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INCORPORATING AUTOMATED VEHICLE IDENTIFICATION DATA INTO ORIGIN-DESTINATION ESTIMATION

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Abstract

This paper presents a methodology for the incorporation of *Automated Vehicle Identification* (AVI) data into Origin-Destination (OD) estimation and prediction. AVI technologies facilitate the collection of useful data, such as point-to-point travel times and subpath flows. A framework for the incorporation of AVI data into the well-established Origin-Destination (OD) estimation and prediction process is presented. Improvements are proposed both for the formulation and the inputs to the OD estimation and prediction model. Furthermore, as the OD estimation and prediction process is often used in a traffic estimation and prediction context, approaches to incorporate AVI data into other areas of the dynamic traffic assignment framework are outlined. Performance and computational issues are also considered, and results of a case study are presented to demonstrate the approach.

Keywords: OD flows estimation and prediction; Automated vehicle identification (AVI) systems; Kalman filter

Topic area: D5 Data Collection Methods

1 Introduction

Traffic congestion -and all its side-effects and adverse impacts- is a key problem of many urban areas. Indeed, traffic conditions are rapidly declining in most urban areas worldwide and the trends do not show any signs of reversal. While several approaches have been proposed for the mitigation of traffic congestion, better management of the existing infrastructure through control strategies and dissemination of relevant information to drivers appears to be the most promising approach. A key component of such an approach is Dynamic Traffic Assignment (DTA) systems that reside at Traffic Management Centers (TMC). Such systems have estimation and prediction capabilities and are capable of generating and evaluating guidance and control strategies.

DTA systems typically comprise two main functions (Ben-Akiva et al., 2002):

- State estimation; and
- Prediction-based information generation

During the *state estimation* phase, real-time information is combined with historical data to capture the traffic conditions that are prevailing in the network. Detailed traffic information that is obtained through the instrumented portions of the network is used to infer the conditions in the parts of the network for which no real-time information is available. This is achieved through an iterative simulation of demand-supply interaction designed to reproduce real-time observations from the surveillance system.

The role of the *prediction-based information generation process* is to generate unbiased and consistent traffic information for dissemination to travelers. Information based on predicted network conditions (i.e. anticipatory information) is likely to be more effective than information based on current traffic conditions because it accounts for the evolution of traffic conditions over time which is what travelers will experience. A detailed treatment of the demand-supply interactions within a state-of-the-art DTA system can be found in Ben-Akiva et al. (2002).

One of the key components of dynamic traffic assignment is the Origin-Destination (OD) estimation and prediction process (Ben-Akiva et al., 2002). OD estimation combines historical and real-time information to obtain dynamic -i.e. time-dependent- demand tables. Furthermore, OD prediction exploits estimated behavioral patterns to anticipate the short-term evolution of demand (Antoniou et al., 1997). Based on the predicted demand, it is possible to generate and evaluate response strategies and generate anticipatory guidance (Bottom, 2000).

Traffic information is usually collected through traffic sensors. While several technologies have been introduced (microwave/acoustic sensors, cameras, etc), the most common implementation is inductive loop detectors. Such detectors can provide counts of individual vehicles crossing the sensor location, as well as occupancy and -using some assumptions- possibly speed data. The problem of state estimation is an under-determined problem, as a relatively small number of measurements is used to infer a much larger number of demand flows. To overcome this issue, researchers use data from other sources. Ben-Akiva (1987) and Ben-Akiva and Morikawa (1989) suggested frameworks for statistical methods to efficiently combine data from diverse sources and applied them in the estimation of origin-destination matrices. A usual source of data in this context is travel demand surveys, that provide *a priori* or historical estimates of the demand flows. While historical data provide important information on the structure of the traffic patterns, however, it is the surveillance data that ultimately provide information about the prevailing traffic conditions.

A promising advancement in data collection for traffic networks has been the use of *Automated Vehicle Identification* (AVI). The underlying principle is based on the *identification* of individual vehicles equipped with an appropriate device (often called *probe vehicles*) in various locations in the network. Analysis of the space-time information collected from this group of vehicles can provide information on their travel patterns, which may then be -cautiously- extrapolated to provide information for the entire population.

The incorporation of multiple data sources into the OD estimation and prediction framework is expected to improve the *observability* of the system, i.e. the ability to determine the state of the system from a set of observed measurements. A larger number of surveillance system measurements improve the ability of the system to isolate and identify the contributions of OD flows to traffic flows.

The remainder of this paper is structured as follows. Section 2 presents an overview of AVI technologies, as a background to the subsequent developments, while Section 3 presents a review of related literature. Section 4 presents the proposed extended OD estimation and prediction framework. Section 5 describes a case study that demonstrates the feasibility of the proposed approach. Finally, in Section 6 conclusions are drawn and future research directions are outlined.

2 AVI - overview and principles of operation

This section presents an overview of AVI systems, their basic principles of operation, and data that they can provide, focusing on the impact that this data may have on OD estimation and prediction.

2.1 Classification of AVI technologies

There are several ways to organize and categorize AVI systems. Table 1 presents a categorization of AVI technologies along two key dimensions. First, based on their coverage of the network, AVI systems can be separated by whether they can track vehicles throughout the entire network (e.g. GPS systems or cell phone tracking systems) or whether they are limited in identifying them in particular locations of the network (e.g. tag identification sensors, or license plate recognition systems).

Table 1. Classification of indicative AVI technologies by scope

		Spatial coverage	
		Area-wide	Short-range
Vehicle coverage	All vehicles	N/A	License plate recongition
	Equipped vehicles	GPS-based Cell phone tracking	Transponder Detection

Another dimension is whether some sort of cooperation is needed from the side of the driver for the system to be able to locate and identify a vehicle. Transponder-identifying systems and GPS systems, for example, require the driver to have an activated device in their vehicle. On the other hand, license plate recognition systems do not require any cooperation from the drivers, given that all vehicles should -by law- have their license plate in a visible position. This distinction can also be interpreted as whether the system is able to locate all vehicles or only a subset of the vehicles.

