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"Travel Demand Modeling"

by

Frank Southworth[1]

and

Laurie A. Garrow[2]

Abstract

This chapter describes the principal types of both passenger and freight demand models in use today, providing a brief history of model development supported by references to a number of popular texts on the subject, and directing the reader to papers covering some of the more recent technical developments in the area. Over the past half century a variety of methods have been used to estimate and forecast travel demands, drawing concepts from economic/utility maximization theory, transportation system optimization and spatial interaction theory, using and often combining solution techniques as varied as Box-Jenkins methods, non-linear multivariate regression, non-linear mathematical programming, and agent-based microsimulation.

Keywords

Passenger and freight flows, time series models, logit models, spatial interaction models, non-linear optimization, microsimulation

1. Introduction

Methods for estimating and forecasting travel demands draw on a number of different disciplines, making use of optimization methods embedded in econometric as well as mathematical programming frameworks, and using microsimulation and agent-based modeling

[1] Senior R&D Staff Oak Ridge National Laboratory and Principal Research Scientist, School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA.
[2] Assistant Professor, School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA.

to generate travel activity patterns from the ground up for entire regional populations of travelers and freight movers. These methods are now well represented in software programs that in today's computers generate demand estimates in anything from a few seconds to a few hours, depending on the size of the task at hand. In this chapter we describe the most common travel demand modeling approaches, the nature of the solution methods used, and the types of data used to fit or "calibrate" them to real-world conditions. A feature of the travel demand literature over the past half century has been the variety of methods that have been applied, with method selection often determined by the nature and quality of available data sources as well as by specific solution needs. Current models can be categorized in a number of ways. One obvious distinction is between passenger demand and freight demand models, although both use similar solution methods. From a practitioners' standpoint the following classification also proves useful:

- location-specific, time-series based demand models
- cross-sectional modeling of origin-to-destination travel, usually broken down by travel mode and/or travel route, as well as by trip purpose or class of commodity shipped.

A few examples of combined time-series/cross-sectional travel demand models have also been developed, but to date have seen limited use due principally to limited data with which to calibrate them.

A second important distinction is between what has been called the "trip based approach", which has been the dominant approach in practice since the 1950's, and the more recent and increasingly popular "activity based approach" to travel demand modeling. The differences between these two approaches are brought out below.

2. Time Series Based Demand Models

Time series data is often used to develop forecasts of the demand for specific transportation facilities such as airports (Hensher, 2002; Andreoni and Postorino 2006; Karlaftis, 2008) and seaports (Veenstra and Haralambides, 2001; Seabrooke et al, 2003), as well as for high volume links within a transportation network (Nihan and Holmesland, 1980; Ghosh et al, 2007). The empirical data used in these models may span a few weeks, a few months, or a few years of prior passenger, freight, or vehicular traffic volume data, and the forecast may be short term, covering the next few weeks or months, or long term, extending projections a number of years into the future. The historical dataset may include data for a single facility or location or may combine data from a number of different locations, such as vessel arrival or departure data collected for all of the ports in a given region or country. In some cases a simple univariate time series model is used, based solely on projecting a past trend in traffic growth or decline forward in time: or a multivariate, causal model may be applied that relates the temporal trend in facility or regional demand to temporal trends in a number of explanatory variables: such as trends in travel prices, disposable incomes, industrial output, and growth in the size of selected traveling populations. In

some instances (e.g. Klodinksi and Al-Deek, 2004) time series data from one modal activity (e.g. number of offloaded seaport containers) has been used to forecasts travel demand for another mode (e.g. the number of trucks serving a seaport).

Past studies offer a variety of methods to choose from, including simple growth factor methods, multiple regressions, exponential smoothing, Kalman filters, multinomial tobits and probits, artificial neural network models, and a variety of autoregressive integrated moving average (ARIMA) models, in the tradition of Box and Jenkins (1970), including variable (VARIMA) and seasonal (SARIMA) models. Commercial software is available for to estimate model parameters, with most solutions based on well established techniques for either minimizing a residual sum of squares function or maximizing a likelihood function associated with the observed time series. Similar techniques have been used in both passenger and freight demand forecasting.

