Estimating Truck Travel Patterns in Urban Areas

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A method for estimating multi-class truck trip matrices from partial and fragmentary observations is presented. Data sets of widely varying character are combined in an efficient and effective manner so that each piece of information plays a role in developing the estimated flows. The method is linked to a geographic information system environment for data management and display of the results. Its use is illustrated through a case study focusing on the Bronx in New York City. Trip matrices are estimated for three truck classes: vans and medium and heavy trucks. Future advances for the method are outlined.

Although trip matrix estimation has been an area of research for some time, interest has increased recently because of the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) and its renewed support for local planning activities. In the New York City area, for example, the New York Metropolitan Transportation Commission (NYMTC), the metropolitan planning organization, has embarked on an extensive effort to update its baseline origin-to-destination (OD) trip matrices (*1*).

It is also becoming more common to treat truck flows explicitly, instead of simply as percentages of estimated automobile flows. Planners have become concerned with the impacts of capital investments on truck flow patterns and want to take those effects into account when evaluating the benefits and costs of alternative capacity and mobility enhancement options.

However, the development of truck trip matrices, at least from currently available data, is a significant challenge. Different agencies often collect and keep various pieces of the data, the sampling bases are different (e.g., with certain truck classes, origins, or destinations being included or excluded), different definitions are used for the items being collected (e.g., heavy truck, medium truck), and different time frames are employed (e.g., different years, seasons, and starting and ending times during the day).

Thus, there is a need for a matrix estimation technique that is tolerant of wide variations in the input data and robust in its estimation of flows. The technique should also be able to sift through the existing data and determine not only the best current estimate of what the flows are, but also what additional data would have the greatest value in improving that estimate.

Such a method and its application to a case study in the Bronx in New York City are described in this paper. Additional details on the material presented, as well as a second complete case study, are contained in a larger report (*2*) from which this paper is drawn.

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REVIEW OF EXISTING FLOW ESTIMATION TECHNIQUES

One of the earliest efforts to formulate the problem of estimating an OD matrix that would produce an observed set of link flows was by Robillard (*3*). He proposed a nonlinear regression model but did not fully appreciate the degree to which the problem is underconstrained. A much more complete solution based on nonlinear programming was offered by Turnquist and Gur (*4*). This work also introduced the concept of a "target matrix" as a way of incorporating information other than link counts, but did not develop the idea fully.

Van Zuylen and Willumsen (*5*) adapted Wilson's idea (*6*) of "entropy maximization" to the problem as a way of differentiating among alternative OD matrices, each of which would produce the same set of link volumes. This work was followed by efforts by several other authors (*7–12*), resulting in a series of improvements to the basic ideas. The underlying theory was improved and greater recognition was given to important empirical problems like inconsistent or missing link data.

An alternative approach was also developed in the early 1980s, based on a more statistical view (*13–17*). This line of work views the problem as a constrained regression, in which parameters of an underlying model are to be estimated so as to yield the "best fit" to the set of observed data. Both ways of viewing the problem lead to some form of optimization formulation, and Brenninger-Gothe, et al. (*12*) have provided an excellent summary of the relationships among many of the models.

The approach presented here contains elements from several of these earlier efforts, but extends the general model formulation in some important respects. First, because of the interest in truck movements, it deals with multiple vehicle classes and data that include observations over different subsets of classes. Some of the previous authors have mentioned multiple-class problems briefly, but their main emphasis has been on passenger automobiles.

Second, the method provides control parameters sufficient to allow specification of both varying degrees of confidence in different observations as well as asymmetric error functions for overestimation and underestimation of observed values. This is similar in some respects to the previous work of Maher (*14*) and Brenninger-Gothe, et al. (*12*), but more extensive.

Third, the model that develops the estimates is designed to accept data in forms other than link counts. The objective is to be able to use all of the available data, in whatever form and from whatever source. This is a much broader objective than is present in the earlier efforts, and requires a more general formulation. The formulation is different from the specification of a "target matrix," which is embedded in most of the earlier efforts, because constraints on row-sums or column-sums, for example in the OD matrices to be estimated, can be specifically created.

DESCRIPTION OF THE METHOD

It is assumed that the analysis network consists of links joined at nodes, and that each link has at least three attributes: (*a*) a directional flag (i.e., $i \rightarrow j$, $j \rightarrow i$, or both); (*b*) a use label (which truck classes are allowed); and (*c*) a travel time (which may vary by time of day). Further, the underlying geography is presumably divisible into exhaustive, non-overlapping zones, such as zip codes or census tracts. Each zone must have a centroid where trips originate and terminate, and that centroid must either be an existing network node or a new node that is attached to one or more existing network nodes by centroid connectors.

A set of truck classes is assumed, based on the Federal Highway Administration truck classes (''*F*'' classes) or some other suitable classification scheme. In the case study presented in this paper, a three-tier classification scheme is used: (*a*) commercial vans, (*b*) medium trucks (two-axle, six-tire and three-axle single unit), and (*c*) heavy trucks (trucks with four or more axles, and all tractor trailers).

Finally, a routing algorithm must be employed to develop link use coefficients for each OD pair (i.e., the proportion of a given OD flow that will appear on a given link). Dial's probabilistic path assignment algorithm (*18*) is used in the example presented later, but other algorithms could be used.

