Dynamic OD transit matrix estimation: formulation and model-building environment

Lídia Montero, Esteve Codina, Jaume Barceló

Dept Statistics and Operations Research-BarcelonaTECH-UPC
Carrer Jordi Girona 1-3
08034 Barcelona-Spain

{lidia.montero, esteve.codina, Jaume.barcelo}@upc.edu

Abstract. The aim of this paper is to provide a detailed description of a framework for the estimation of time-sliced origin-destination (OD) trip matrices in a transit network using counts and travel time data of Bluetooth Smartphone devices carried by passengers at equipped transit-stops. A Kalman filtering formulation defined by the authors has been included in the application. The definition of the input for building the space-state model is linked to network scenarios modeled with the transportation planning platform EMME. The transit assignment framework is optimal strategy-based, which determines the subset of paths related to the optimal strategies between all OD pairs.

Keywords: Demand Estimation, Information Systems, Advanced Transport Information Systems, Kalman Filtering

1 Motivation

In the context of estimating private transport demand, Origin-to-Destination (OD) trip matrices describe the number of trips between any origin-destination pair of transportation zones in a study area. For private vehicles, route choice models describe how trips select the available paths between origins and destinations and, as a consequence, the number of trips using a given path (or path flow proportions) in private transportation modes. The route choice proportion can vary depending on the time-interval in dynamic models, since the traffic state and the temporal dimension are considered. When a public transportation network is the object of study, OD matrices describe the number of transit trips between OD pairs or OD stops.

While an average OD table for a whole period of interest is acceptable for an urban transportation planning study, OD matrices over consecutive time intervals are required for modeling and/or optimizing dynamic system operations. For all formulations of static traffic or transit assignment models (Florian and Hearn [1]), as well as dynamic models involved in ATIS (Advanced Transport Information Systems) (see Ashok et al. [2]), they assume that a reliable estimate of an OD matrix is available and constitutes an essential input for describing the demand in predicting traffic state evolution over the network. Since OD trips are not directly observable, indirect estimation methods have then been proposed. These are the so-called matrix adjustment methods, whose main modeling hypothesis can be stated for a transit networks as follows: if assigning an OD transit matrix to a network defines the number of passengers in all segments of transit line itineraries sharing a network link, then the same OD transit matrix can be estimated as the inverse of the assignment problem.

ICT (Information and Communication Technologies) sensors can also provide data for estimating dynamic OD transit matrices, though this has received little attention in the literature because of the difficulties in collecting real-time passenger loads. However, with the new technologies, applications for transport planning have been proposed by several authors ([3, 4]), with a particular focus on transit OD inference.

Wong and Tong [5] proposed a maximum entropy estimator, employing the schedule-based approach for dynamic transit assignment. Ren [6] proposed a generalized least squares bi-level approach for estimating time-dependent transit matrices in congested schedule-based transit networks where automatic passenger counts and prior OD matrices are available. The proposal was tested on a toy network, but no recent works from the author have confirmed any offline or online applicability to large scale transit networks.

Real-time transport information systems or traffic management applications have an additional requirement for estimating dynamic OD matrices: a short time response (less than 15 min) for estimating and for forecasting the dynamic matrix and network estate over the next 30 min horizon.

Almost 20 years ago, memory space was expensive and unavailable on ordinary laptop computers. Because of this, linear Kalman filtering (KF) approaches for estimating dynamic trip matrices were considered inefficient, and unable to satisfy the requirements of on-line applicability, as indicated by Wu [7]. A linear KF prototype, coded in MATLAB [9] (Barceló et al [8,10]), has proven to meet the requirements for on-line applications using traditional data collection and new ICT data.