3. Cross-Sectional, Trip Based Demand Modeling

Once the issue becomes one of forecasting the demand for multiple origin-to-destination (O-D) travel movements, and the geographic context moves away from a single facility or travel corridor, then data limitations play a major role in model selection, as they have done in model development over the past fifty years. In particular, when we enter the realm of regional transportation planning we are dealing with the estimation and forecasting of hundreds, even thousands, of spatially explicit O-D movements within, as well as into, out of, and through a planning region (see the popular textbooks by Meyer and Miller, 2001, and Ortuzar and Willumsen, 2001).

The high costs of collecting this sort of O-D data on personal or business travel activities means that most demand models are based on the responses provided by a sample of households or companies to a travel questionnaire, from which are developed an hopefully representative set of daily trip rates (trip frequencies) and trip lengths, broken down by trip purpose or commodity class, as well as data on the modes and sometimes also the routes selected. While this approach can work quite well for the purpose of understanding current activity rates and even the geographic range of individual travel activity patterns, it is necessarily only a surrogate for a proper behavioral analysis of how such travel decisions as mode and destination choices evolve over time, and as households and businesses themselves evolve. A preferred method for capturing such behavioral connections is to carry out panel surveys, in which the same establishment (i.e. a household or a business) is re-surveyed one or more times after a suitable time interval: the challenge being to avoid attrition in the sample, especially as the time interval increases (see Golob, et al 1997). Such sampling typically occurs in two or more “waves” and as such introduces an element of time series modeling into the estimation process. To date, however, only a limited number of such panel datasets have been collected and applied. Most planning models make use of travel surveys that draw a different sample of respondents from

one survey to the next, often at an interval of five or more years. As a result, most applications of regional travel demand models have placed a good deal of reliance on the variability caused by a combination of differences in a respondent's household or company structure along with differences in responses created by the different geographic locations and site specific conditions they find themselves dealing with.

3.1 Disaggregate, Behavioral Models

Discrete choice (or "logit") models based on utility maximization theory are commonly used to represent how individuals or companies make travel and shipment decisions. Discrete choice models are used to predict the probability a decision-maker will choose one alternative among a finite set of mutually exclusive and collectively exhaustive alternatives. A decision-maker can represent an individual, a group of individuals, a government, a corporation, etc. Discrete choice models relate to demand models in the sense that the total demand for a specific good (or alternative) is represented as the collection of choices made by decision-makers.
Utility is a scalar index of value that is a function of attributes and/or individual characteristics. Utility represents the "value" an individual places on different attributes and captures how individuals make trade-offs among different attributes. Individuals are assumed to select the alternative that has the maximum utility. Alternative *i* is chosen if the utility individual *n* obtains from alternative *i*, U_{ni}, is greater than the utility for all other alternatives. The utility for alternative *i* and individual *n*, U_{ni}, has an observed component, V_{ni}, and an unobserved component, commonly referred to as an "error term," ε_{ni}. Formally, $U_{ni} = V_{ni} + \varepsilon_{ni}$, where $V_{ni} = \boldsymbol{\beta}' x_{ni}$

Specific choice probabilities for different discrete choice models are obtained by imposing different assumptions on the distribution of these error terms and/or by assuming that $\boldsymbol{\beta}$ varies across decision-makers. The assumption that unobserved error components are independently and identically distributed (iid) and follow a Gumbel distribution with mode zero and scale one, $\boldsymbol{\varepsilon} \sim \text{iid}\, G(0,1)$, results in the binary logit (in the case of two alternatives) or the multinomial logit model (in the case of more than two alternatives) (McFadden, 1974). Under these assumptions, MNL choice probabilities are given as:

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{j \in C_n} \exp(V_{nj})} \qquad (1)$$

where C_n is the set of alternatives (or choice set) faced by individual *n*. The assumption that the error terms are iid G(0,1) is advantageous in the sense that the choice probability takes on a closed-form expression that is computationally simple. However, the same assumption imposes several restrictions on the binary logit and multinomial logit (MNL) models. The first key

restriction is the independence of irrelevant alternatives (IIA), a property which states that the ratio of choice probabilities P_{ni} / P_{nj} for $i, j \in C_n$ is independent of the attributes of any other alternative. In terms of substitution patterns, this means a change or improvement in the utility of one alternative will draw share proportionately from all other alternatives. In many applications, this may not be a realistic assumption. For example, in mode choice model applications, one would expect that bus would compete more with other public transit modes than auto. Consequently, much of the research in the travel demand modeling community over the past 30-40 years has been focused on incorporating more flexible substitution patterns. The most commonly used model in practice that helps relax the IIA property while maintaining a closed-form expression for choice probabilities is the NL model (McFadden, 1978; Williams 1977). Dozens of other models have been developed for travel demand modeling applications, including those belonging to the generalized nested logit (GNL) class (Wen and Koppelman 2001) and/or the Network Generalized Extreme Value (NetGEV) class (Daly and Bierlaire 2006). Garrow (2010) provides an extensive review of these models in her text and focuses on applications of these models to the airline industry. Ben-Akiva and Lerman (1985), Train (2003), and Koppelman and Bhat (2006) are other key introductory texts on applying discrete choice models for travel demand applications.

The second key limitation of MNL models is that the β parameters represent "average" population values. The multinomial probit (MNP) model (Daganzo 1977) was one of the first discrete choice models that was used to incorporate more flexible substitution patterns and/or random taste variation. However, due to computational limitations, the ability to use the probit model was limited. It was not until the past decade that an alternative to the probit model, namely the mixed logit model, was introduced.

Conceptually, the mixed logit model is identical to the MNL model except that the parameters of the utility functions for mixed models can vary across individuals, alternatives, and/or observations. However, like the probit model, this added flexibility comes at a cost – choice probabilities can no longer be expressed in closed-form. Due to improvements in computational power, however, it is now feasible to use mixed logit models for travel demand modeling applications. Indeed, the number of publications using mixed logit models has expanded exponentially since 2003 and mixed logit models have been applied in numerous other transportation contexts spanning activity-based planning and rescheduling behavior models (Akar et al, 2009; van Bladel et al, 2009; Bellemans et al, 2009), mode choice models (Duarte et al, 2009; Meloni, Bez, et al, 2009), residential location/relocation decisions (Eluru et al, 2009), and consideration of physical activity in choice of mode (Meloni, Portoghese, et al, 2009).

Similar models have recently become popular with freight modelers. Some authors have also combined traditionally separate choice dimensions (see Section 3.2 below). For example, Train

and Wilson (2006) used a MNL logit to analyze the choice of mode by agricultural product shippers, making use of both revealed and respondent state preference data to calibrate their model. Jiang et al (1999) use a NL model to estimate the demand for alternative freight modes in which all for-hire modes are compared within the same nest, and their averaged, inclusive value utility then compared with the private carriage (in Europe own-account) modal service option. An Heteroscedastic Extreme Value (HEV) choice model has also been used in freight mode choice applications (Holguin-Veras, 2002; Norojono and Young, 2003). See Jeffs and Hills (1990) for a discussion of the explanatory variables often found to be significant in freight tmode choice.

3.2 Aggregate, Four-Step Planning Models

In the United States each metropolitan area as well as each state develops databases and models to estimate current, or baseline, traffic volumes using its major transportation facilities, and links these estimates to regional economic activity and demographic forecasts in order to predict future traffic flows. These forecasts are used in turn to inform the investment of large sums of public money in expanding or improving transportation services within the region. For the past fifty years or so this process has been supported, notably in large urban or metropolitan regions, by the four-step transportation planning model shown in Figure 1. Most commonly applied to passenger, or personal travel forecasting, this approach begins by modeling the frequency with which households engage in travel, estimating the number of trips generated daily for a number of different trip purposes: with separate model calibrations for example, for commuting to work, shopping, traveling to school, and making personal business, social and recreational trips; with a distinction also common between home-based and non-home-based trips. The four sequential, modeling steps can be represented in very general terms as:

Trip (or Freight) Generation: $\underline{O}_{ip} = F(\underline{X}_{ip})$ and Attraction: $\underline{D}_{jp} = F(\underline{X}_{jp})$ (2a)