Types of Input Data

A set of postulates concerning input data augments the basic assumptions. The data are of three types:

1. Link volumes or classification counts;
2. Partial OD estimates for various zones, time periods, and truck classes; and
3. Originating/terminating data (e.g., the number of trucks within certain classes or sets of classes originating or terminating in a particular zone or entry node on the network's periphery).

Link Volume Data

The link volume (LV) data provide estimates of link flows for the network. For example, a classification count provides truck volumes by direction, vehicle type, and time of day for a given location. Turning counts and data from automatic counters provide similar information, especially if they classify vehicles (e.g., a video-based detection scheme).

The model constraints must relate the truck classifications in these volume counts to the classifications employed in the analysis. For example, assume that a count for link *j* includes both two-axle, six-tire trucks, and three-axle trucks in the same group, whereas on link, *k*, three-axle trucks are grouped together with four-or-more axle trucks. If these two counts are denoted as C_j and C_k respectively, and the model variables V_{2j} and V_{2k} refer to link flows of two-axle, six-tire trucks, V_{3j} and V_{3k} represent three-axle trucks, and V_{Hj} and V_{Hk} represent four-or-more axle trucks, then the following constraints capture the information contained in both counts:

$$V_{2j} + V_{3j} = C_j \tag{1}$$

$$V_{3k} + V_{Hk} = C_k \tag{2}$$

OD Data

OD data provide estimates of flow matrix entries. Typically, such data come from surveys of vehicles crossing a given link or passing through a network gateway. A survey conducted at an internal location generates observations for selected trip table cells, and an inbound survey provides estimates for one row (''from'' entries), and an outbound survey the estimates for one column (''to'' entries).

Constraints link these observations to trip matrix cells. For example, let Figure 1 depict a situation in which one zone structure (e.g., zones *A*, *B* and *C*) is used for modeling purposes and another (e.g., zones *X* and *Y*) was used for an OD survey. Constraints are needed that relate the observed trips (to and from zones *X* and *Y*) to those being modeled (i.e., zones *A*, *B*, and *C*). Specifically, if an observation exists (from a survey) of trips from *X* to *j*, denoted by T_{Xj}, a constraint can be created, as follows:

$$T_{Aj} + T_{Bj} + T_{Cj} \geq T_{Xj} \tag{3}$$

Note that this constraint is written as a less-than-or-equal-to constraint because the aggregation of model zones *A*, *B* and *C* is larger than the survey zone *X*. Hence, the observation should be a lower bound on the total estimated trips from the three zones (*A*, *B* and *C*) to Zone *j*.

OT Data

Originating/terminating (OT) data provide observations of flows destined to or originating from some specific location in the network (i.e., row and column totals). A count of truck trips originating within a given zone or combination of zones represents a row total; an estimate of trucks outbound at a gateway node (e.g., at a bridge or toll plaza) is a column total.

As with the LV and OD data, constraints translate and relate the observation-related truck classes to those used in the model:

$$\sum_{k \in K_x} \sum_{d} v_{odk} \geq V_{ox} \qquad \forall\ o, x \tag{4}$$

where

V_{ox} = the observed volume in truck class cluster *x* originating at node (zone centriod or gateway node) *o*,
K_x = the set of truck classes *k* contained in the observation, and
v_{odk} = the variable for the number of trucks of type *k* going from origin *o* to destination *d*.

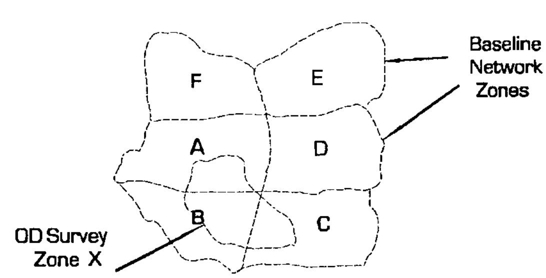

FIGURE 1 Zone mapping illustration.

Overall Model Description

In summary, estimation of the trip matrices is treated as a large-scale linear programming problem in which the objective is to minimize the weighted sum of all deviations from the observed values, given (*a*) the choice variable definitions provided by the user (i.e., truck classes and zone structure), (*b*) the network definition, and (*c*) the link use coefficients provided by the traffic assignment algorithm.

Mathematically, the model can be stated as follows:
Minimize

$$\sum_{k} [w_k^d (d_k^- + d_k^+) + w_k^e (e_k^- + e_k^+)] \quad (5)$$

Subject to

$$\sum_{m \in M_k} \alpha_{mk} x_m + e_k^- - e_k^+ + d_k^- - d_k^+ = b_k \quad \forall k \quad (6)$$

$$e_k^- \leq E_k^- \quad \forall k \quad (7)$$

$$e_k^+ \leq E_k^+ \quad \forall k \quad (8)$$

$$e_k^-, e_k^+, d_k^-, d_k^+ \geq 0 \quad \forall k \quad (9)$$

The b_k values are observations (LV, OD, OT) relevant to the problem under consideration. The weights w_k^d and w_k^e ($w_k^d > w_k^e$) are attached to "large" and "small" deviations, respectively, from the observed value, b_k. The magnitudes of "large" deviations (negative and positive) from b_k are denoted by d_k^- and d_k^+, with e_k^- and e_k^+ denoting the magnitudes of "small" deviations. E_k^- and E_k^+ are limits on the magnitude of deviations that may be considered "small." In addition to the b_k, the values of w_k^d, w_k^e E_k^- and E_k^+ are inputs to the model that characterize the penalty functions for observation k. The values of d_k^-, d_k^+, e_k^- and e_k^+ are model outputs that reflect the deviations to be minimized.

