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DEMAND FORECASTING IN TRANSPORT: OVERVIEW AND MODELING ADVANCES

ABSTRACT

The main purpose of this paper is to comprehensively explore and productively overview the growing research field of demand forecasting in transport. In this analytic context, it seeks to describe, critically discuss and fruitfully elaborate on relevant mechanisms and models of demand forecasting, as well as on the particular development and implementation of systematic (or system-wide) approaches. The overview of various theoretical and methodological developments in current prediction models eventually advocates the use of consumer demand models (of dynamic character) to predict demand shares among alternative modes of transport.

Keywords: Transport models, traffic forecasts, household expenditure, consumer demand, intermodal competition.

JEL Classification Codes: C50, D11, L90, L91, R41.

1. INTRODUCTION

Modern societies experience a growing demand for passenger and freight movement. Accurate forecasting of the total passenger and freight demand and the competitive (or substitutive) and complementary relationships among transport modes are necessary inputs in planning, designing, evaluating and regulating transport and supply chain systems. Transport investment, especially investment in highway, rail, airport and sea port infrastructure requires long-term financial commitments and the sunk costs can be very high if the investment projects fail to fulfill their design capacities. Therefore, accurate prediction of the long-term demand for using transport or some other public capital (e.g., water supply, electricity, fuel, information and communication) infrastructure often forms an important part of the overall project appraisal.

Also, the prediction of the transport demand and competition relationships can support the marketing and strategic planning of the transport firms, and the efforts for decoupling economic growth from transport intensity and promoting more energy-efficient and environment-friendly means of transport (CEC, 2006). From the perspective of firms, estimates of expected consumer demand constitute a crucial element in all scheduling and planning activities, in order to improve the business profitability. Thus, public transport operators and logistics firms have major interest in developing and interpreting the results of accurate and reliable demand forecasting models.

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The above tasks also stress the need for estimating relevant own- and cross-price elasticities as well as level-of-service elasticities for different transport modes and commodities. Furthermore, the rapid growth of transport technology and policy initiatives for the provision of integrated transport services underline the need for development and implementation of systematic (or system-wide) approaches. Such approaches can identify the trends of transport demand, and the complementarity and substitution relationships among alternative transport modes. The next section analyzes major determinants of demand, which are usually considered in the specification of forecasting transport models. Next, the forecasting mechanisms involved in the traditional four-stage transport planning process are presented. An overview of forecasting methods in transport is then provided, with particular emphasis on system-wide approaches in transport demand forecasting. A number of theoretical and methodological developments in current prediction models are reported. Especially, the use of consumer demand models is advocated to predict demand shares among alternative modes of transport. Data needs and limitations are also examined.

2. DETERMINANTS OF TRANSPORT DEMAND

The demand for passenger and freight transport and logistics services is influenced by a multitude of factors, which are considered in the relevant prediction models. The economy, as reflects the Gross Domestic Product (GDP) or total added value of a country, and the gross output or added value of a region, affects the general derived demand. The current global economic crisis had an evidently large impact on the amount of international freight transport services as well as on the demand for transport products and services, especially on the maritime and aviation sectors. The structure of the economy, in terms of the resources, goods, and services, e.g., specialization on particular products, and cultural, trade and tourism services, affect the level of transport demand and modal shares.

The supply or upgrading of transport infrastructure and services of better quality (higher frequencies, larger seat capacities, higher speed, increased safety and comfort), as well as the supporting infrastructure (e.g., those of Intelligent Transport Systems or ITS) may result in induced demand. Enhanced utilization of existing transport infrastructure capacity (e.g., through implementing congestion mitigation measures) can increase the level-of-service, in terms of travel speeds, reliability and safety, reduce operating costs and raise transport demand.

The technology containerization, double stacking, automation and robotics, handling and interchange systems, and automated terminals are key determinants of the transport demand shares across different types of facilities and regions. Also, enhanced packaging and recycling processes may add value to the provided services and offer increased transportability of products. Such technological changes can additionally involve 'smarter', less energy intensive and more flexible fleets that increase occupancy rates and offer reverse distribution.