2.2 Principles of operation

AVI applications are based on the detection and identification of individual vehicles in several locations as they traverse the network. A basic concept in processing probe vehicle (or AVI) data is the *matching* of subsequent detections. When the equipped vehicle approaches the first sensor, its unique *signature* is recorded by the sensor and transmitted to the central data collection facility, along with the sensor ID and the time-stamp of the detection. A similar process takes place when the same vehicle approaches all downstream sensors. Data is collected in a central facility, where it is processed and the necessary information is extracted.

Thus, equipped vehicles effectively become *probes* that provide a packet of raw traffic information during each detection. Each raw data instance comprises three tokens:

1. **vehicle location**: the location of the equipped vehicle during the detection (e.g. surveillance camera or transponder detector location, GPS unit or cell phone coordinate);

2. **vehicle *signature***: a unique identifier of the tracked vehicle, through which multiple detections of the same vehicle in subsequent sensor locations can be associated; and

3. **vehicle tracking time-stamp**: providing the time that the detected vehicle crossed the reporting sensor location.

The vehicle *signature* is dependent on the type of AVI system. For transponder based systems the ID of the transponder can be used. Similarly, for GPS applications a unique identifier associated with the GPS device can be used, while the license plate is the de-facto signature in license plate recognition applications. In order to appease privacy concerns, these vehicle signatures can be scrambled at the sensor, thus ensuring that the actual vehicle information can not be reconstructed. An analysis of the privacy concerns associated with the use of ETC transponders is presented by Ogden (2001).

Raw data from all sensors are collected in a central location where they are stored. A wealth of information can be inferred from this raw data. By comparing the time-stamp of successive readings of a particular vehicle's (scrambled) signature, the system can compute the travel time experienced by that vehicle for the network portion between the two sensor locations. Based on the individual travel times experienced by probe vehicles detected by the same set of sensors, estimates of the time dependent subpath travel times can be obtained. Investigation of the way that vehicles detected by one sensor are distributed among downstream sensors can provide valuable information regarding route choice fractions in various decision points in the network.

Furthermore, origin/destination data can also be obtained from raw AVI data. However, this assumes that AVI detections can be made sufficiently close to the origins or destination, so that there is no ambiguity as to which origin or destination this vehicle belongs to. Extrapolation of the partial origin/destination data that are obtained from the *probe* vehicles to the entire vehicle population can provide time-dependent estimates of OD flows.

Finally, probe vehicle data can be used for the generation of actual paths in a network (for example, a library of paths can be generated by adding all paths that were followed by at least one *probe* vehicle).

2.3 Indicative AVI technologies

Several technologies can be used for the tracking of *probe vehicles* in an AVI environment, including:

- *In-vehicle Global Positioning System (GPS) receivers*
- *In-vehicle transponders (tags) in combination with fixed roadside sensors*
- *License-plate recording, using roadside closed-circuit TV (CCTV) cameras*
- *Cell phones tracking (or self-reporting)*

A brief description of these technologies follows.

In-vehicle Global Positioning System (GPS) receivers: The use of GPS receivers provides the ability to obtain very detailed, continuous data on the vehicle location. From this information, other data can be inferred (such as speed and acceleration). However, this method requires additional equipment on the vehicle and is not very well suited for real-time operations because the data is collected in the in-vehicle unit and needs to be transmitted to a central server from processing. GPS add-ons for wireless Personal Digital Assistants (PDAs) overcome this problem, but the cost increases to impractical levels (for wide applications) and the cooperation of the driver is needed (Quiroga et al., 2002).

In-vehicle transponders (tags) in combination with fixed roadside sensors: This method provides time-stamped detection of the equipped vehicles in the sensor locations. Travel time, path and subpath flows, and path choice information for the equipped vehicles can be inferred by matching vehicle tag IDs recorded in several locations. The advantages of this approach include the ability to collect data centrally, in real-time, and without the active cooperation of the drivers. Implementations that use existing in-vehicle transponders (such as the Electronic Toll Collection, ETC, tags (Mouskos et al., 1998)) eliminate the need for additional in-vehicle equipment and take advantage of the high market penetration of such transponders in some markets (Morris, 1996, Park and Rilett, 1998). Data obtained from such systems is being used for incident detection (Mouskos et al., 1998) and travel time prediction (Kuchipudi and Chien, 2003).

License-plate recording, using roadside closed-circuit TV (CCTV) cameras: CCTV and visual detection technology have improved dramatically during the past years. While manual license plate recording data have been used for traffic surveys for many decades, the use of optical recognition to automate these measurements has made license-plate recording a possible source of real-time traffic information. However, detection accuracy is still not without problems, especially during adverse lighting and weather conditions.

Cell phones tracking (or self-reporting): Cell phones have been thoroughly investigated as a source of incident detection (Mussa et al., 1998, McLean, 1991) and travel time information (Smith et al., 2003) with positive results. Despite the high-penetration of cell phones, this method suffers from the need for driver participation, the manual nature of the information processing, as well as the possible reporting bias. If and when cell phone tracking becomes available, this method may become a feasible way of gathering real-time traffic information. The recent interest in the *Enhanced-911 (E-911)* initiative may provide the platform for such applications.

While not inherently an AVI technology, it is worth noting that conventional loop detectors can also be used for vehicle reidentification and consequently traffic monitoring purposes. These approaches use pattern recognition technologies and assign a unique "signature" to each vehicle (Oh and Ritchie, 2003, Coifman and Cassidy, 2002).

2.4 Data considerations

In general, AVI systems provide information about a sample of the driver population, which is analyzed and used as a starting point for the estimation of information on the entire driver population. There are several considerations about the inherent biases of the data that is obtained from such non-random sampling processes. First, although AVI data may give very complete information on the travel patterns of drivers of equipped vehicles and the conditions that they experience, the fraction of such users in the total traffic stream will generally vary by time of day, vehicle class and facility, and may not always be accurately known. The problem then is to infer information about all travelers from very detailed observations of a (possibly non-representative) subset of them. The second issue concerns the geographic dispersion of the sensors. Due to practical limitations, the number of available sensors in most applications will not cover the entire network in such a way that all OD pairs and links are covered. Thus, incomplete information will be provided, and the conditions at locations without detectors will have to be inferred from other observations and historical information.