The major outputs of the model, besides the observation deviations, are the variables x_m, which represent the entries in the OD matrices for the truck classes considered. The subscript m is used to denote a "market"—a combination of an OD pair and truck class. Thus, vans from origin A to destination B constitute one market, three-axle trucks from A to B are a second, and vans from C to D are a third.

The values of α_{mk}, which measure the extent to which x_m contributes to creating b_k, are inputs to the model. These are specified in different ways for different types of observations, as described more fully in the next section. M_k is the set of markets that contribute to the generation of b_k.

Use of a piecewise-linear objective function has four major advantages. First, it allows greater sensitivity to large errors than to small ones, in the same way that would be accomplished by minimizing a squared-error function. However, by using a piecewise-linear function, the second advantage of being able to solve the model using commercial large-scale linear programming software can be achieved. Third, by varying the weights associated with different observations, differing degrees of confidence can be reflected among the various observations. Finally, by varying the weights (and limits) associated with positive or negative deviations from the observed (target) value, asymmetric error functions can be created for specific observations, reflecting the fact that it may be important for the model not to underestimate (or overestimate) certain values. The value of these features is best illustrated through a case study application.

CASE STUDY ANALYSIS

The case study focuses on the Bronx in New York City. The network used to conduct the analysis is shown in Figure 2. The Cross-Bronx Expressway (I-95), from the George Washington Bridge at the western side of the study area to the Bronx-Whitestone and Throg's Neck Bridges in the southeastern corner of the area, is a primary corridor for truck flows. The connection to the Bruckner Expressway (I-95 and I-278) at the eastern side of the study area forms a heavily used route to New England. It has been estimated, for example, that more than 13,000 trucks cross the George Washington Bridge eastbound on an average weekday (*19*). In addition, the Hunt's Point area (south of the interchange between the Bruckner Expressway and the Sheridan Expressway—I-895) is the location of the major fresh meat and produce wholesale markets for New York City, generating approximately 15,000 truck trips per day (*20*).

Three time periods and three truck classes are considered. The time periods are 6 to 10 a.m. (a.m. peak), 10 a.m. to 3 p.m. (midday), and 3 to 8 p.m. (p.m. peak). The truck classes are vans (light-duty trucks with two axles and four tires), medium trucks (two-axle, six-tire, and three-axle single unit trucks), and heavy trucks (those with four or more axles, and all tractor-trailer units). A total of nine OD matrices need to be estimated. These matrices are generated three at a time—a van, medium, and heavy matrix—for a given time period. This takes maximum advantage of the overlap among the data sources available without creating complexity (e.g., trying to take into account interplay among the time periods).

Zone and Network Definition

As shown in Figure 3, the study area has 20 internal zones based on zip codes. Ten Bronx zip codes in the northern part of the study area are collapsed into three zones because the land use in these areas is primarily residential or parkland. Also, all 11 of the zip codes in northern Manhattan are collapsed into two zones, one to the north of the George Washington Bridge and one to the south.

Seven external zones augment these internal ones, providing a way to represent flows to and from major traffic generators:

100: George Washington Bridge,
101: I-87 (New York State Thruway),
102: I-95 (New England Section of New York State Thruway),
103: Throg's Neck Bridge (I-295),
104: Bronx-Whitestone Bridge (I-678),
105: Triborough Bridge (I-278), and
106: Manhattan south of 110th Street.

Nodes in the original network data base are used as zone centroids. No special nodes are created, nor are centroid connectors designated.

Model Constraints

The model for this situation contains 180 realizations of Equation 6: 44 OD constraints, 52 OT constraints, and 84 LV constraints.