The spatial structure of cities - and of systems of cities - influences the amount of travel, in terms of ton-km and passenger-km, and modal choice. A dispersed and low-density urban area is typically connected with longer trip distances and lower mass public transit ridership than a high-density urban area. Planning and traffic regulations, and measures to strengthen mixed-use urban developments may adversely affect the travel distances and travel frequency, and promote more environmentally friendly and energy efficient transport modes, including cycling and pedestrian movements.

The ongoing economic process of globalization does have a positive impact on ton-km traveled, particularly through air cargo and long-distance maritime services, and on passenger-km through international air transport services. The promotion of intermodal and combined transport, for instance, through appropriate technologies and construction and operation of freight villages, encourage the use of railroad and short-distance shipping in the European Union. Moreover, international agreements concerning trade and transport can increase trans-national traffic flows, reduce delays and cross-border bottlenecks, and raise the level-of-service through simplified customs procedures. Such international agreements may refer to the Open Skies agreement between EU and the USA, the development of free trade zones in the Mediterranean regions, and (infrastructure, tariff and regulation) agreements in the road and rail transport sector between the countries around the Black Sea and Eastern Mediterranean region.

The design and spatial organization of inventories, warehousing and just-in-time practices can significantly affect the amount of shipments and line hauls. Institutional changes (e.g., market deregulation/liberalization), like those promoting the use of third-party logistics (3PL) services, and strategic alliances between carriers, shippers, producers and retailers, can increase the level of competition, and potentially yield lower distribution costs, improve the level-of-service and increase transport demand. Government and/or regulator (financial, administrative, environmental and other) policies which affect fuel costs, taxes, and subsidies do also have an impact on passenger and freight transport demand. Summing up, all the above factors should be carefully considered in specifying and assessing the performance of transport prediction models.

3. DEMAND FORECASTING IN THE TRANSPORT PLANNING PROCESS

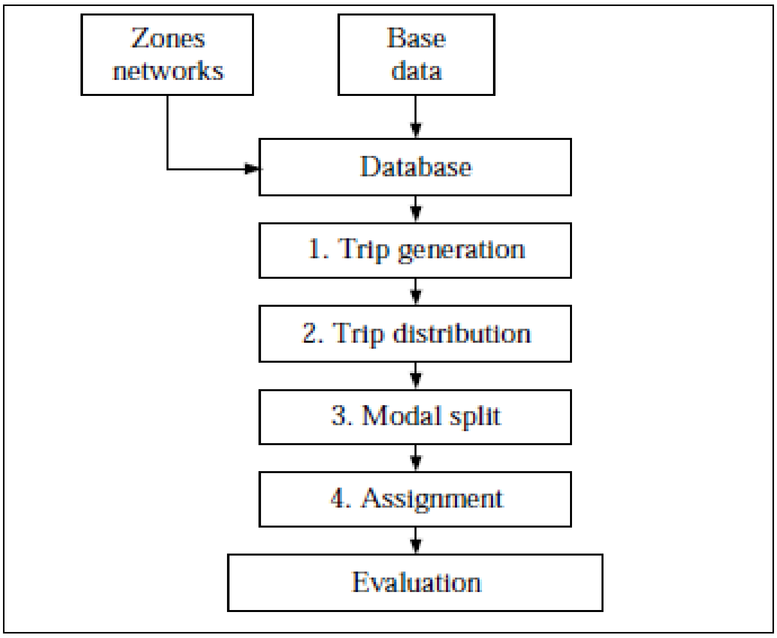
Transport demand forecasting models can be generally categorized according to the steps involved in the traditional four-stage transport planning process (see Figure 1). These steps include: (a) trip generation, (b) trip distribution, (c) modal split (or mode choice), and (d) traffic assignment.

