trip VMT divided by the number of vehicle occupants. This method produced an average daily VMT per capita rate from NPTS of 12.93 miles.

Preparing the NPTS travel data for the modeling task involved intensive data processing. It was necessary to prepare travel profiles for each individual and then analyze these profiles and make judgments to partition travel into work-nonwork purposes and local-intercity place of occurrence. To do this, trips were organized into travel chains, based on time of occurrence. Once the chains were formed, work travel in the chain was identified and the mileage and travel costs in the chain apportioned to work or nonwork based on assignment rules.

Several aspects of the NPTS data complicated this procedure. First, travel information in NPTS is reported in two ways. A 24-h trip log records all travel within the household for a given travel day. This history is supplemented by a 14-day travel-period log that reports only long-distance travel (more than 75 miles from home one way). The 24-h report includes long-distance (intercity) travel, but there was concern that these data alone would be inadequate in frequency and completeness to support development of separate intercity VMT models. Hence, it was decided to incorporate the 14-day data. This decision was ultimately a costly one. Although the two trip reports were allegedly compatible, and in fact contiguous in time-period coverage, linking the two logs uncovered numerous differences in definition and missing or fallacious reporting of data elements critical to the linking process. In addition to the above, trip linking was made difficult by a high rate of missing or seemingly incorrect data items, such as date and time of occurrence of trip, trip purpose, respondent identification, and VMT or distance. Assumptions were substituted where these items were missing, which resulted in peculiar trips and VMT allocations.

An effort was also made to estimate travel cost from information in the travel records, preferably both operating and out-of-pocket costs. Out-of-pocket costs were limited to parking charges and information on lodging (number of nights and number of occupants) from which costs could be estimated if a lodging fee were assumed. Operating costs were separated into fuel-related and other costs of operation. For the nonfuel portion, vehicles were divided into size classes by curb weight. Cost-per-mile figures representing operating costs less fuel expense were derived from FHWA data on the cost of operating an automobile (preliminary 1979 data) by class and were applied to VMT to estimate cost. For the fuel portion of cost, VMT was multiplied by the price of gasoline per gallon divided by the reported miles per gallon for the given vehicle. Because neither gasoline price nor regional identifiers were reported in NPTS, a national estimate of $0.656/gal was used to compute cost. It was eventually found, however, that combined miles per gallon had been reported for only 13 percent of all vehicles and curb weight (used to compute class) for 47 percent of all vehicles. As a result of the limitations in the inputs, so little variation was produced in the cost variable that the measure was regarded as useless and was dropped.

From the standpoint of VMT, the magnitude of the assumptions made to make up for missing data elements in using the approach outlined above resulted in highly unreliable estimates of VMT by purpose and location of travel. These unrealistic VMT estimates constituted outliers to the model and produced unsatisfactory estimation results. As a result, travel purpose and location distinctions and the methodology used to produce them were dropped.

Ultimately, a less sophisticated approach was adopted that took into account the limitations of the data. A single daily VMT estimate was developed for each sample individual by using only those trips in the 24-h travel record. These data were used to construct a single model of individual VMT that incorporates individual and household composition factors (t-ratios are in parentheses):

$$\begin{aligned}\text{DVMT/cap} = {} & 10.75 + \underset{(11.4)}{6.17}\,\text{WORKSTAT} + \underset{(13.3)}{7.45}\,\text{DRIVLIC} \\ & + \underset{(7.3)}{1.45}\,\text{VEHICLES} + \underset{(4.2)}{0.32}\,\text{INCOME} \\ & + \underset{(2.4)}{1.10}\,\text{WEEKDAY} - \underset{(6.0)}{0.97}\,\text{AGE} \\ & - \underset{(6.6)}{0.87}\,\text{MEMBERS} - \underset{(3.1)}{1.31}\,\text{SEX}\end{aligned} \tag{1}$$

where

DVMT/cap = daily individual VMT,
WORKSTAT = employment status of individual (0 = unemployed, 1 = employed),
DRIVLIC = driver status of individual (0 = nondriver, 1 = licensed driver),
VEHICLES = number of motorized vehicles owned by household,
INCOME = annual household income,
WEEKDAY = whether travel day was a weekday (weekend = 0, weekday = 1),
AGE = age of individual (years),
MEMBERS = number of household members, and
SEX = sex of individual (male = 1, female = 2).