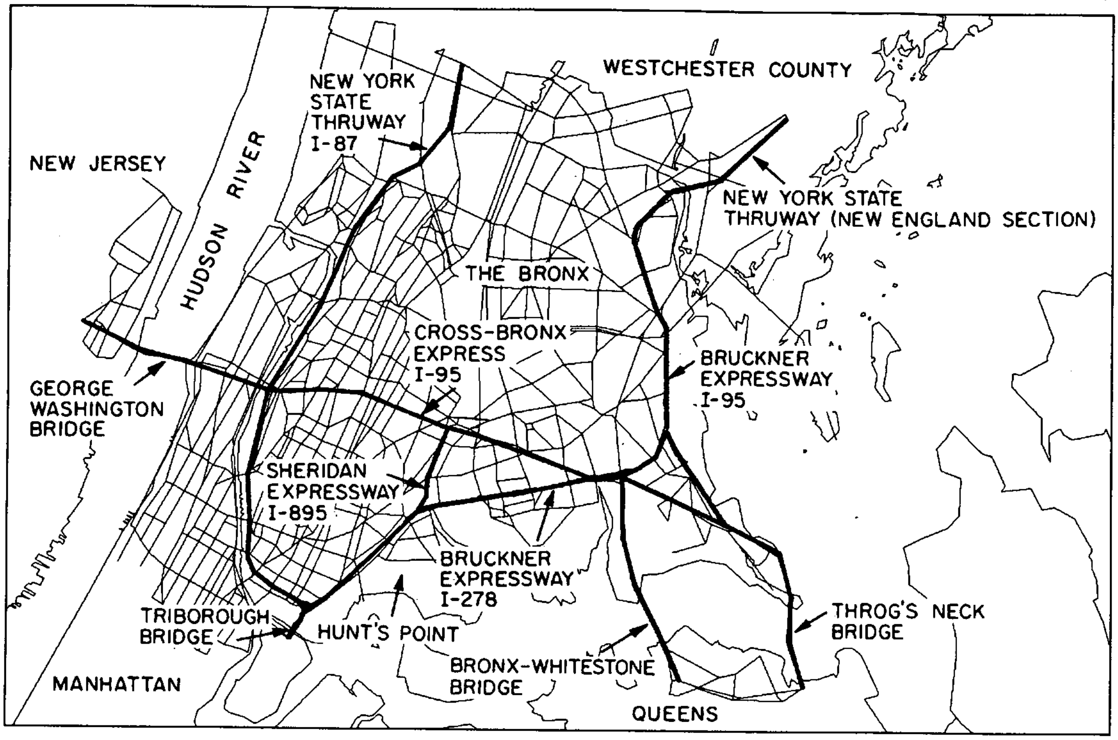

FIGURE 2 Case study network.

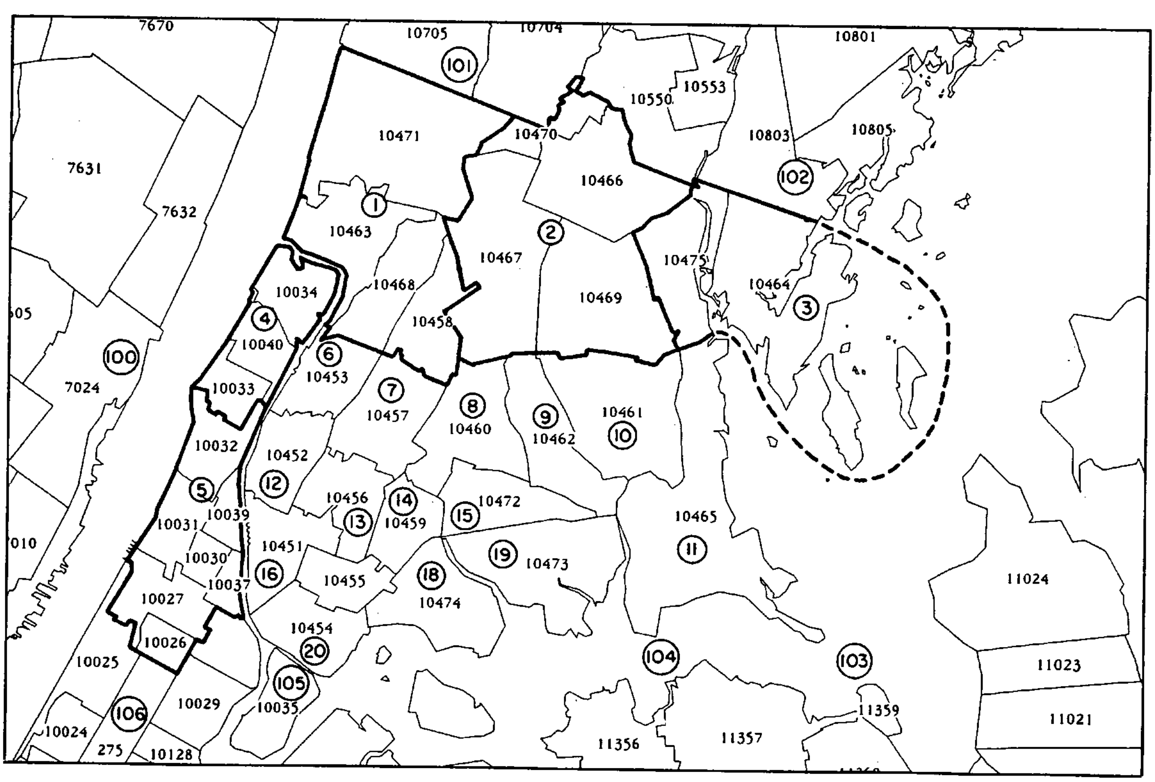

FIGURE 3 Bronx area zip codes and case study zones.

The following three subsections provide examples of how these constraints are developed.

OD Constraints

The 1991 Port Authority of New York and New Jersey (PANYNJ) Truck Commodity Survey and the 1988 Triborough Bridge and Tunnel Authority (TBTA) Truck Survey contain data about flows between a given bridge and a location within the study area. For example, the PANYNJ data capture eastbound flows crossing the George Washington Bridge and the TBTA surveys are for southbound trips at the Triborough, Whitestone, and Throg's Neck Bridges because that is the direction in which tolls are collected.