Trip (or Freight) Distribution (Flow): $\underline{T}_{ijp} = F(\underline{O}_{ip}, \underline{D}_{jp}, \underline{c}_{ijp})$ (2b)

Modal Split: $\underline{T}_{ijpk} = F(\underline{T}_{ijp}, g_{ijpk}, \underline{c}_{ijpk})$ (2c)

Route Assignment: $\Sigma_p \underline{T}_{ijpkr} = \underline{T}_{ij*kr} = F(\underline{T}_{ij*k}, g_{ij*kr}, \underline{c}_{ij*kr})$ (2d)

where F( ) means "a function of", and where i = a trip origin (i =1 2,…I), j = a trip destination (j = 1,2,…J), $\underline{O}_i$ = the number of trip origins out of i, $\underline{D}_j$ = the number of trip destinations into j, T = a daily (or annual) measure of travel demand, and where $\underline{T}_{ijpkr}$, for example, refers to the number of trips taken daily (or annually) from i to j for purpose p by mode k and route r; c = transportation costs, and $\underline{c}_{ijkr}$ for example, refers to the cost of transporting a passenger or unit

of freight from i to j by mode k on route r. Finally, $\underline{X_i}$,$\underline{X_j}$ and $\underline{g}$ refer to matrices of explanatory variables associated with specific steps in the flow estimation process.

The principal reason for the sequential nature of this approach was the failure of early modeling efforts to capture each of these four policy relevant aspects of travel demand within a single model calibration step; with the variables best explaining mode choice, for example, differing from those yielding good estimates of the other three choices. For the purpose of producing planning and policy relevant outputs, each step in the process is executed at an aggregate, or traffic analysis zone (TAZ) level, with the largest metropolitan regions broken down into hundreds of TAZs for the purpose of estimating origin-to-destination (O-D) flows between all TAZ pairs. In practice, such TAZs are often equated with Census blocks, block-groups or tracts, in order to make use of federally supplied estimates of the number of households and businesses within each TAZ. At the statewide level in the United States, and at the national level in many smaller countries such TAZs may be equated with counties. Within metropolitan areas the focus here is on automobile and truck flows, as well as public transit bus and rail movements. At the statewide level other, non-highway modes enter the picture, notably air, rail and water transport.

Variants on the same four step modeling process have also been used to forecast daily and annual freight flow volumes, with the focus on truck freight movements over urban and intercity highways, and using a three step process where modal split is not required, but adding an additional sub-model where flows are estimated initially not in number of trips but in number of tons of different commodities shipped, which then need to translated into the number of vehicle (i.e. truck) trips using suitable tons/truck loading factors. A popular functional form for all four modeling steps, for both passenger and freight demand modeling, is the logit model, with linear and log-linear regressions also popular for the trip generation stage. However, most regional transportation planning models then merge the truck freight and passenger automobile flows to produce passenger car equivalent (pce) O-D flow matrices, in which the larger trucks are allocated pce values much greater than 1.0 before assigning them to the same highway network. Where this loading leads to high levels of traffic volume to capacity (v/c) ratios the use of congestion sensitive route choice algorithms have become the norm, notably traffic route assignments based on Wardrop's (1952) user optimal equilibrium principle, in which travelers select their routes is such a way that their aggregate flow patterns lead to identical travel times between all routes used to travel between any given O-D pair of places.

[Insert Figure 1 about here]

Finally, a look at Figure 1 also reveals an important feedback loop between the trip destination, mode and route choice sub-models. By iterating in this manner, and maintaining convexity in the sub-model solutions, it is possible to bring the flows and costs at each modeling set to a stable

solution: such that no further significant changes occur in either O-D costs or O-D trip volumes, i.e. bringing destination, mode and route choices to a cost-flow balance. However, extension of this procedure to trip generation is rarely attempted using traditional model formulations, largely because daily trip frequencies are relatively insensitive to trip cost differences at the level of spatial aggregation to which these planning models are typically applied. Indeed, the entire four step sequential modeling process has received growing criticism from a number of quarters over the past four decades, not only for its limited behavioral basis, but also for its lack of a cohesive conceptual framework. One response has been the rapid evolution of the disaggregate demand models reviewed above. A second response has been to develop more closely integrated, "combined" choice models that work through economically based equilibrium formulations of the entire flow modeling process (Boyce, 1998). The text by Oppenheim (1995) describes and links both approaches together. These combined models use technical advances in non-linear mathematical programming solution techniques, model formulations based on variational inequalities, and computationally efficient solution methods tied to link-node, path-based network formulations of not only the physical traffic flows themselves but also of the entire process of identifying and tracking travel choices through numerous decision-making steps.