The model explains daily individual VMT with an r^2 of 0.102 (10 048 observations). The estimated coefficient for each of the eight independent variables is of plausible sign and magnitude and is significant at the 95 percent level. The structure of the model implies that an individual's daily VMT will be higher if he or she is employed, has a driver's license, and as household income and number of vehicles owned by the household increases. Individual daily VMT declines with a decline in household size, as the individual becomes older, and for females. The relatively low r^2 results from the large variation in a single day's measure of individual VMT.

Before the model was used in forecasting, a calibration step was necessary. Since census data were to be used to forecast with the model, 1977 population characteristics from the census were supplied to the model and the resultant VMT rate was compared with the NPTS sample. The constant term was adjusted from 5.28 to 10.75 in order to equate predicted VMT per capita with the base rate in module 1. Forecasting with module 3 showed an additional 15.0 percent growth in national VMT over the 21.4 percent forecast in module 1, an increase attributable to changes in the rate of individual VMT production.

COMMERCIAL VMT

The objectives in modeling commercial VMT were similar to those in modeling personal VMT. In seeking relations that include the economic and geographic determinants of VMT, a cross-sectional, as opposed to time-series, methodology was used. Three data-related problems were identified in attempting to model commercial VMT:

1. Separating commercial from personal (light-truck) VMT,
2. Separating short-haul (intrastate) from long-haul (interstate) truck travel, and
3. Achieving a measure of the actual commercial VMT occurring in the state of observation.

Our initial efforts in modeling commercial VMT used 1976 Highway Statistics data as modified in Table 1-8 of the Regional Transportation Energy Conservation Data Book (10), which attempted to break down commercial VMT by state. Extensive model development was attempted with these data without success. Models had poor r^2's as well as implausible coefficients.

In analyzing the failure encountered in using these data, it was concluded that it was incorrect to combine short- and long-range truck travel in the same model. Therefore, a new approach was formulated to model short- and long-haul commercial VMT separately. This approach was keyed to the use of data from the 1977 TIUS.

TIUS reports truck registration and use (VMT) by state. Through the information provided, truck use may be linked to such characteristics as truck size and weight, fuel type [gasoline, diesel, or liquefied petroleum gas (LPG)], range of operation (local, short-range, or long-range), and major use class.

Initial inspection of the data suggested that the distinction between local and interstate truck travel could be achieved by separating gasoline and diesel in the belief that long-distance truck travel is dominated by diesel-powered trucks whereas short- to medium-distance traffic is dominated by gasoline-powered trucks. To validate this assumption, inspection of truck characteristics by range of operation in TIUS showed that more than 82 percent of all long-range truck miles (defined as more than 200 miles from base) was driven in diesel-powered trucks. Conversely, about 90 percent of all truck miles for local and short-range travel (less than 200 miles) was driven by gasoline-powered trucks, and 97.7 percent of all gasoline-powered truck miles occurred in short-range or local travel.

As a result of these considerations, gasoline-powered (and LPG) truck VMT was selected as the measure for interstate commercial VMT, and diesel-powered truck VMT was selected as the measure for interstate VMT. This decision left two additional data problems, however. One problem was that personal truck use was also embedded in the TIUS estimate of truck VMT. The second problem was that TIUS reported VMT by state of registration of the vehicle whereas VMT by state of occurrence was required for the modeling strategy.

The problem of personal truck use was easily rectified. An analysis of personal truck use showed it to be almost entirely in gasoline-powered trucks and within 200 miles of base. Thus, by assuming that gasoline-powered truck VMT within the state of registration was roughly equal to gasoline-powered truck VMT occurring in that state, a relatively clean estimate of intrastate commercial VMT was obtained by subtracting personal truck VMT from total gasoline-powered truck VMT.

Resolving the intercity truck VMT problem was somewhat more complex, since the bulk of TIUS diesel VMT was likely to have occurred outside of the state of vehicle registration. It was reasoned that the best proxy for interstate VMT occurring in a given state was the diesel fuel consumed in that state, which is roughly equivalent to the fuel purchased in that state. This hypothesis is supported by a fuel-tax bond guarantee imposed on truckers by individual states, which requires payment of fuel taxes compatible with the miles driven in that state, to ensure that truckers will pay their determined share of highway costs and not purchase fuel in a state that has lower tax rates (11). Therefore, the total national diesel truck VMT reported by TIUS was distributed to the respective states based on 1977 diesel-fuel purchases. This was done by multiplying 1977 state diesel-fuel purchases for highway use, as reported in FHWA Highway Statistics (3, Table MF-25), times a calculated national average of 4.206 vehicle miles/gal.