From these data, generation of the OD constraints is a four step process:

1. Establish the mapping between the survey's zones and those used in the case study. These are the "inclusion rules" discussed earlier pertaining to Equation 3;
2. Expand the survey responses to total truck flows based on counts of trucks by truck type for the same 15-min time periods for which the survey data were collected;
3. Combine the two-axle, six-tire, and three-axle volumes because these both fall into the medium category being used in the modeling effort.
4. Aggregate these observations (for both medium and heavy trucks; vans were not surveyed) into OD flow observations based on the "inclusion rules" from Step 1.

OT Constraints

From the TBTA toll data, the Hunt's Point Access Study, the Bronx Truck Route Study and toll data from the New York State Thruway Authority, it was possible to generate 48 OT constraints. The following example, using the Thruway Authority data, shows how these constraints were created.

For the New Rochelle toll plaza, the Thruway had eastbound volumes by truck class and hour. This information provides an estimate of truck trips "terminating at" or destined for Zone 102. To create an OT constraint from these data involves computing truck volumes by truck class (medium and heavy only, no vans) and time period (a.m., midday, and p.m.). The result is 60 total observations (3 time periods × 2 truck classes × 10 days).

Unlike most of the other data sources, for which only one observation is available, these data provide an explicit statistical rationale for specifying the E_k^+ and E_k^- values. Given the data in the following table, these can be set to the values of the standard deviations for the six observations.

	Medium Trucks		*Heavy Trucks*	
Time Period	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
6 a.m. to 10 a.m.	618	37	784	44
10 a.m. to 3 p.m.	852	52	1,118	81
3 p.m. to 8 p.m.	458	22	787	106

Thus, any model solution within one standard deviation of the observed sample mean will be considered "close," in the sense of having only a small deviation from the observed values.

Link Volume (LV) Constraints

Data from various data sources allowed development of 154 link volume constraints (*21–23*). For example, the Bruckner/Sheridan Interchange Study (*20*) provided data sufficient to generate 12 observations per time period. This data source can be used to illustrate how the LV constraints are developed, and how the link and node structure of the network model affects the way in which flow volumes must be specified.

The Bruckner/Sheridan Study provides four pieces of data for each location counted: total traffic in the a.m. peak hour, total traffic in the p.m. peak hour, annual average daily traffic (AADT) and total daily trucks, as shown in Figure 4. To estimate truck volumes for the 6 to 10 a.m. and 3 to 8 p.m. periods, the following steps are followed:

1. Expand the peak hour traffic volumes to full-period volumes using expansion factors developed by the Planning Division of the New York State Department of Transportation [Erlbaum, N. LDV and HDV Truck Percentages for Mobile 4.0. Internal memorandum, New York State Department of Transportation, Albany, Aug. 9, 1991];
2. Estimate peak period truck flows by vehicle class on the basis of classification counts collected at the same location in a separate study (*24*);
3. Estimate midday flows on the basis of AADT value and hourly distribution data from the Planning Division (*25*); and
4. Assign these volumes by truck class and time period to specific links at the interchange. The unusual part of this process is that the various ramp counts must be aggregated to form link counts for use with the network model. The total exiting and entering volume is assigned to just one link, the ramp link representing all of the exiting and entering movements in this section of the network.

Resolving Inconsistencies in the Data

Because several different sources have been used to generate the individual observations, consistency is a problem that must be faced. A good example of this involves the flows from the George Washington Bridge to the Throg's Neck Bridge (Zone 100 to Zone 103). The Port Authority Truck Commodity Survey (*19*) shows this flow as being 327 medium trucks and 481 heavy trucks during the a.m. peak, 220 and 381 during the midday, and 150 and 190 during the p.m. peak. However, the 1989 TBTA Truck Survey (*26*), which sampled trucks that were Queens bound at the Throg's Neck Bridge, showed only 180 medium and heavy trucks for this same flow in the a.m. peak, and 190 and 250, respectively, for the midday and p.m. peaks. The Port Authority-based values are between 1.3 and 4.5 times larger, with the largest difference in the a.m. peak. There are several possible reasons for this difference, including the following:

1. The expansion from survey proportions to total flow proportions is in error;
2. The translation of survey origins and destinations into zone definitions used in this analysis is incorrect;
3. The estimate of flow proportions by time of day in the TBTA data is in error;

4. The differences exist because the data were collected about two years apart;
5. The survey results are erroneous in one or both surveys; or
6. Some combination of these reasons.

The expansion from survey proportions to total flow estimates has been done differently for the two surveys. For the PANYNJ survey, both the raw survey responses and the toll booth counts of trucks by hour during the survey period are available. For the TBTA survey, the available data are total percentages of trucks by aggregated origin areas, and the aggregate estimate of truck flows by time of day. Thus, the expansion of the TBTA survey results is subject to much larger potential errors, particularly by time of day.

The specification of origin and destination areas in processing of the two surveys is also done differently. In the TBTA survey, it is assumed that the reported origin area "New Jersey" corresponds to the George Washington Bridge (Zone 100). In the Port Authority survey, the reported destination is a PANYNJ zone number, and several zones in eastern Queens, Nassau County, and Suffolk County have been aggregated into the analysis Zone 103.

The fact that the surveys are two years apart is also a potential source of significant variation in results. However, to minimize this likelihood, the TBTA survey data have been expanded using the May 1991 toll data. This should effectively remove the differences in time period as significant sources of error.