3.1 TRIP GENERATION

Trip generation from and attraction to specific origin-destination (or production-attraction) traffic zones in which the study area is partitioned are based on the socio-economic, demographic and land use characteristics of each zone. Most of the trip generation studies employ econometric and, at a lesser extent, time series analysis techniques. The econometric models use linear or log-linear regression analysis to estimate the relationship between transport demand and its determinants.

Figure 1

The traditional four-stage transport planning model



The time series techniques involve extrapolate historic trends in transport demand into the future without considering the underlining causes of the trends. The most frequently used methods in this approach include (seasonal) exponential smoothing and Box-Jenkins procedure, which can predict the medium- or long-term demand for shipment of goods and movement of passengers.

In the trip generation stage, econometric models are established to forecast passenger transport demand, in terms of passenger vehicle trips or passenger vehicle kilometer traveled (VKT) based on future population projections. Freight demand is typically estimated by use of econometric models, in terms of freight vehicle trip, freight VKT, and freight vehicle ownership. Demand for light truck and regular truck is sometimes estimated in separate models. These passenger and freight demand prediction models can be estimated for both weekday/weekend, and by travel distance, region and trip purpose (or type of commodity). The linear regression model of trip generation can be generally expressed as follows:

$$y = a + \sum_{i=1}^{k} \beta_i x_i \,, \tag{1}$$

where y is the dependent variable (e.g., generated passenger or freight VKT), x_i are the independent (explanatory) variables related to the attributes of passengers/freight and transport system, and β_i are the corresponding coefficients to be estimated during the model calibration process.

Category analysis is also used to predict passenger transport demand by specific set of criteria, such as car ownership, household size and income ranges. The following set of equations can be regarded as typical example models of this approach:

$$y_{ik} = HH_i R_{iG} f_{ik} \tag{2}$$

where y_{ik} are the generated passenger trips at traffic zone i with purpose k, HH_i is the number of households at zone i, R_{iI} is the trip production rate of households of income group G (e.g., between 1000 – 1500 Euro) and f_{ik} is the proportion (%) of total trips to be made at traffic zone i with purpose k.

$$y_{ik} = HH_i R_{iC} f_{ik} \tag{3}$$

where R_{iC} is the trip production rate of households with car ownership index C (e.g., 1.5 private passenger cars per household member).

$$y_{ik} = \sum_{n=0}^{3} HH_i P_{in} R_{inG} f_{ik} \tag{4}$$

where P_{in} is the proportion of households with n number of private passenger cars and R_{inG} is the trip production rate of households with n number of private passenger cars belonging to income group G.

3.2 TRIP DISTRIBUTION

Trip distribution refers to the allocation of the trip demand among traffic origin-destination pairs, according to the distance or some other trip cost (impedance) function designating the (time, monetary or generalised) cost between zone pairs. The result of this step is the construction of a complete origin-destination (O-D) table. The cost (impedance) function of travel between an origin-destination pair $i-j$ of spatial (or time) separation d_{ij} can be expressed through an exponential relationship:

$$f(d_{ij}) = e^{-c(d_{ij})}, \tag{5}$$

where $c > 0$ is a cost coefficient to be calibrated. Then, the predicted number of trips to be carried out between $i-j$ pair can be given through a (doubly constrained) gravity model of trip distribution as follows:

$$y_{ij} = \alpha_i P_i \beta_j A_j f(d_{ij}), \tag{6}$$

with (possible) constraints on the total number of produced and attracted trips:

$$\sum_j y_{ij} = P_i, \tag{7}$$

$$\sum_i y_{ij} = A_j, \tag{8}$$

where P_i are the predicted trips produced from zone i, A_j are the predicted trips attracted to zone j, and α_i and β_j are the corresponding origin and destination balancing factors of the gravity model to be calibrated. The estimation of the (doubly constrained) gravity model follows an iterative optimization process until satisfying the predetermined convergence criteria (see Sen and Smith (1995)). Dynamic extensions of the gravity model in transport systems have been suggested in (Dendrinos and Sonis, 1990; Tsekeris and Stathopoulos, 2006).