3.3 Mathematical Programming Formulations

The logit discrete choice model can also be derived as an optimization problem, which in its aggregate, planning level application has well-known convex programming solution. Texts by Wilson (1970), Erlander and Stewart (1990) and Lee (2004), among others, explore these formulations. For example, for a set of annual (or daily) trip volumes, T_{ij}, between origin locations i = 1,2,…I and destination locations j = 1,2,…J, Wilson (1970) shows that the following *entropy maximizing* trip distribution (destination) model

$$\text{Max } L(T) = -\Sigma_i\Sigma_j (T_{ij}/T) \ln (T_{ij}/T) \qquad (3)$$

$$\text{subject to: } \Sigma_j T_{ij} = O_i \quad \text{for all } i \quad \text{and} \quad \Sigma_i T_{ij} = D_j \quad \text{for all } j \qquad (4)$$

$$\text{cbar} = (1/T) * \Sigma_i\Sigma_j T_{ij} * c_{ij} \quad \text{and all } T_{ij} \geq 0 \qquad (5)$$

was solved by the following *doubly constrained* spatial interaction model:

$$T_{ij} = A_i * B_j * O_i * D_j * \exp(-\beta * c_{ij}) \qquad (6)$$

where O_i = the volume of travel (e.g. number of trips) generated by TAZ i, D_j = the volume of travel attracted to TAZ j, and where the A_i and B_j are two sets of matrix "balancing factors" given as:

$$A_i = 1 / [\textstyle\sum_j B_j * D_j * \exp(-\beta * c_{ij})] \quad \text{for all } i \qquad (7)$$

and

$B_j = 1 / [\sum_i A_i * O_i * \exp(-\beta c_{ij})]$ for all j (8)

which, via iterative application, satisfy these two "trip end" constraint sets (7) and (8). Here β represents the sensitivity of travelers (or in the case of freight movements, shippers) to additional travel cost. Applying a suitable non-linear search method, a value of β is sought that satisfies the system's average cost constraint () above, while also meeting the two sets of trip end constraints. A little thought here also shows that, by setting all B_j's (A_i's) to a value of 1.0, yields a trip origination (trip attraction) constrained model in aggregate logit form.

Subsequently, Erlander (1977) showed how this model can also be re-stated as an equivalent cost-minimization model of the form:

Minimize C(T)

subject to: $\Sigma_j T_{ij} = O_i$ for all i and $\Sigma_i T_{ij} = D_j$ for all j

$L(T) = - \Sigma_i \Sigma_j (T_{ij}/T) \ln (T_{ij}/T) \geq L0$, and all $T_{ij} \geq 0$

where L0 = a minimum acceptable level of trip dispersion.

Numerous extensions of this sort of approach have been used since the 1970s to formulate and solve increasingly more elaborate travel demand (O-D flow inclusive) models, including the "joint" solution of optimal O-D flow and traffic route assignment models (see Erlander 1977) as well as jointly optimized O-D, mode and route choice solutions, in freight (see Ham et al, 2005, for example) as well as passenger travel. These approaches also set the table for the solution of much broader optimization problems that include optimal land use as well as optimal travel pricing mechanisms within their spatially explicit price-versus-volume based equilibrium solutions (see Wilson et al, 1981; Lee, 2004 for examples).