Although the differences in these observations are quite substantial, particularly in the a.m. peak period, a decision was made to use both observations with relatively loose "small deviation" limits indicating low confidence in the specific observations. The optimization model then balanced off the differences, together with all other observed values entered as data.

Results of Analysis

Nine OD matrices and associated sets of link flows are generated for the network. The flow pattern for all trucks in the p.m. peak period is shown in Figure 5. Note the large volumes on the major expressways and bridges: (*a*) across the George Washington Bridge, particularly in the westbound direction; (*b*) in both directions on I-87 running north into Westchester County; (*c*) on the Cross-Bronx Expressway and out to the northeast on the New England Section of the New York State Thruway; (*d*) on the Bruckner Expressway, particularly southbound toward the Triborough Bridge; and (*e*) across the Bronx-Whitestone and Throg's Neck Bridges in both directions.

There are also significant flows on some arterials, notably Westchester Avenue and White Plains Road, as well as in the southwestern section of the Bronx. The latter is a direct result of the land use data input to the model, which indicates a very high density of truck trip ends in that part of the analysis area.

The flows of heavy trucks are almost all on the expressway system, as illustrated in Figure 6. The largest volumes are on the George Washington Bridge, the Cross-Bronx Expressway, and the Bruckner Expressway. It is also true that heavy truck flows in the p.m. peak period are principally external-external, going from the George Washington Bridge to Connecticut. This flow pattern

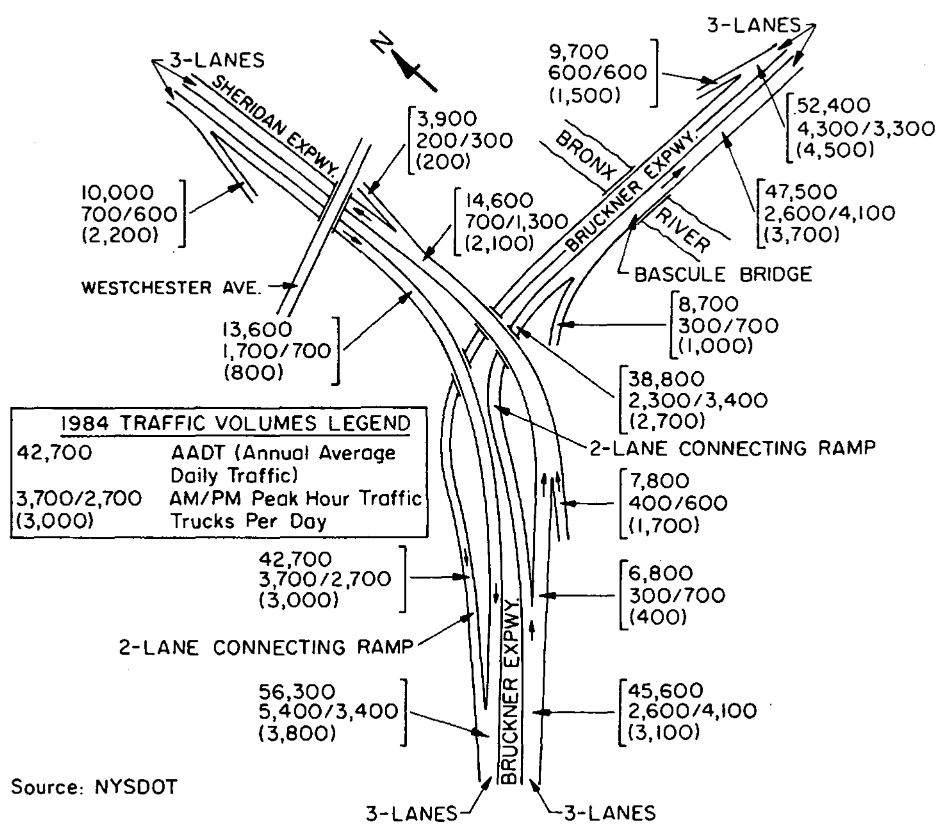

FIGURE 4 Bruckner/Sheridan Interchange.