3.3 MODE CHOICE

Mode choice implies the modal split of the O-D trip demand for the available means of transport along the origin-destination pairs. This step typically considers the distinction between private and public transport (both vehicular and railroad) traffic (see Ortuzar and Willumsen, 2001). In the discrete choice theoretic framework (see Ben-Akiva and Lerman, 1985), the utility function U of a user can be generally expressed as:

$$U_{in} = V_{in} + \varepsilon_{in}, \tag{9}$$

where V_{in} is the systematic utility component that individual n associates with alternative i in the choice set. In the above equation, the utility is modeled as a random variable in order to reflect the uncertainty through the error term ε. A linear in the parameters function is denoted as follows:

$$V_{in} = \sum_{k=1}^{K} \beta_k x_{ink}, \tag{10}$$

where β is the vector of K coefficients associated with the alternative choices (here, of transport modes) and x are the explanatory variables or attributes of alternative i. Assuming the ε follows a logistic (Gumble) distribution, the probability Π that a given individual n chooses alternative i is given by:

$$\Pi_i = \frac{e^{\mu V_{in}}}{\sum_j e^{\mu V_{in}}}, \tag{11}$$

where μ is a parameter and j denotes an alternative of i. The above equation denotes the multinomial logit model which is widely applied in the mode choice analysis.

3.4 TRAFFIC ASSIGNMENT

The traffic assignment process maps the predicted O-D trip demand per mode into the transport network paths and constituent links, based on the prevailing supply conditions. The solution of the capacity-restrained traffic assignment problem is equivalent with that of Nash equilibrium in game theory. Specifically, according to the first principle of Wardrop (1952), an equilibrium state is reached in the transport network when all users choose paths so that experience the least travel cost and no bilateral change of route can be further made to reduce path travel cost. Consider a network where traffic flow q_a traverses link a of path k between origin r and destination s, with c_a being the travel cost experienced by the users of that link. Also, f_k^{rs} is the path flow along k and q^{rs} is the trip demand between origin r and destination s. Then, the traffic assignment problem can be mathematically expressed as a minimization problem, as follows:

$$Min \sum_a q_a c_a \ , \tag{12}$$

with the following constraints

$$\sum_k f_k^{rs} = q^{rs} \ , \tag{13}$$

and

$$f_k^{rs} > 0 \tag{14}$$

A number of additional constraints can be also imposed to ensure the flow propagation between consecutive links, and the first-in first-out (FIFO) principle at network intersections.

3.5 EXTENSIONS OF THE FOUR-STAGE TRANSPORT PLANNING PROCESS

A typical problem met in the application of the sequential transport planning process is the inconsistency of the resulting predictions, when the output of a later stage (e.g., O-D path costs obtained from the traffic assignment stage) becomes input in an earlier stage (e.g., O-D trip cost in the trip distribution stage). This shortcoming has triggered the development of the so called combined transport planning models, which involve the simultaneous estimation of two or more stages of the overall process. Such models include the combined trip distribution and traffic assignment model, the combined trip distribution and mode choice model, the combined trip distribution, mode choice and traffic assignment model, and so on. Further extension of the combined transport planning models to include long-term (residential and/or employment) location choices, land values and housing rents based on changes in accessibility etc., have resulted in the so called combined urban location and travel choice models (Boyce and Bar-Gera, 2004). Other relevant extensions include integrated land use-transport modes, encompassing wider location choices.

Furthermore, the consideration of the time dimension in departure time choice leads to the formulation of dynamic trip demand models. The consideration of the time-varying traffic conditions in transport networks subsequently leads to the deployment of dynamic traffic assignment (DTA) models. These models are particularly important for the investigation of the users' behavior and network performance under the effects of Intelligent Transport Systems (ITS) applications and other dynamic transport management measures.

4. OVERVIEW OF DEMAND FORECASTING METHODS IN TRANSPORT

A wide range of forecasting methods have been proposed in the field of transport and logistics. These models can be generally distinguished into: (a) deterministic vs. stochastic, (b) static vs. dynamic, (c) macroscopic (or aggregate) vs. microscopic (or disaggregate), and (d) analytical vs. simulation models. The combination of macro-level (e.g., region- or nation-wide) transport demand forecasting models, typically based on variants of the four-stage planning model, with microscopic or mesoscopic traffic simulation approaches, tend to be commonplace nowadays in U.S. transport planning communities (Holyoak and Stazic, 2009).