Kostakos *et al* [3] proposed the use of passengers' Bluetooth mobile devices to derive passenger OD matrices in a simplified context. A Bluetooth device set to *discoverable mode* must respond to a discovery request by transmitting its unique Bluetooth identifier (12 hex digits) and device class (6 hex digits), since a Bluetooth scanner located on vehicle units constantly scans the presence of the various devices it encounters (along with the date and time). Extending this idea, our aim is to explore the possibility of using the experience in private networks to estimate on-line dynamic OD transit matrices. To do this, we use ICT data, counts and travel times, provided by a sample of passengers with Smartphones and BT/Wifi signals are captured by Wi-Fi antennas, which are located in a subset of transit stops. A *prior* historic OD transit matrices estimated off-line is also used.

The remainder of this paper is structured as follows. A section with the previous experience of the authors is presented, followed by a description of the model formulation for estimating dynamic OD matrices in transit networks. The model-building environment for validation is outlined next. The paper concludes with a discussion and concluding statements.

2 Previous experience

In [8], we used counts and travel times provided by Bluetooth devices to estimate dynamic OD matrices for commuters driving their own cars, either on freeways or in urban networks. In that work, we proposed space-state formulations by means of linear Kalman filters (KF). For linear freeways, traditional and ICT data at entry ramps were required. Bluetooth equipped vehicles were identified by antennas (in the following ICT sensors) located on some freeway sections. Equipped vehicles provided accurate travel time data from their entry points up to the freeway points they went through, where they were detected by ICT sensors.

A prevailing basic hypothesis is that equipped and non-equipped vehicles follow common OD patterns. A common dynamic horizon was defined to be 1.5 to 3 hours, and it was divided into time-intervals of between 1 to 5 minutes in length. We adapted an idea proposed by Lin and Chang [11] and proposed our own linear KF formulation that relates state variables and observations. Congestion effects of traffic dispersion were taken into consideration, since time-varying model parameters were derived from travel times provided by the sample of equipped vehicles.

We proposed a flexible formulation suitable for urban networks, and also for freeways as a particular case of a network, where state variables were defined as deviates (Ashok and Ben-Akiva [2]) of the number of OD equipped vehicles for intervals along the *most-likely OD paths* with respect to *a priori* historic values. Dynamic User Equilibrium (DUE) based on the historic time-sliced OD matrix was computed to define the set of *most likely OD paths.* The proportion of OD flows using the selected paths was not taken as input, as it is considered indirectly by some authors through assignment matrices. The measurements were: the link flow counts on traditional detectors, link flow counts of equipped vehicles in a subset of links where ICT sensors were located, and travel times of equipped vehicles between ICT sensors.

We achieved a linear KF formulation dealing with congestion in freeways and networks. Our approach exploited ICT travel time measurements from equipped vehicles in order to estimate discrete travel time distribution (H bins were used for adaptive approximations). Travel times collected from ICT sensors were incorporated into the proposed model [8]. Throughout this paper, they are referred as time-varying model parameters. It was not necessary that vehicles reach their destination, since the measured travel times from any previously crossed ICT sensor updated the discrete travel time approximations at any intermediate sensor that they passed through. Therefore, completed trips were not the only source for updating time-varying model parameters in the program KFX3 implemented in MATLAB [9].

2.1 Proposed framework for time-sliced OD transit estimation

The research experience gained for estimating OD trip matrices and the extensive computational experience [8, 10] of simulating data determined the crucial design factors to be considered. The computational results reported that it is possible to apply a linear KF approach for estimating dynamic OD trip matrices in real-time applications, since a half-hour forecast takes less than 2 min using MATLAB [9].