Unlike conventional traffic sensors, where raw data is often aggregated, it is very important to retain the data obtained from AVI applications in their raw form. This raw data is necessary for the *tag matching* process, during which subsequent detections of the same vehicle *signature* are grouped together to describe this vehicle's trip.

3 Review of related work

The problem of OD estimation and prediction has been well studied over the last two decades (Cascetta, 1984, Okutani, 1987, Cascetta et al., 1993, Ashok and Ben-Akiva, 1993, Ashok, 1996, Ashok and Ben-Akiva, 2000, Ashok and Ben-Akiva, 2002). A detailed presentation of the OD estimation and prediction literature is outside the scope of this paper. In the majority of the relevant literature, OD estimation is based on historical demand information and link count data. This review focuses on extensions to the OD estimation and prediction framework that utilize richer data.

Ashok (1996) introduced the notion of direct measurements for the incorporation of probe vehicle information in the OD estimation and prediction formulation that he proposed. By definition, a *direct measurement* provides a preliminary estimate of an OD flow. A direct measurement can thus be expressed as:

$$\mathbf{x}_h^a = \mathbf{x}_h + \mathbf{u}_h \qquad (1)$$

where $\mathbf{x}_h^a$ denotes the *a priori* or preliminary estimate of $\mathbf{x}_h$ and $\mathbf{u}_h$ is a vector of random errors. In the case of information obtained from probe vehicles (with known origin and destination), direct measurements may be represented by:

$$\mathbf{x}_h^a = \mathbf{E}_h \mathbf{x}_h^{probe} \qquad (2)$$

where $\mathbf{x}_h^{probe}$ represents the number of probe vehicles corresponding to each OD pair departing during interval h. The matrix $\mathbf{E}_h$ is diagonal and represents an "expansion" factor to account for the fact that probe vehicles constitute only a fraction of the total number of vehicles in the network.

van der Zijpp (1996) combined volume counts with trajectory information obtained from automated license-plate surveys for the estimation of OD flows. The model is based on split probabilities.A measurement equation for the trajectory counts is specified and split probabilities are estimated from combined link volume counts and trajectory counts. The estimation of the split probabilities from combined data is performed in a way similar to that for the link counts. This method of estimating split probabilities from combined data was tested by the author in experiments using synthesized data. These experiments showed that using combined data consistently led to lower errors of estimation relative to the case where only traffic counts were used.

Dixon and Rilett (2000) use AVI information for OD estimation. They define the boundaries of their network as the AVI sensor locations, thus having direct OD information which they use to generate all other inputs to their model, such as link volumes, link choice proportions, and OD observations. This assumption, however, is very limiting in terms of the applicability of their model. The authors propose several estimators based on generalized least square and Kalman Filtering algorithms and evaluate their algorithms on a freeway stretch with on- and off-ramps, (i.e. route choice is not considered).

Mishalani et al. (2003) evaluate the role of various types of surveillance data in the real-time estimation of dynamic OD flows at the intersection level. Turning fraction and travel time data was collected from video cameras at three adjacent intersections. OD estimation using link counts was used as the base case. Additional scenarios involved the incorporation of turning fractions at the intersections, travel times, and combination of turning fractions and travel time. The main finding of the study was that intersection turning fraction data significantly improves the quality of the OD flow estimates, while the use of link travel time data in addition to turning fractions can also improve the quality of OD flow estimates.

4 Modeling framework

The proposed methodology builds upon the OD estimation and prediction framework presented by Ashok and Ben-Akiva (1993) and formulated as a *state-space* model using deviations (instead of the actual flows). For a discussion of the advantages of the use of deviations (instead of the actual flows) the reader is referred to Ashok and Ben-Akiva (1993). A *state-space* model is formulated as a set of:

- Transition equations; and
- Measurement equations.

Denoting by $\mathbf{X}_h = \mathbf{x}_h - \mathbf{x}_h^H$ the deviation of the vector $\mathbf{x}_h$ (representing the number of vehicles between each OD pair departing their origins during time interval h) from the corresponding updated historical estimate $\mathbf{x}_h^H$, the transition equation can be expressed in matrix form in terms of deviations as:

$$\hat{\mathbf{X}}_{h+1} = \sum_{p=h-q}^{h} \mathbf{f}_h^p \mathbf{X}_p + \mathbf{w}_h \tag{3}$$

where $\hat{\mathbf{X}}_{h+1}$ is an estimate of $\mathbf{X}_{h+1}$, $\mathbf{f}_h^p$ is the matrix of effects of $\mathbf{X}_p$ on $\hat{\mathbf{X}}_{h+1}$, $\mathbf{w}_h$ is a vector of Gaussian, zero-mean, uncorrelated errors, and q is the degree of the autoregressive process.

The deviation of the vector of observed link flows $\mathbf{y}_h$ from the best estimate, based on the available assignment matrices and estimated demand, is denoted:

$$\mathbf{Y}_h = \mathbf{y}_h - \sum_{p=h-p'}^{h} \mathbf{a}_h^p \hat{\mathbf{x}}_p \tag{4}$$

where $\mathbf{a}_h^p$ is an *assignment* matrix of contributions of OD flow $\mathbf{x}_p$ to link flow $\mathbf{y}_h$, and p' is the maximum number of time intervals taken to travel between any OD pair of the network.

The measurement equation, which relates deviations in the unknown OD flows to deviations in the observed link counts, can thus be stated in matrix form as follows:

$$\mathbf{Y}_h = \mathbf{A}_h \mathbf{X}_h + \mathbf{v}_h \tag{5}$$

where $\mathbf{A}_h = \mathbf{a}_h^h$ is the assignment matrix mapping the drivers that departed in interval h to the link counts observed in interval h and $\mathbf{v}_h$ is the vector of measurement errors, assumed to be zero-mean, uncorrelated as well as uncorrelated with the transition errors $\mathbf{w}_h$.