The use of a single variable or multiple variables in the model specification gives rise to univariate vs. multivariate prediction models, respectively. The univariate time-series analysis of transport demand includes Kalman filtering, smoothing and Box-Jenkins procedures. Other procedures refer to the application of Generalised Autoregressive

Conditional Heteroskedastic (GARCH) models, which have been widely used in the financial modeling context in order to investigate the volatility of the time series. The dynamic or time-varying forecasting models encompass the Compertz growth and learning curve models (e.g., to predict car ownership levels), autoregressive processes, autoregressive distributed lag model (ADLM), autoregressive (integrated) moving average (cause-effect) model (AR(I)MA(X)), seasonal regression models (e.g., those of additive seasonality, multiplicative seasonality and seasonal fractional models) and time varying parameter (TVP) models. Other models refer to gradual switching regression, support vector regression and transfer function models. Multivariate models include the multivariate ARIMA, state-space models and the multivariate GARCH.

Another distinction includes the use of exact analytical vs. approximate models, such as those employing Artificial Intelligence techniques. These techniques have attempted to address complex issues associated with the intrinsic stochasticity, non-linearity and non-stationarity of transport flow time series. Such models encompass fuzzy rule-based methods, evolutionary computation, swarm intelligence, neural network techniques and hybridized (e.g., geno-fuzzy, neuro-fuzzy etc) approaches.

The artificial neural network (ANN) method is a computing technique that tries to imitate the learning process of a human brain. The unique features of ANNs, such as the ability to adapt to imperfect data, nonlinearity, and arbiter function mapping, make this method a useful alternative to the classical (statistic) regression forecasting models. Empirical evidence shows that ANNs generally outperform the classical time-series and multiple regression models in traffic forecasting.

The genetic algorithms (GAs) rely on a stochastic process, which utilizes information about the performance of the system to be optimized in relation to values of different control parameters. In this process, an initial population of candidate solutions is tested and, subsequently, a new, genetically improved population is produced which contains candidates with a higher probability to reach the optimal solution. Each of the candidate solutions consists of a sequence of values of the control variables, and it takes the form of a string (chromosome), i.e., a binary coded value forming a string of 0s and 1s or real numbers in the decimal numbering system, called alleles. The GA stochastic process is composed of three genetic operators, which refer to the reproduction, crossover and mutation.

Moreover, Bayesian statistical inference methods enable the representation of causal dependencies between sets of random variables and the computation of the joint posterior distribution of these random variables, conditional on prior distributions of each variable and data. The computation of the posterior joint distribution can be performed using Markov Chain Monte Carlo (MCMC) or Latin Hypercube simulation methods to account for unobservable sources of risk in transport forecasts.

In order to avoid the spurious regression which often appears in traditional regression analysis based on ordinary least squares (OLS), great effort has been made to further advance the econometric approach in the context of transport modelling and forecasting. Modern econometric methods, such as the vector autoregressive (VAR) and error correction model (ECM) have emerged as the main forecasting methods. In contrast with the other single-equation models, where the explanatory variables included should be exogenous, the VAR and VEC models treat all variables as endogenous, and each variable is specified as a linear relationship of the others. More sophisticated procedures, such as General-to-specific (GETS) models, can allow for non-linear and asymmetric relationships between variables.

A growing number of both simulation and empirical studies have appeared in the literature over the last decades to find ‘optimal’ combinations of forecasts. Traditional approaches presented in such studies for combining forecasts are focused on linear combination methods, such as successive averaging, various types of unconstrained or constrained Least-Squares techniques and multiple objective linear programming models. More recent efforts include the development of Bayesian updating procedures for combining information (probabilities, probability distributions, or forecasts) from various prediction mechanisms.