Data on gasoline- and diesel-powered truck VMT were then used to construct separate travel models, and the results were good. The diesel model is given below (t-ratios are in parentheses):

$$D_i = \underset{(13.2)}{100.2} + \underset{(7.0)}{0.170}\,MFG_i + \underset{(2.3)}{0.053}\,AFF_i + 0.329\,BRLA_i - \underset{(4.6)}{1555}\,DNY - \underset{(3.1)}{386}\,DX1 - \underset{(3.5)}{623}\,DX2,5 \quad (2)$$

where

D_i = millions of 1977 diesel truck miles occurring in state i, from Highway Statistics;
MFG_i = 1977 manufacturing earnings for state i, from OBERS projections ($000 000s);
AFF_i = 1977 earnings from agriculture, forestry, and fisheries for state i, from OBERS ($000 000s);
$BRLA_i$ = product of state land area (LA) (miles²) times a calculated bridge index (BR) to reflect the amount of through travel in state i attributable to its location in the national grid;
DNY = dummy variable to control for unobserved attributes in New York State;
DX1 = dummy variable to control for unobserved attributes in region 1 (New England states); and
DX2,5 = dummy variable to control for unobserved attributes in region 2 (mid-Atlantic states) and region 5 (east north central states).

This model predicts interstate truck VMT based on the state's own manufacturing and agricultural earnings from OBERS projections (12) and a "bridge index" that represents the amount of traffic passing through the state based on its land area and position in the national grid. The model has an r^2 of 0.912 (n = 45), and each of the coefficients is significant and of the correct sign.

The bridge index is probably the most valuable relation in the model. It estimates the potential for pass-through or bridge traffic in the state by first estimating the goods flow between all other state pairs (using the product of commercial earnings from OBERS projections divided by the square of the separating distance) and then applying a circuity factor to estimate the portion of traffic between each state pair likely to be diverted through the state of observation. This is represented mathematically as

$$BR_i = \sum_{\substack{j=1 \\ k=1 \\ i \neq k \neq j}}^{51} TRAFFIC_{j,k} \cdot CIRCUITY_{i,j,k} \quad (3)$$

where

i = state of observation;
$TRAFFIC_{j,k}$ = amount of commercial traffic generated by state pairs j and k, for all j and k where $j \neq k \neq i$, represented by $(earnings_j \cdot earnings_k)/distance_{jk}^2$; and
$CIRCUITY_{i,j,k}$ = circuity encountered by traffic between j and k that would have to pass through state i, represented by $distance_{jk}/(distance_{ji} + distance_{ik})$.

The bridge index handles the anomaly in forecasting that certain states or regions exhibit high VMT although they themselves generate modest economic activity.

The gasoline model is given below (t-ratios are in parentheses):

$$\underset{}{\text{Log } G_i} = \underset{}{0.548} + \underset{(20.7)}{0.730} \log E_i + \underset{(12.1)}{0.328} \log A_i + \underset{(3.7)}{0.168} \log DSC - \underset{(2.5)}{0.383} \log V_i \quad (4)$$

where

G_i = hundreds of thousands of nonpersonal gasoline-powered truck miles for state i (7);
E_i = total 1977 commercial earnings for state i, from OBERS ($000 000s);
A_i = state land area (mile²);
DSC = dummy variable to control for unobserved attributes in south central region; and
V_i = percentage of civilian labor force unemployed in state i in 1977 (from the Statistical Abstract of the United States).

This model predicts gasoline-powered truck (intrastate commercial) VMT as a function of state commercial earnings from OBERS projections (12), state land area, and the rate of unemployment from the Statistical Abstract. The model has an r^2 of 0.949 (n = 46), and all coefficients are significant and of the correct sign.

By using the models with forecast-year conditions, commercial VMT for the year 2000 was forecast as 1080.3 million daily individual VMT. This represents an increase of 208.5 percent over the 1977 level of 517.9 million, or a 3.24 percent rate of increase per year.