Ashok (1996) proposed an extension of the OD estimation process to incorporate *direct* measurements of OD flows. By definition, a direct measurement provides a preliminary estimate of an OD flow; under some conditions on the location of the AVI sensors, it is possible to obtain such measurements for some OD pairs from an AVI system. Assuming deviations form, Equation 1 can be written as:

$$\mathbf{E}_h^{-1}\mathbf{x}_h^{probe} - \mathbf{x}_h^H = \mathbf{x}_h - \mathbf{x}_h^H + \mathbf{u}_h \tag{6}$$

An equivalent way of representing Equation 6 is:

$$\begin{aligned} &\mathbf{x}_h^{probe} - \mathbf{E}_h\mathbf{x}_h^H = \mathbf{E}_h\mathbf{X}_h + \mathbf{E}_h\mathbf{u}_h \Rightarrow \\ &\mathbf{Y}_h^{probe} = \mathbf{E}_h\mathbf{X}_h + \mathbf{u}_h^* \end{aligned} \tag{7}$$

where $\mathbf{E}_h$ is a diagonal matrix and represents an "expansion" factor to account for the fact that probe vehicles constitute only a fraction of the total number of vehicles in the network, $\mathbf{Y}_h^{probe} = \mathbf{x}_h^{probe} - \mathbf{E}_h\mathbf{x}_h^H$ is the deviation of the vector of observed probe vehicle flows $\mathbf{x}_h^{probe}$ from the best estimate, based on the available expansion matrix $\mathbf{E}_h$ and the historical demand, $\mathbf{X}_h = \mathbf{x}_h - \mathbf{x}_h^H$ is a vector of deviations of the OD flows for time interval h, and $\mathbf{u}_h^*$ is a vector of Gaussian, zero-mean, uncorrelated errors. Each entry in the matrix $\mathbf{E}_h$ represents the inverse of the fraction of AVI vehicles. Thus, matrix $\mathbf{E}_h^{-1}$ is guaranteed to be invertible since it is diagonal with elements ≥ 1.

In order to be able to specify direct measurements, however, a number of fairly restrictive requirements must be satisfied, i.e. AVI sensors must be located close enough to origins and destinations so that there is no ambiguity as to which OD pair detected vehicles belong to. Additional information can be obtained from the AVI data by grouping appropriate pairs of AVI detector locations that define *subpaths*. Successive AVI detections of vehicles in both detectors of the same subpath will then provide flow information for this subpath. Similarly to the way that the OD flows are mapped to the link counts, it is possible to map the OD flows to subpath flows. An additional measurement equation in terms of deviations (in matrix form), reflecting the contribution of the OD flows to the subpath flows, can then be written:

$$\mathbf{Z}_h = \mathbf{G}_h\mathbf{X}_h + \boldsymbol{\eta}_h \tag{8}$$

where $\mathbf{Z}_h = \mathbf{z}_h - \sum_{p=h-p'}^{h}\mathbf{G}_h^p\hat{\mathbf{x}}_p$ is a vector of deviations in the subpath flows, $\mathbf{X}_h = \mathbf{x}_h - \mathbf{x}_h^H$ is a vector of deviations of the OD flows for time interval h, and $_h$ is a vector of Gaussian, zero-mean, uncorrelated errors. $\mathbf{G}_h^p$ is an $(n_{subpath} \times n_{OD})$ matrix that maps the subpath flows observed in time interval h (as obtained by combination of sequential AVI measurements of the same vehicle) to the OD flows that departed in time interval p (In a way similar to the way the assignment matrix maps the link counts to the OD flows). A subpath flow measurement implies that the vehicle has crossed the downstream detector. Therefore, flows observed at time interval h imply that they capture vehicles that capture the downstream detector within interval h. For notational simplicity, $\mathbf{G}_h^h$ is equivalent to $\mathbf{G}_h$.

Equations 7 and 8 can then be used to *augment* Equation 5, thus providing a single measurement equation:

$$\mathcal{Y}_h = \mathcal{A}_h \mathbf{X}_p + \mathcal{V}_h \qquad (9)$$

where:

$$\mathcal{Y}_h = \begin{bmatrix} \mathbf{Y}_h \\ \mathbf{Y}_h^{probe} \\ \mathbf{Z}_h \end{bmatrix}, \ \mathcal{A}_h = \begin{bmatrix} \mathbf{A}_h \\ \mathbf{E}_h \\ \mathbf{G}_h \end{bmatrix}, \text{ and } \mathcal{V}_h = \begin{bmatrix} \mathbf{v}_h \\ \mathbf{u}_h^* \\ \boldsymbol{\eta}_h \end{bmatrix}.$$

The complete state-space model would then comprise Equations 3 and 9, where the state is defined by the vector $\mathbf{X}_p$ of deviations of OD flows from historical estimates.

The assignment matrix **A** is the key input in the conventional state space model. It maps the OD flows into link counts. A thorough treatment of the intricacies associated with this matrix can be found in Ashok (1996) and Ashok and Ben-Akiva (2002). Generally, the assignment fractions depend on a large number of parameters, including travel times and route choice fractions. The assignment matrix is in general not known and in the context of OD estimation within a DTA system it is computed indirectly.

In the extended problem that is being considered here, two additional matrices become important, denoted in the previous section by **E** and **G**. We call these matrices *expansion matrix* and *AVI-assignment matrix* respectively. The analytical computation of these matrices is again very difficult. However, these inputs can be computed indirectly, similarly to the way that the assignment matrix is computed. Naturally, this introduces a degree of uncertainty about the quality of the provided matrices.

5 Case study

A case study has been performed to demonstrate the value of additional data sources (e.g. information obtained from AVI systems) in terms of improvements in the accuracy of the OD estimation and prediction framework. Synthetic data generated from the *simulation laboratory* environment MITSIMLab have been used. MITSIMLab (Yang, 1997, Yang and Koutsopoulos, 1996) is a simulation laboratory for evaluation of Dynamic Traffic Management systems). MITSIMLab represents the *"real world"* and provides measurements. A subset of the loop detector locations have been designated as AVI sensor locations. MITSIMLab can provide both aggregate link counts at the sensor locations and detailed measurements of the individual *equipped* vehicles that are detected by the AVI sensors. The overall methodology is outlined in Figure 1.