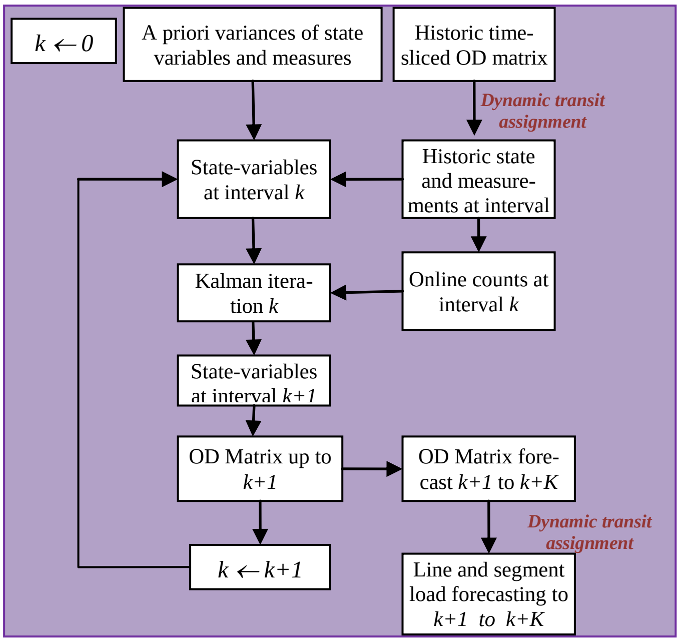

Fig. 1. Framework for Estimating and Predicting in ATIS

The conclusions about the key design factors taken into account were:

- The penetration rate of ICT is a critical factor, but not controllable.
- The detection layout defined in terms of the number and location of detectors, which is in practice frequently determined by budget constraints.
- The quality of the historic time-sliced OD matrix used to initialize the KF algorithm and *a priori* covariance matrices involved in the KF process.

Thus, we conclude that, one cannot skip off-line estimation of a reliable historic (time-sliced) OD matrix when defining an on-line framework. So far, this lesson is considered in the framework for estimating the time-sliced OD transit matrices shown in **Fig**.1.

3 Formulation of the model

Notation is defined in Table 1. Some additional aspects to the data model and formulation that have to be considered are:

- The demand matrix for the period of study is assumed to be divided into several time-slices, accounting for different proportions of the total number of transit trips in the time horizon.

- The approach assumes an extended space state variable for M+1 sequential time intervals of equal length Δt (between 5 and 10 min), in order to consider non-instantaneous travel times. M should guarantee traversal of the network.
- Bluetooth antennas are ICT sensors assumed to be located at (some) transit-stops.
- OD paths are those involved in optimal strategies for OD pairs for the period of study. They can be computed by any transportation planning software including a strategy-based equilibrium transit assignment using historic demand. We do not have a strategy-based dynamic transit assignment tool available, so we considered EMME [12] to define state-variables in our tests. The description of paths involved in optimal strategies from centroid *i* to *j* going through ICT sensors (pairs of ICT sensors) can be systematically programmed in any language (although this is not trivial), from the EMME output to the input files for the MATLAB data model.

Table 1. Definition of model variables

$\tilde{Q}_l(k)$, $\tilde{q}_l(k)$:	Historic total number of passengers and equipped passengers accessing a transit unit and first detected at stop *r*, related to centroid *i* in flow conservation *l* at time interval *k*.
$Q_l(k)$, $q_l(k)$:	Total number of passengers and equipped passengers accessing a transit unit and first detected at stop *r*, related to centroid *i* in flow conservation *l* at time interval *k*.
$\tilde{y}_q(k)$, $y_q(k)$:	Historic and actual number of equipped passengers crossing at time interval *k* either the *q* sensor or destination sensor *s, for a pair of ICT transit stops q=(r,s)*
$G_{ije}(k)$, $\tilde{G}_{ije}(k)$ $g_{ije}(k)$, $\tilde{g}_{ije}(k)$:	Total number of current $G_{ije}(k)$ and historic $\tilde{G}_{ije}(k)$ passengers, as well as the current $g_{ije}(k)$ and historic $\tilde{g}_{ije}(k)$ equipped passengers accessing centroid *i* at time interval *k* and heading towards *j* using path *e*.
$\Delta g_{ije}(k)$:	State variables are deviates of equipped passengers from centroid *i* during interval *k* headed towards centroid *j* using path *e* with respect to average historic data $\Delta g_{ije}(k) = g_{ije}(k) - \tilde{g}_{ije}(k)$.
$\mathrm{z}(\mathrm{k})$, $\tilde{\mathrm{z}}(\mathrm{k})$:	The current and historic measurements of equipped passengers during interval *k*, a column vector of dimension Q (counts) plus L (flow conservation equations).
$u_{rs}^{h}(k)$:	Fraction of equipped passengers that require *h* time intervals to reach sensor *s* at time interval *k from sensor r* during time interval $[(k-h-1)\Delta t \quad , \quad (k-h)\Delta t]$. Time-varying model parameters.
$\bar{t}_{rs}(k)$:	Average measured travel time for equipped passengers that reach sensor *s* at time interval *k from sensor r*