Nonetheless, there are many cases where linear combination may result in the optimal combination at a particular point, but not the best forecast, by failing to make full use of the existing individually processed information. In particular, such cases can arise when the relationship between individual forecasting models and the 'best' forecast is not limited to a linear relationship, due to the combination of models with different functional form, such as the Kalman filter with a linear form and the ANN models with nonlinear form. In such cases, the true underlying conditional expectation of the forecast can be a nonlinear function of the information sets on which the individual forecasts are based, resulting in a bias to the linearly combined forecasts.

Therefore, nonlinear combination of forecasts should be preferred, in which case the forecasting function can be viewed as a nonlinear information system processing the information provided by the individual forecasting models. In such a case, Artificial Intelligence-based techniques should be favored in comparison to the existing statistical approaches. This is because the latter are cumbersome to apply when using real-world complex datasets, requiring assumptions on complicated multivariate likelihood functions and error distributions. However, only a limited number of Artificial Intelligence techniques have been hitherto proposed and tested to produce nonlinear combinations of forecasts, including ANN models and fuzzy systems.

5. SYSTEM-WIDE APPROACHES IN TRANSPORT DEMAND FORECASTING

Most of the existing demand models in transport and logistics, especially those composed of a single equation, imply a separability of the services offered by different transport modes. Namely, they consider demand responses to changes in tariffs (or fares) or service levels only in a specific market. Nonetheless, failure to include the effect of changes in prices and service levels of competing modes can lead to bias in the demand elasticity estimates. Several transport demand models have been employed to jointly estimate changes in both the levels and shares of demand for two or more transport modes. These models mostly correspond to abstract-mode, modal-split and discrete-choice (such as, logit) approaches. The structural equation models (SEMs) provide a flexible framework for expressing cross-equation interrelationships among dependent and explanatory variables, while the seemingly unrelated regression (SUR) techniques are employed to address problems of biased parameter estimation due to cross-equation error correlation.

In addition, agent-based simulation approaches (Teodorovic, 2003; Ivaldi and Vibes, 2008) are increasingly implemented in the last years to address the complex phenomena of transport and supply chain processes (e.g., see Liedtke (2009), Roorda et al., 2010). They can microscopically represent the various forces acting upon a particular agent or actor of the system, e.g., individual, household, firm, government, at any location, thus deriving a discrete step-by-step simulation of its trajectory. This approach enables the path dependency and occurrence of outcomes which may deviate from a single steady-state equilibrium point in the prediction horizon. This deviation is due to the consideration of bounded rationality, varying degrees of intelligence and autonomy, learning capabilities and unique characteristics of myopic agents.

The ability to capture both the intra-personal variability in the perceptions and attitudes of each individual as well as inter-personal variability allows the bottom-up emergence of diverse types of behavioral response mechanisms to covariates of demand.

Agent-based models facilitate the representation of the interaction among individuals and the collective dynamics of congestion phenomena, in contrast with the conventional discrete choice models which tend to produce biased outputs. Nonetheless, the current inability of agent-based models to provide reliable forecasts beyond a short prediction horizon has rendered them most useful for transport policy and sensitivity analysis, rather than for medium- or long-range transport planning purposes.

System-wide economic forecasting models may include computable general equilibrium models or partial equilibrium models. In the partial equilibrium models, which are the most commonly adopted, the pricing of marginal transport cost produces optimal welfare when there are no pricing constraints in the transport sector, while the generalized equilibrium models focus on the interaction between transport pricing and inefficiencies in the rest of the economy. TREMOVE is an important partial equilibrium model, which is widely used in Europe for the evaluation of (environmental) policies in the transport sector. It uses nested constant elasticity of substitution functions to simulate interactions between road and public transport pricing and demand profiles, assuming that the total labour supply is fixed.

All the aforementioned approaches typically rely on *a priori* restrictions on the demand elasticities and intermodal substitutability, which are not underpinned by the economic theory of demand. On the contrary, analytical, system-wide modeling approaches are consistent with the theory of consumer demand. This framework allows determining the substitution and complementarity relationships among different transport modes, through the cross-price elasticity measures, together with the own-price and income effects.