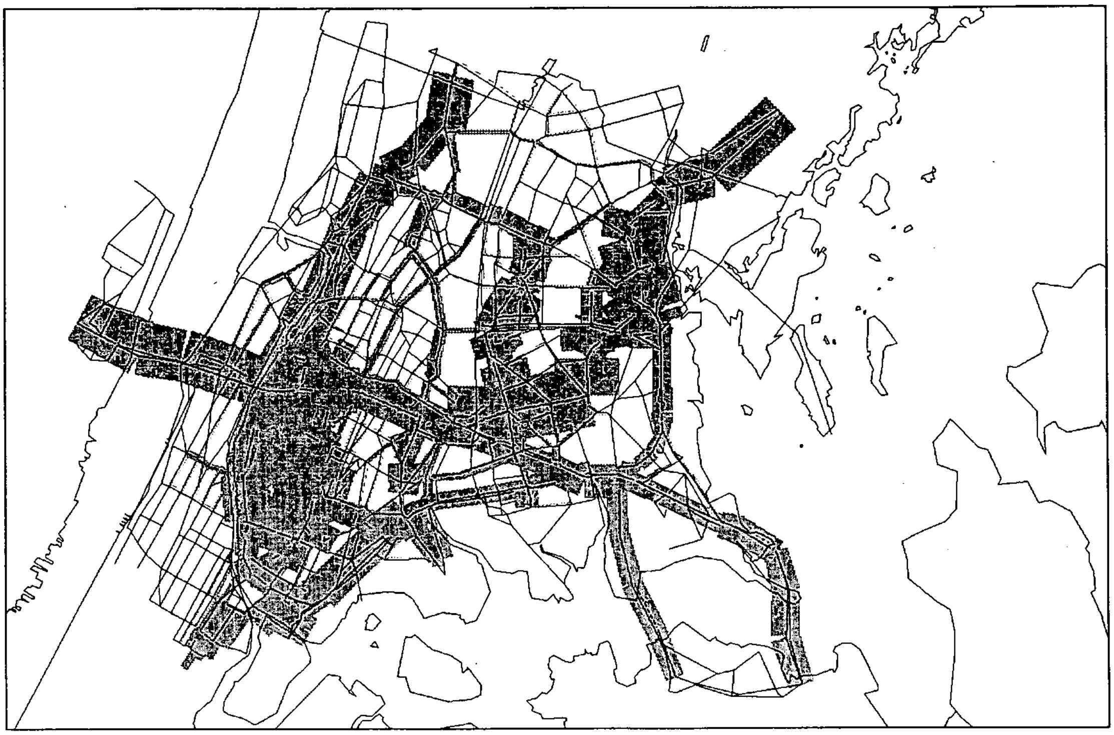

FIGURE 5 Total truck flows in p.m. peak (3 to 8 p.m.); maximum one-way flow is 4,000 trucks.

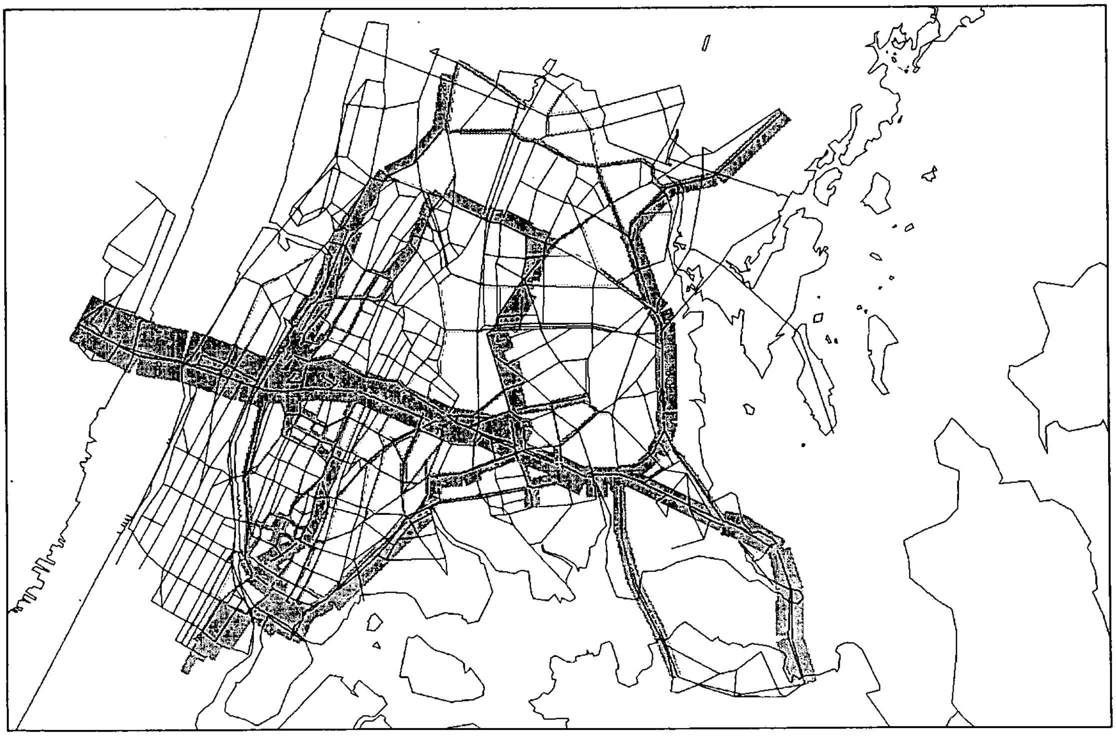

FIGURE 6 Heavy truck flows in p.m. peak (3 to 8 p.m.); maximum one-way flow is 2,000 trucks.

is quite evident in the input data from the PANYNJ Truck Commodity Survey gathered at the George Washington Bridge. Secondary flows of importance in the overhead heavy truck movements are (*a*) northbound traffic on I-87 into Westchester County and (*b*) southbound traffic across the Throg's Neck Bridge to Long Island.

These overhead (external zone to external zone) trips for the network are shown in a three-dimensional way in Figure 7. Note that the trip table is relatively sparse. This must be expected from an optimization that is based on linear programming. (The authors are currently exploring an additional step in the overall model that would produce more highly populated trip tables.) Note also that most of the volume is originating at Zone 100. This is a result of the OD constraints from the PANYNJ Truck Commodity Survey taken at the George Washington Bridge. These constraints force a large number of origins at Zone 100, and distribute the destinations roughly as they appear in the final solution. Because these constraints apply only to eastbound trips, there is little to force overhead trips in the westbound direction.