Similar programming models have also been applied to freight demand estimation and forecasting, but with the T_{ij}'s increasingly solved for in terms of tons shipped, rather than number of vehicle trips, notably by combining Leontief's input-output approach to capturing inter-industry interactions with the spatial interaction models of the type represented by equations (6)-(8) above to create inter-regional or multi-regional input-output models of commodity flows. When combined with logit or other discrete choice model of mode selection (e.g. of truck vs. rail vs. waterway vs. intermodal truck-rail or truck-water transport) these modeling frameworks are now beginning to be applied in statewide freight demand forecasting in the United States as well as in nationwide freight demand forecasting in Europe and elsewhere (see the review of freight demand models by Southworth, 2009).

4. Activity Based Approaches, Microsimulation and Agent-Based Modeling Tools

All of the modeling approaches described in Section 3 above have been applied to forecasting the number of passenger or freight trips associated with a region's population distribution and its travel generating land use patterns. In doing so these trips are effectively abstracted from the often complex set of family influenced decisions being made by individual travelers and the company logistics-based decisions being made by shippers of goods. In effect, the approach has proved to be a very cost effective way of simplifying the travel demand process: by treating non-travel decisions as largely exogenous to the production of trips. Also beginning in the 1950's (see McNally and Rindt, 2008) but only gaining any noticeable level attention by the 1970's, was a more behaviorally attractive but at the same time more conceptually as well as computationally demanding *activity-based approach* (ABA) to travel demand modeling. In this approach travel activities are more closely linked to the complex scheduling decisions associated with a good deal of household travel, or as McNally and Rindt (2008, Section 3.1) put it: "The ABA takes as the basic unit of analysis the travel-activity pattern, defined as the revealed pattern of behavior represented by travel and activities (both in-home and non-home) over a specific time period (often a single day)." Hence an individual's single day travel activity schedule might look something like that shown in Figure 2, in this instance for a two adult, one child family.

A little thought about the many variables that might affect such a daily activity pattern indicates that this sort of modeling can become quite complex. It can also become computationally very time consuming if thousands, or even millions of such patterns need to be simulated in support of project assessments and other planning applications. Fortunately, the tremendous advances in computational speeds over the past five decades have now provided a practical means of addressing this problem. As a result an increasingly popular means of repeatedly generating large numbers (thousands, millions) of such individual travel activity patterns is to use microsimulation. Both Monte Carlo-based and cellular automata-based methods are being used to associate specific attributes (of the traveler, the vehicle, the cargo, the geography) with each trip simulated, using repeated sampling from pre-defined statistical distributions to create a synthetic population of travelers and/or their trips. This is done by first of all building individual traveler profiles, sometimes termed *synthetic travelers*, by drawing sample traveler characteristics from statistical distributions of, for example, different age, income, and employment groups. These travelers are then assigned a specific travel activity pattern, typically a daily pattern. When the simulator is asked to select the traveler's trip frequency, mode, route, or destination this means drawing from a set of probabilities that have themselves already been modeled using either logit or similar demand models of the type discussed above, or using a rule-based activity scheduling algorithm (see, for example, Pendyala et al, 1998). Once generated, these individual traveler activity patterns can then be aggregated to produce an estimate (and subsequently a forecast) of the number of trips taking place between any pair of locations, by vehicle type (and by vehicle occupancy if the method used is sophisticated enough to match up

trips involving more than one family member). Besides this natural aggregation property, microsimulation is also an especially efficient method for representing sequential events, allowing a natural incorporation of system dynamics. This includes the generation of multi-trip, multi-purpose daily tours or "trip chains" of the sort shown in Figure 2.

[Insert Figure 2 about here]

Miller (2003) provides a review and a brief history of the best known microsimulation models in both North America and Europe. See also Kitamura, et al (2000). In the United States this includes the Transportation Analysis and Simulation System, or TRANSIMS[3]: a model, or more correctly modeling system, developed over the past decade by Los Alamos National Laboratory and its contractors for the U.S. Department of Transportation. The modeling approach and its many software modules is downloadable and is extensively documented (Hobeika, 2005). In Europe the Multi-Agent Transport Simulation Toolkit (MATSim)[4] is a similarly complex, and agent-based (see below) micro-simulation modeling system (Balmer et al, 2006) that was also developed around an activity-based approach to household travel forecasting.