6. CONSUMER DEMAND SYSTEMS

In consumer demand systems, travel expenditure shares as dependent variables constitute important transport policy variables and proxies for the demand for each transport mode. A number of empirical studies can be found in the literature for the system-wide analysis of transport consumption (expenditure) patterns. These studies employ either time series or cross-section data at the aggregate or disaggregate (individual or household) level. On the one hand, the analysis of travel expenditures with disaggregate information is typically based on the use of cross-section data from consumer or household sample surveys. In such studies, the interest concentrates on the relationship, in terms of the aggregate elasticity value, between expenditure on a particular item and income, holding prices constant, through using the well-known Engel curve analysis. Namely, this kind of analysis does not help determine the level of competition among alternative passenger transport modes, since price effects are considered as fixed.

System-wide consumer demand models can be described as simultaneous systems of expenditure equations that approximate the utility-maximizing behavior of consumers. The generalized theory of consumer demand provides a sound economic background and interpretation in the system-wide analysis of expenditure patterns with regard to consumer behavior when changes occur in variable factors such as own price, income and substitute goods (or services). In the current context, consumer demand models can allow the joint determination of different mode choice preferences by considering cross-price effects.

There has existed for some time a variety of aggregate demand systems for investigation of the budget allocation preferences of consumers (for a comprehensive review, see Andrikopoulos and Brox (1997)). These include the Linear Expenditure System (LES) and the Rotterdam system. However, the Almost Ideal Demand System (AIDS), referred to here as AI (Deaton and Muellbauer, 1980), is considered to be the most empirically robust and consistent with the general theories of demand and choice. The AI system is based on a multi-stage budgeting process where, first, utility-maximizing consumers allocate their total budget between travel and the other commodities, and, then, allocate expenditures among individual travel commodities. Different from the single-equation econometric models, AIDS is a system-of-equations approach, normally employed to examine transport demand in a number of destinations or markets, and uses transport expenditure shares as dependent variables. The AIDS approach has a much stronger underpinning of economic theory. Hence, it is more powerful than its single-equation counterparts with respect to transport demand elasticity analysis, such as substitution and complementary effects between alternative destinations under study.

7. DATA SOURCES AND LIMITATIONS FOR TRANSPORT DEMAND ANALYSIS

As far as data issues are concerned, the data collection frequency can be annual, quarterly, monthly, for long-range or medium-term forecasting purposes, or even hourly or of a few minutes for the case of real-time travel prediction purposes. The data may focus on specific points of the transport network, traffic analysis zones, and regions/countries as origins or destinations. The use of both cross-sectional and time-series information can simultaneously capture spatial and temporal variations affecting transport demand, giving rise to dynamic panel data regression approaches (Tsekeris, 2008). The appropriate treatment of dynamics through such approaches is crucial for avoiding possible bias in the elasticity estimates of transport demand and estimating both short- and long-run elasticities. In addition to the use of transport flow (number of passenger, amount of cargo, pass-km and ton-km) data from censuses, household travel surveys, firm surveys, interviews and diaries, transport expenditure can be used to capture the transport demand of households and firms, capturing both the amount and frequency of travel.

Approaches to human interactions and mobility mostly relied on census and survey data were often incomplete and/or limited to a specific context. Ongoing advances in information and telecommunication technologies opened the path to the general exploitation of proxy data for human interaction and mobility, such as transport expenditure. Analogously, modern mobile phones and personal digital assistants combine sophisticated technologies such as Bluetooth, Global Positioning System, and WiFi, constantly producing detailed traces on our daily activities. Popular websites for currency tracking (for instance, http://en.eurobilltracker.com and www.wheresgeorge.com) collect a massive number of records on money dispersal that can be used as a proxy for human mobility.