It was impossible in either the gasoline or the diesel model to incorporate fuel price and availability of highway system level of service. Gross highway supply measures and volume-capacity ratios were derived by using HIPS data. However, these did not provide meaningful relations in the models. Fuel-price data were difficult to find and must be viewed as a major limitation in constructing policy-sensitive VMT models. The major sources of fuel-price data consulted were the Oil and Gas Journal, Platts Oilgram, and the Lundberg Survey. In general, information on diesel fuel pricing was scarce, allegedly because diesel has not been a regulated fuel. Prices were available only for a 33-state sample in Platts Oilgram, and these were 1975 prices. The diesel price variable was significant in the model and the coefficient carried the correct sign but, because the magnitude of the effect was exaggerated, the variable was dropped. For gasoline price, a complete and current sample of prices for each state and the District of Columbia was assembled by using data on a 55-city sample provided in the Oil and Gas Journal. However, when it was entered into the model, gasoline fuel price was not significant under any formulation. Ultimately, a sensitivity analysis framework that used existing estimates of fuel-price elasticity was used to estimate the impact of fuel price on future commercial VMT.

SUMMARY

Numerous problems are encountered in attempting to develop relations to explain and forecast national VMT by using currently available data. Relations developed by using the methods and data described in this paper produce credible VMT forecasts, based on the logic of the models and comparison with other efforts (13). However, much remains to be done before a forecasting capability is achieved that is sensitive to important policy issues. None of the models described in this paper considers the importance of fuel price and availability, transportation level of service, or the effects of competing models.

The motivation for the project work was the recent availability of the 1977 NPTS data. However, extensive work with NPTS showed that it was not an ideal data set for comprehensive statistical model development. NPTS does not report sample location, which makes it impossible to associate travel be-

havior with geography or land use, or with travel cost as it is affected by regional fuel price. The information reported on travel alternatives is inadequate for determining the impact of public transportation on VMT, and the absence of locational information makes it impossible to externally supply this information. Finally, because of loose reporting of trip details, it is costly, if not impossible, to perform fine-grained analysis of behavior by trip purpose, local versus intercity travel, and other factors that influence travel choice. The more conventional sources of VMT data, including the FHWA Highway Statistics, were virtually useless for deterministic modeling.

The experience with commercial VMT was positive in terms of models with strong statistical characteristics and credible forecasts. The decision to use TIUS was an important step in the process, and the techniques used to factor the TIUS data were perhaps the major innovation of the project. With the separation of personal and commercial truck, the separation of intrastate and long-distance truck, and the reallocation of VMT to the state of occurrence, TIUS became a current and effective data source for modeling commercial VMT. The commercial VMT models presented here, however, are still very limited in terms of their capability to examine policy effects.

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Improved Method of Grouping Provincewide Permanent Traffic Counters

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An improved method of grouping provincewide permanent traffic counters on the basis of their seasonal variation in traffic flows is proposed. The method uses two standard procedures: (a) hierarchical grouping, which is one of a variety of clustering techniques, and (b) Scheffe's S-method of multiple group comparisons. The proposed method has several advantages over existing grouping methods, which are largely subjective and manual in nature. The new method is simple, objective, computer-oriented, and statistically credible. In addition, application of the method to Alberta's traffic-counter data indicates that the method is rational for such considerations as trip purpose and trip-length distribution. It is believed that this technique can lead highway agencies to a better understanding of the functional classification of their road systems and help them to develop improved seasonal expansion procedures for estimating average annual daily traffic from sample traffic counts. Finally, the new method has implications for a standard functional classification of roads on a provincial and national basis. It is hoped that such a classification can lead to an overall consistency in the planning and design of roads for both safety and economy purposes.

From past traffic-counting experience, it is known that volume at a given roadway location varies from hour to hour, day to day, and month to month throughout the year. Such a variation in traffic volume is important to many users of traffic data. The average annual daily traffic (AADT) volume is perhaps the most common measure of traffic data used by transportation planners and engineers. It is primarily the AADT and certain other traffic peaking characteristics, such as peak-hour factor, that are used in planning and designing roadway facilities.

Several traffic-counting programs are undertaken by provincial and local roadway agencies to obtain values of AADT on road sections. The most commonly used programs are (a) continuous counting by perma-