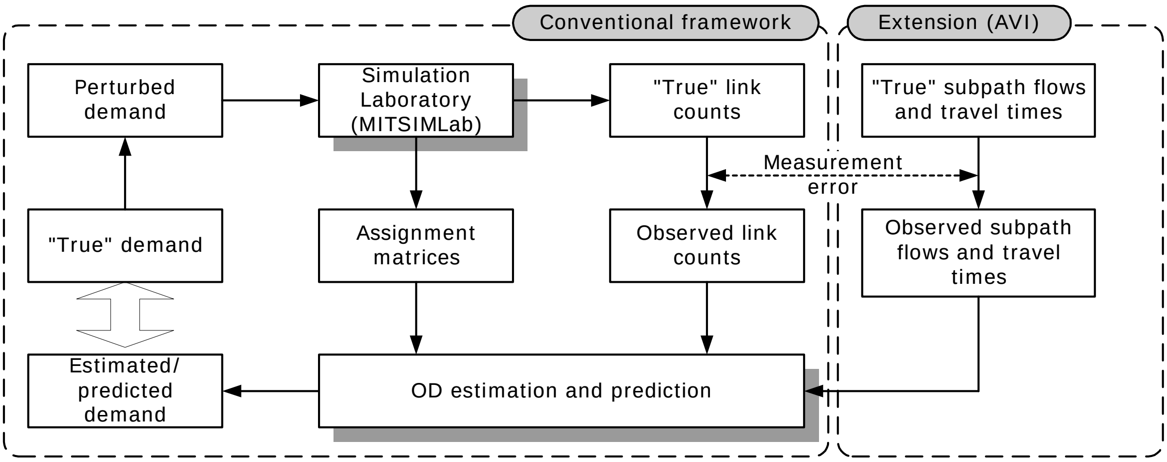

Figure 1. OD estimation (and prediction) using synthetic data

The simple network shown in Figure 2 was used for this case study. Three loop detectors are located in the network, which provide regular point measurements. Furthermore, sensors that provide AVI functionality are also located in the same locations, thus providing subpath information as shown in Figure 2.

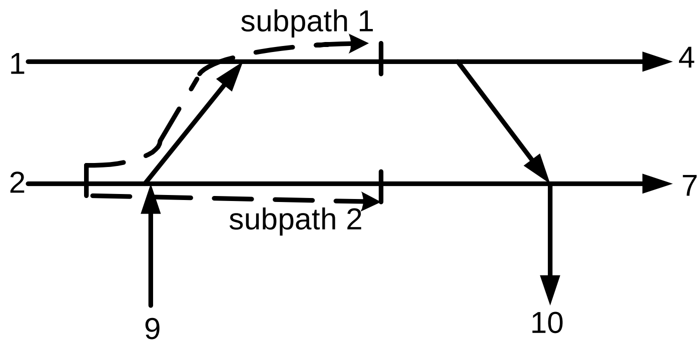

Figure 2. Case study network

OD estimation and prediction is performed both in the base case (no AVI information) and in the presence of AVI information. The impact of the additional information in the estimation accuracy is assessed, as well as the additional computational load that it entails. The demand is generally from left to right or east to west. Six OD pairs (8→7, 1→7, 1→10, 8→4, 1→4, and 9→7) load vehicles in the network. Knowledge of the true assignment matrix is assumed.

A high-demand day (i.e. higher than the historical) is assumed. The demand pattern is similar to the morning peak. The link flow measurements are corrupted with noise (resulting in counts uniformly distributed in [80%,105%] of the true link flows) in order to capture the sensor measurement errors. Current AVI technologies report accuracies in the order of 99% (Mouskos et al., 1998); hence no measurement error was assumed for the AVI data. The assumption of independent measurement errors for the two data sources is justified, as the sensors use different technologies with distinct performance characteristics. It should be noted, however, that only two of the 6 OD flows are actually captured by the AVI systems. This implies that AVI information only contributes to the estimation of the OD flows that are covered by the AVI-defined subpaths.

Table 2 shows the obtained RMSN values for the OD estimation and prediction (for one and two intervals into the future). Furthermore, the results are shown graphically in Figure 3.

Table 2. Overall fit of the OD estimation and prediction

	Estimation	One-step prediction	Two-step prediction
Historical	0.2376	0.2376	0.2376
Link counts	0.1099	0.12	0.1278
Link counts + AVI	0.0932	0.1031	0.1123

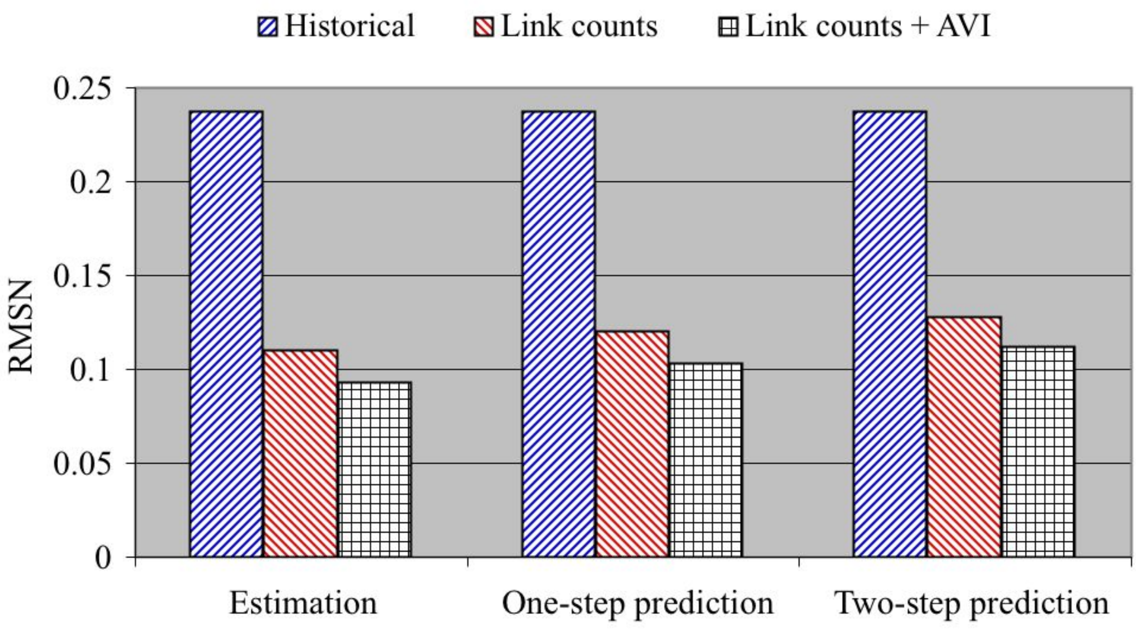

Figure 3. Overall fit of OD estimation and prediction

The estimated and predicted demand for an OD pair that is captured by AVI information is presented next. The improvement obtained from the incorporation of AVI information is apparent. During the peak period the demand is estimated with less than 3% error. Figure 4 shows the estimation results for the entire simulation period, while Figures 5 and 6 show the one-step and two-step prediction results respectively.