Microsimulation also lends itself well to the construction of freight movements. In Canada, Hunt (2006) described the use of microsimulation to generate daily multi-stop pickup and delivery truck tours based on the output from logit regression models which are used to select such attributes as the next stop's trip purpose, its location and departure time interval. The approach can also be used to build vehicle shipments from the ground up, beginning with the selection of the origination point, the size and nature of the cargo to be moved, through the detailed scheduling as well as routing of the vehicles used to move it, while also recognizing any physical constraints on its transportation (see Xu et al, 2003). Microsimulation is also proving to be useful in the modeling of freight through complete multi-stage product supply chains (Boerkamps, et al, 2000 in the Netherlands; Wisetjindawat, et al, 2005 in Japan; in which the movement dynamics may play themselves out over many days or even weeks at a time). In Massachusetts, Xu et al (2003) use micro-simulation to model the routing of trucks over transportation networks as part of a much broader approach to freight modeling that incorporates a pseudo-real-time information simulator linked to a complete supply chain decision-making simulator (based on a very formal mathematical treatment of the freight movement problem as a variational inequality by Nagurney et al (2002).

Some of the most promising opportunities associated with microsimulation in the near future are likely to be tied to recent advances in travel data collection, and specifically to vehicle and cargo

[3] http://tmip.fhwa.dot.gov/community/user_groups/transims

[4] http://www.matsim.org

tacking technologies such as Global Positioning satellites (GPS) and radio frequency identification devices (RFIDs). These "IT" based data collection methods are bringing a much needed visibility to the step-by-step movements of both people and goods. This includes the digital recording and storage of detailed personal travel diaries as well as electronic freight data manifests, each creating a new opportunity to establish both the realism and statistical reliability of microsimulation-based travel forecasting methods.

A natural adjunct to both ABA and microsimulation modeling entering the travel demand literature with increasing frequency is an approach known as agent-based modeling, or ABM. Given a set of allowable actions and possible strategies for action, ABM allows a population of autonomous agents, such as a group of households or freight shippers or receivers (= agents) to interact among themselves to determine how much and what types of travel to engage in, with individual agent behaviors based on an agent's current status, its objective, and its history of past actions. Like microsimulation, ABA supports a bottom-up approach to estimating travel activity patterns, and as such seems well suited to travel activity systems in which individual tripmaking behaviors can be aggregated, sometimes yielding unexpected system-level *emergent behaviors* (Sanford Bernhardt, 2007). This point gets directly to a key weakness in current trip based an aggregate passenger and freight demand models: the difficulty we have in linking our forecasts of travel activity to causal mechanisms and hence, by implication, to policy instruments based on the expected behavior of passengers, shippers, carriers, receivers, warehousers, and third party logistics agents. Rindt, Marca and McNally (2002), and Zhang and Levinson (2004) describe early efforts to develop agent-based passenger demand models. Venkat and Wakeland (2006) and Hunt and Stefan (2007) describe the use of ABM modeling to simulate commercial freight movements.

5. Summary

The past half century has seen considerable technical as well as conceptual innovation in travel model design, calibration and application. One notable line of advance has been the recognition that modeling approaches with very different origins, in economic/utility theory, in system optimization, in categorically based statistical analysis, in spatial interaction theory, and in agent-based and rule based microsimulation, can all contribute to a better understanding as well as better means of estimating the demand for travel. Just how well these and other methods contribute to better forecasts remains to be seen, and needs to be supported by a retention of historical data sources that will allow modelers to look back, as well as forward, and learn from their past efforts.