SUMMARY

Presented in this paper is a method for synthesizing truck flow patterns from partial and fragmentary observations. The method can estimate such matrices from data typically available: link volumes, classification counts, cordon counts of trucks entering and exiting the study area, and partial observations of the OD flows themselves. The method

- Makes maximum possible use of existing information,
- Works with many different types and combinations of data,
- Deals effectively and efficiently with new types of data and new forms of information,
- Generates multi-truck class OD flow matrices,
- Deals with multi-time period problems, and
- Accommodates network use restrictions (e.g., no trucks or heavy trucks) and changes in those restrictions.

As such, the tool has real and immediate practical value. As evidence of this, New York State Department of Transportation is currently developing a User's Manual that explains how the method should be applied and how the input data should be developed. In addition, NYMTC (*1*) in a recent project chose to use this method to update trip tables in the New York metropolitan area.

The tool also has potential applications beyond those illustrated in this paper. In the case study presented, trip matrices have been estimated for a set of truck classes, but redefinition of these classes to reflect commodity groups is conceptually straightforward. Redefinition of the network and zone scale used would also make this technique applicable to interregional freight flow estimation. In light of the changing freight flow patterns across the United States, and, for example, the potential implications of the North American Free Trade Agreement, such interregional use of this method might be quite beneficial.

Continuing research by the authors is focusing on extending the usefulness of the tool and finding improved ways to assess the benefits and costs of "goods mobility enhancements" in urban areas. These include dedicated-use lanes, new and improved freeway ramps, truck-only highways, and intelligent vehicle-highway systems–elated services for commercial operations. The process involved in assessing such changes clearly depends on a method

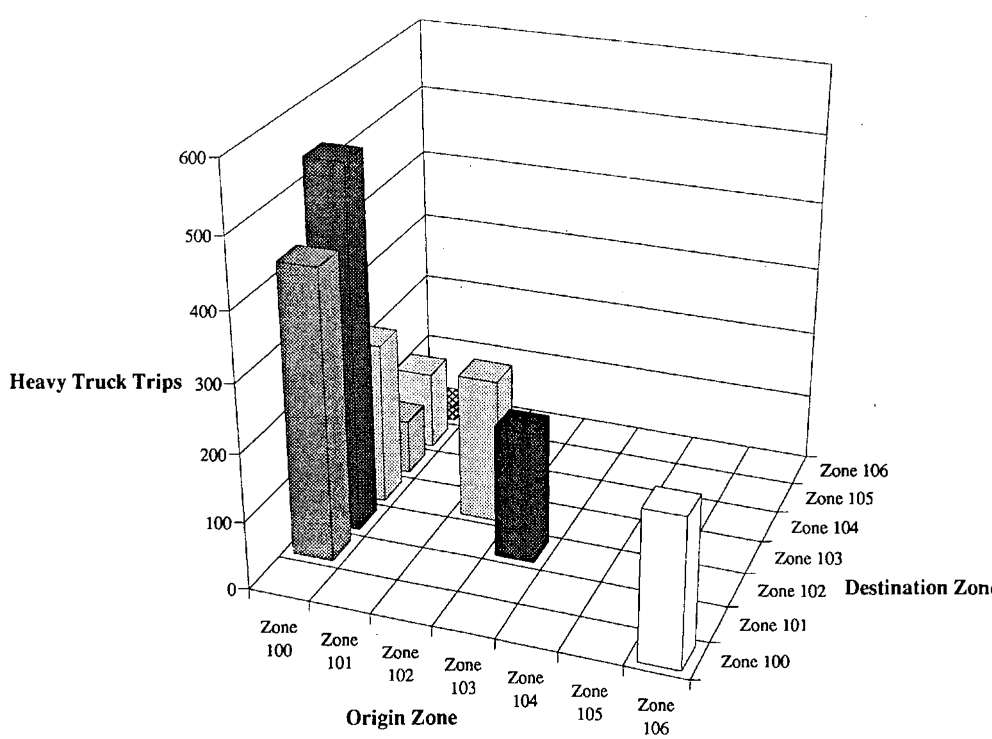

FIGURE 7 Overhead heavy truck trips in p.m. peak (3 to 8 p.m.).

by which trip matrices are estimated so that flow changes can be assessed in light of the network improvements being contemplated.

Flow changes on the highway network as a result of goods mobility enhancements will involve automobile as well as truck traffic. The nature of the truck flow changes is likely to be related to commodities being carried as well as to the physical characteristics of the trucks. Thus, there is need to extend the type of flow estimation model described in this paper to include commodity groups in the vehicle-class definition and to include interactions between the truck and automobile flows. These extensions are currently under way.

As the need to be more efficient in the use of existing capacity increases and the demand for real-time flow management grows, the value in having up-to-date and accurate information about network flow patterns will continue to increase. Eventually, the data collection and processing will become more automated and more accurate, so that less human intervention is necessary and more effective decisions can be made. This project is part of that evolutionary process and the tools and techniques developed help form the underpinnings for future, more comprehensive treatments of the problem.

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