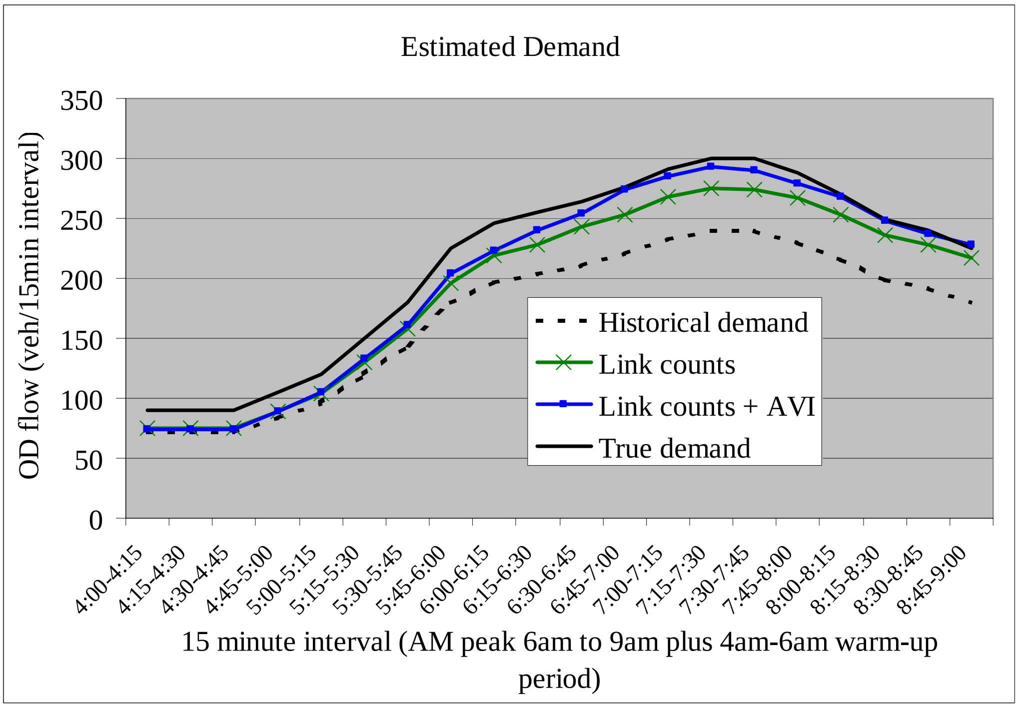

Figure 4. OD estimation results

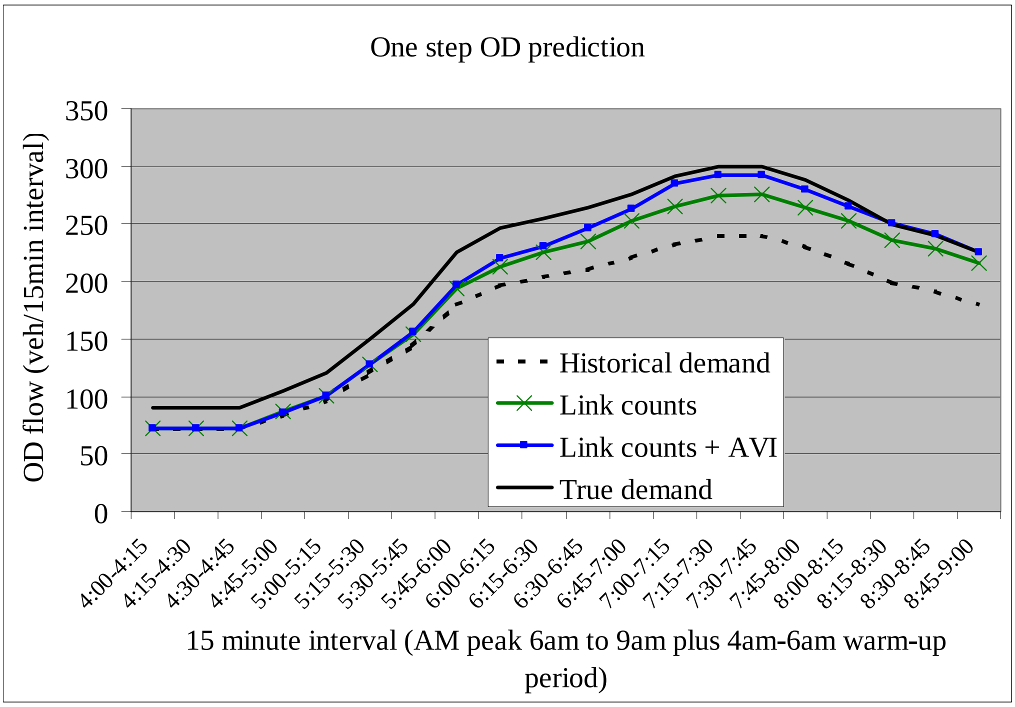

Figure 5. One-step OD prediction results

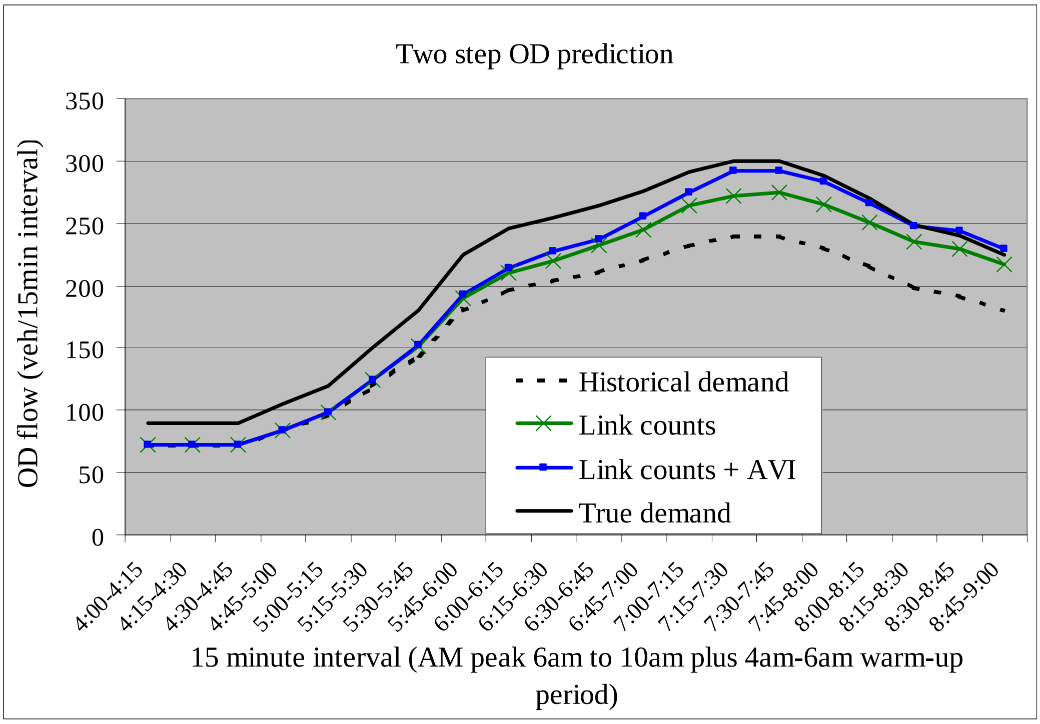

Figure 6. Two-step OD prediction results

6 Conclusions

A methodology has been presented for the incorporation of additional sources of information into the OD estimation and prediction framework. The development of the methodology has been based on AVI data, as these are very relevant and likely to become widely available soon. Preliminary results from a case study using synthetic data have been presented, indicating that indeed the additional information *can* improve the ability of the system to accurately capture prevailing traffic conditions and improve its predictive capabilities. The consequences of this finding are significant, particularly for the generation of traffic information and anticipatory guidance.

Future research directions include the incorporation of AVI information to a complete DTA system. Besides the enhanced OD estimation and prediction framework, the additional information can be exploited on the demand side as improved travel time information can be used for more accurate modeling of pre-trip behavior decisions. On the supply side there is again a potential for multiple use of the AVI data. First, the direct travel time measurements obtained by the matching of sequential readings of the equipped vehicles -as they travel through the network- provide an additional source of information for the en-route behavioral models. Furthermore, the existence of additional data (in the form of actual path and subpath flows and travel times) allows for better (off-line) calibration of the supply simulator, and could also be used for periodic *steering* of its parameters in response to the prevailing traffic conditions. One of the key benefits from this improvement will be the generation of a *better* assignment matrix through the use of both better parameter calibration and direct information on point-to-point travel information. The assignment matrix is the key input to the OD estimation and prediction process and a more realistic assignment matrix may significantly influence the ability of the system to predict future traffic conditions accurately.

Traffic estimation and prediction is a fixed point problem requiring iterations between the demand and supply components. In the presence of link counts alone, the only means of determining whether the simulated conditions match the observed is through comparison of the (observed vs. the simulated) link counts. The number of control variables is thus limited and may not cover the entire network sufficiently or uniformly. However, in the presence of AVI measurements, it is possible to use the subpath flows and travel times as additional observations, thus providing a better *coverage* of the network. Furthermore, observed route choice fractions (obtained by appropriate subpath flows) can be used as additional conditions for the validation of the (en-route) behavioral models within the supply simulator.