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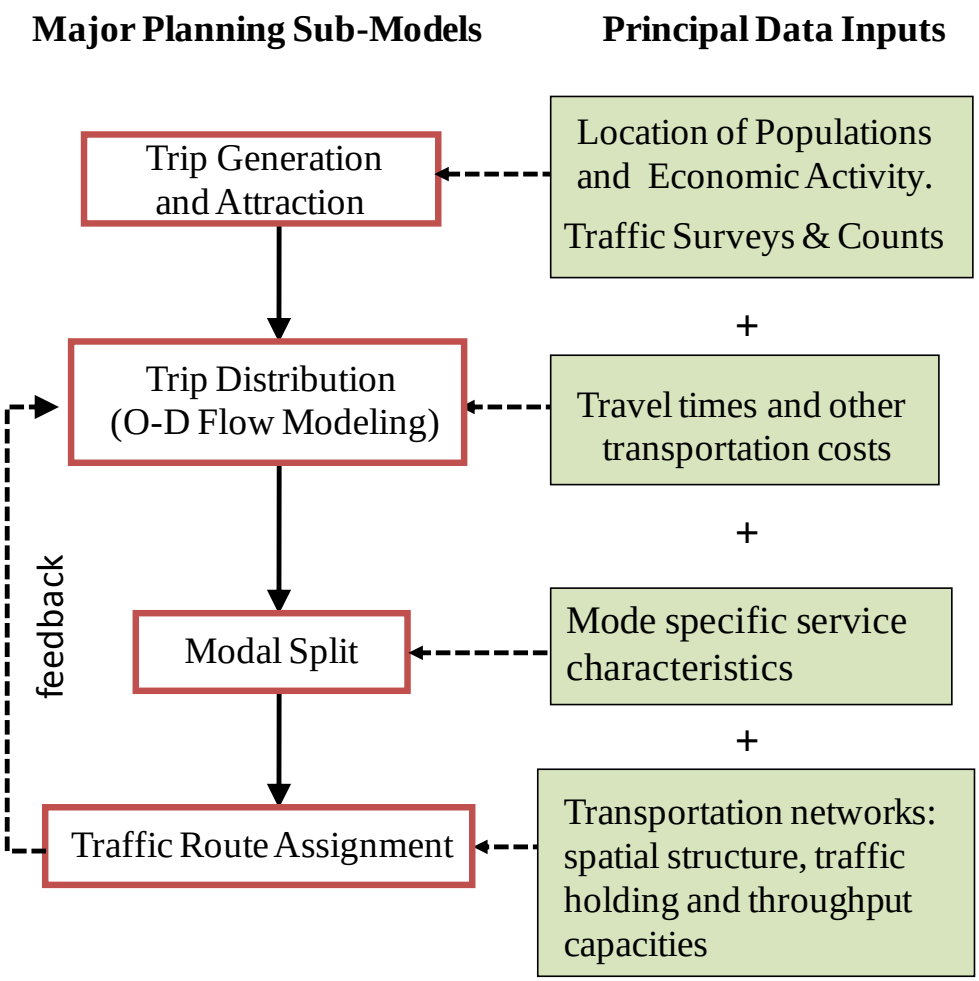

Figure 1. Four Step Transportation Planning Model

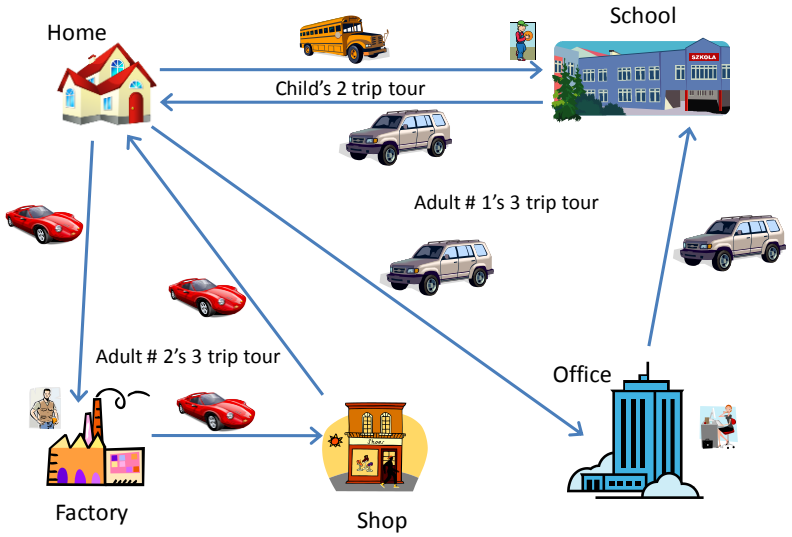

Figure 2. A daily multi-trip chaining example for a 3 person household