Traditional data sources employed in the analysis of transport expenditures can significantly affect the underlying assumptions and quality of estimation results of the various methods. These traditional sources can be generally distinguished into four categories:

(a) Household Budget Surveys (HBS) or Consumer Expenditure Surveys (CES) at the level of households or individuals,
(b) Household or personal travel surveys and travel diaries,
(c) The system of National Accounts,
(d) Revenues of public transport firms (or carriers) originated from fares.

The use of Household Budget Surveys or Consumer Expenditure Surveys has been generally found to provide a more consistent analysis of the travel consumption patterns, in comparison to the use of data from household or personal travel surveys or diaries and data from National Accounts. Most travel surveys do not investigate consumer expenditure behavior, while others tend to overestimate travel money budgets, since they concentrate only on local areas and, hence, they typically underestimate money expenditures for long-distance trips. In addition, HBS are conducted on a factual basis, in comparison to the frequential basis of travel surveys, which lead to the overestimation of the most repeated and frequent expenditure items (typically, those related to private vehicle and public transport).

Moreover, the use of disaggregate data from stated preference surveys concerning the willing-to-pay for different travel services and goods, through employing discrete-choice models, enriches the existing knowledge on travel consumption behavior. Specifically, such data allow representing the effect of a range of hypothetical scenarios involving price variations as well as changes in other (personal, social, economic, institutional and regional) factors influencing demand on household travel budget shares for specific (origin-destination) markets and sets of alternative modes of transport.

The possibility of travel expenditure aggregation for distinct population groups with different socio-economic (e.g., by income, education and car ownership) and demographic (e.g., by gender, age of household head and number of household members) characteristics can provide further insight into the analysis of travel consumption and market competition conditions. For instance, estimation of income and price elasticities for various population groups would allow a more detailed examination of the distribution of the impact of a petrol price increase or public transport fare reduction on travel budget allocation among low, medium and high income households. In turn, this outcome might help support the formulation of specific transport policies (e.g., subsidies and travel discounts) for target population (e.g., multi-member and low-income families, student) groups.

8. CONCLUSIONS AND OUTLOOK

Current problems related to transport demand forecasting are mainly associated with the consistency and comparability of elasticity estimates resulting from different modeling approaches, natures of data, measuring units and countries. Combined travel demand models can substantially generate consistent estimates of trip generation, trip distribution, modal split and network assignment without major increases in neither computational nor data requirements relative to the four-step forecasting approach. Despite that the availability of many different models would possibly suggest that the best practice would have been identified, the forecasting accuracy of long-term travel forecasts cannot generally be considered as satisfactory. Demand shocks due to the recent economic crisis, natural and man-made disasters and other unexpected events may exacerbate accuracy losses. New system-wide approaches to transport are still required, which would better correspond to the vital need for a fiscally, socially and environmentally sustainable development, as well as to the recognition and acknowledgment of travel as a mainly derived demand. The exploitation of new data sources from advanced (e.g., web-based) communication technologies can address some of the existing limitations in transport demand analysis. In addition, recent modeling advances can improve the behavioral generality of these models, by linking aggregate travel demands to individual-level choice theory in a theoretically consistent manner and developing linkages to dynamic travel demand estimation.

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PREDVIĐANJE POTRAŽNJE U PRIJEVOZU: PREGLED I NAPREDAK U MODELIMA

SAŽETAK

Cilj ovog rada je opsežno istražiti i dati produktivan pregled rastućeg polja istraživanja predviđanja potražnje u prijevozu. U tom analitičkom kontekstu, rad želi opisati, kritički raspraviti i uz konkretne rezultate obraditi relevantne mehanizme i modele predviđanja potražnje, kao i specifičan razvoj i implementaciju sistematskih pristupa. Pregled raznih teoretskih i metodoloških napredaka u trenutnim modelima predviđanja zagovara korištenje modela potrošačke potražnje (dinamičkog karaktera) za predviđanje udjela potražnje među alternativnim načinima prijevoza.

Ključne riječi: *modeli prijevoza, predviđanje prometa, potrošnja kućanstva, potrošačka potražnja, konkurencija među načinima prijevoza*