While this data may significantly improve the *off-line* calibration process, it may also prove to be useful for periodical *on-line* fine-tuning of the parameters of the supply simulator. In particular, given a well-calibrated initial condition of the system parameters, real-time information can be used to *steer* the simulation parameters as required in response to variations in the prevailing traffic conditions.

Furthermore, case studies with real data will provide more convincing evidence on the contribution of richer data in the OD estimation and prediction process, and travel time estimation and prediction in general. The following paragraphs outline specific directions for further research.

The incorporation of the additional real-time data is expected to improve the ability to estimate and predict OD flows accurately. Nevertheless, as indicated by the augmentations of the problem's state-space formulation, the computational complexity also increases. As the problem size increases, more efficient algorithms and techniques need to be implemented in order to achieve real-time performance. Kalman filtering (Kalman, 1960) and (constrained) least squares minimization are two well-established techniques for solving the state-space model formulated for the OD estimation and prediction. A *square-root* Kalman filter that solves the single data-source time-space model (as defined by equations 3 and 5) is described in Antoniou et al. (1997). Least square methodologies for the single-source problem have also been formulated and implemented (Brandriss, 2001). The suitability of various algorithms and methodologies needs to be investigated, e.g. the efficient constrained least square minimization algorithm proposed by Bierlaire and Crittin (2001), as well as a Kalman filtering algorithm for real-time applications (Chui and Chen, 1999) that does not require direct matrix inversions. The latter algorithm is a combination of the sequential and square-root Kalman filter algorithms with the additional assumption of a diagonal variance of the measurement equation. Also, trade-offs between computational complexity and accuracy can be identified and evaluated.

The extended OD estimation and prediction framework presented in this paper will also need to be further validated, and in particular in terms of its robustness and numerical stability. Measurement errors and missing observations are likely to impair the performance of the models. It is important to assess their impact to the performance of the algorithms. This analysis can be based on random and systematic perturbations of the key inputs to the algorithms, including travel time estimates, subpath flows, and assignment matrices. Furthermore, the numerical properties of the models when the inputs take exceptionally small or large values need also be investigated.

References

Antoniou, C., Ben-Akiva, M., Bierlaire, M., and Mishalani, R., 1997. Demand simulation for dynamic traffic assignment. In Proceedings of the 8th IFAC Symposium on Transportation Systems, Chania, Greece.

Ashok, K., 1996. Estimation and Prediction of time-dependent Origin-Destination Flows. PhD thesis, Massachusetts Institute of Technology.

Ashok, K. and Ben-Akiva, M., 1993. Dynamic O-D matrix estimation and prediction for real-time traffic management systems. In Daganzo, C., editor, Transportation and Traffic Theory, pages 465-484. Elsevier Science Publishing.

Ashok, K. and Ben-Akiva, M., 2000. Alternative approaches for real-time estimation and prediction of time-dependent origin-destination flows. Transportation Science, 34(1):21-36.

Ashok, K. and Ben-Akiva, M., 2002. Estimation and prediction of time-dependent origin-destination flows with a stochastic mapping to path flows and link flows. Transportation Science, 36(2):184-198.

Ben-Akiva, M., 1987. Methods to combine different data sources and estimate origin-destination matrices. In Gartner, N. and Wilson, N., editors, International Symposium on Transportation and Traffic Theory, pages 459-481. Elsevier Science Publishing Company Inc.

Ben-Akiva, M., Bierlaire, M., Koutsopoulos, H. N., and Mishalani, R., 2002. Real-time simulation of traffic demand-supply interactions within DynaMIT. In Gendreau, M. and Marcotte, P., editors, Transportation and network analysis: current trends, pp. 19-36. Kluwer Academic Publishers. Miscellenea in honor of Michael Florian.

Ben-Akiva, M. and Morikawa, T., 1989. Data fusion methods and their applications to origin-destination trip tables. In WCTR Proceedings.

Bierlaire, M. and Crittin, F., 2001. An efficient algorithm for real-time estimation and prediction of dynamic OD tables. Technical Report #RO-010808, ROSO-DMA-EPFL. Submitted to Operations Research.

Bottom, J. A., 2000. Consistent Anticipatory Route Guidance. PhD thesis, Massachusetts Institute of Technology.

Brandriss, J. J., 2001. Estimation of origin-destination flows for dynamic traffic assignment. Master's thesis, Massachusetts Institute of Technology.

Cascetta, E., 1984. Estimation of trip matrices from traffic counts and survey data: A generalized least squares estimator. Transportation Research, 18B(4/5):288-299.

Cascetta, E., Inaudi, D., and Marquis, G., 1993. Dynamic estimators of origin-destination matrices using traffic counts. Transportation Science, 27(4):363-373.

Chui, C. K. and Chen, G., 1999. Kalman Filtering with Real-Time Applications. Springer-Verlag.

Coifman, B. and Cassidy, M., 2002. Vehicle reidentification and travel time measurement on congested freeways. Transportation Research Part A, 36(10):899-917.

Dixon, M. P. and Rilett, L. R., 2000. Real-time origin-destination estimation using automatic vehicle identification data. In Proceedings of the 79th Transportation Research Board Meeting, Washington, D.C.

Kalman, R. E., 1960. A new approach to linear filtering and prediction problems. Journal of Basic Engineering, 82(1):33-45. Transactions of the ASME.

Kuchipudi, C. M. and Chien, S. I. J., 2003. Development of a hybrid model for dynamic travel time prediction. In Proceedings of the 82nd Annual meeting of the Transportation Research Board.

McLean, C. H., 1991. Cellular phones - a key traffic management component. Technical report, ITE Compendium of Technical Papers, Institute of Transportation Engineers, Washington, DC.

Mishalani, R. G., Coifman, B., and Gopalakrishna, D., 2003. Evaluating real-time origin-destination flow estimation using remote sensing-based surveillance data. In Presented at the Transportation Research Board 82th Annual Meeting, Washington, D.C.

Morris, S. P., 1996. EZ-Pass and TRANSMIT using electronic toll tags for traffic monitoring. In National Traffic Data Acquisition Conference (NATDAC ”96): Proceedings, volume 1, pp. 289-298, New York. New York State Thruway Authority.

Mouskos, K. C., Niver, E., Pignataro, L., Lee, S., Antoniou, N., and Papadopoulos, L., 1998. TRANSMIT system evaluation - final report. Technical report, New Jersey Institute of Technology.

Mussa, R. N., Matthias, J. S., Upchurch, J. E., Rollier, D. A., and Zaniewski, J. P., 1998. Modeling detection of incidents by drivers. Transportation Research Part C: Emerging Technologies, 6(1-2):129-139.

Ogden, K. W., 2001. Privacy issues in electronic toll collection. Transportation Research Part C, 9:123-134.

Oh, C. and Ritchie, S. G., 2003. Anonymous vehicle tracking for real-time traffic surveillance and performance on signalized arterials. In Proceedings of the 82nd Annual meeting of the Transportation Research Board, Washington, D.C.

Okutani, I., 1987. The Kalman filtering approach in some transportation and traffic problems. In Gartner, N. and Wilson, N., editors, Transportation and Traffic Theory, pp. 397-416. Elsevier Science Publishing.

Park, D. and Rilett, L. R., 1998. Forecasting multiple-period freeway link travel times using modular neural networks. Transportation Research Record, 1617.

Quiroga, C., Perez, M., and Venglar, S., 2002. Tool for measuring travel time and delay on arterial corridors. In ASCE 7th International Conference on Applications of Advanced Technology in Transportation, pages 600-607, Cambridge, MA.

Smith, B. L., Zhang, H., Fontaine, M., and Green, M. 2003. Cellphone probes as an ATMS tool. Technical Report STL-2003-01, Smart Travel Laboratory, University of Virginia, Charlottesville, Virginia.

van der Zijpp, N., 1996. Dynamic Origin-Destination Matrix Estimation on Motorway Networks. PhD thesis, Transportation Planning and Traffic Engineering Subsection of the Faculty of Civil Engineering of Delft University of Technology.

Yang, Q., 1997. A Simulation Laboratory for Evaluation of Dynamic Traffic Management Systems. PhD thesis, Massachusetts Institute of Technology.

Yang, Q. and Koutsopoulos, H. N., 1996. A microscopic traffic simulator for evaluation of dynamic traffic management systems. Transportation Research Part C: Emerging Technologies, 4(3):113-129.