The total number of origin and/or destination centroids (related to transportation zones) is I; the total number of ICT sensors is P, located either at bus-stops or at segments in the inner network; and the total number of paths corresponding to optimal transit strategies from the historic OD transit assignment for the period of study is K. Q is the number of pairs of ICT sensors *(r,s) plus* individual sensor counts *q* to be considered. We estimate OD transit trips between OD pairs, not between transit-stops.

The state variables $\Delta g_{ije}(k)$ are assumed to be stochastic in nature, and OD path flow deviates at the current time *k* are related to the OD path flow deviates of previous time intervals by implementing an autoregressive model of order r <<M; the state equations are:

$$\mathbf{\Delta g}(k+1) = \sum_{w=1}^{r} \mathbf{D}(w)\mathbf{\Delta g}(k-w+1) + \mathbf{w}(k), \tag{1}$$

where $\mathbf{w}(k)$ is zero mean with diagonal covariance matrix $\mathbf{W_k}$, and $\mathbf{D}(w)$ are transition matrices which describe how previous OD deviates $\mathbf{\Delta g_{ije}}(k\text{-}w\text{+}1)$ affect current flows $\mathbf{\Delta g_{ije}}(k\text{+}1)$ for $w = 1,\ldots,r$. In our tests, we assume simple random walks to provide the most flexible framework for state variables, if no convergence problems are detected. Thus, our first trial is $r=1$, and $\mathbf{D}(\mathbf{w})$ becomes the identity matrix. The relationship between the state variables and the measurements involves *time-varying model parameters* (congestion–dependent, since they are updated from sample travel times provided by equipped passengers) in a linear transformation that considers:

- The number of equipped passengers first detected in the system at equipped transit-stops r, related to origin zones through explicit flow conservation equations l during time intervals in k ,..., $k\text{-}M$, $q_l(k)$.
- H<M *time*-varying *model parameters* in form of *fraction matrices*, $\left[u_{rs}^h(k)\right]$, where the H adaptive fractions are updated from measures provided by ICT sensors. Direct samples of travel times allow the updating of discrete approximations of travel time distributions.

At time interval k, the values of the observations are determined by those of the state variables at time intervals k, $k\text{-}1$, …, $k\text{-}M$.

$$\mathbf{\Delta z}(k) = \mathbf{F}(k)\mathbf{\Delta g}(k) + \mathbf{v}(k), \tag{2}$$

where $\mathbf{v}(k)$ is white Gaussian noise with covariance matrix $\mathbf{R_k}$. $\mathbf{F}(k)$ maps the state vector $\Delta\mathbf{g}(k)$ onto the current blocks of measurements at time interval k: counts of equipped passengers at ICT sensors, accounting for time lags and congestion effects.

The solution should provide estimations of the OD transit matrix between OD pairs for each time interval up to the *k-th* interval, once observations of equipped passengers at the transit stops equipped with Wi-Fi antennas up to the *k-th* interval are available. KF prediction of OD trips for ICT equipped passenger up to some intervals ahead must be considered and expanded upon in accordance with historic profiles (for day-type and time-period), in order to feed a dynamic transit assignment tool that will provide the forecasted travel times, line loads and boardings/alightings at transit-stops in the short-future. We consider a 30 min forecasting horizon.

4 Model Building environment

The formulation has been programmed as a MATLAB prototype (named KFX3T). Correct codification has been verified, but the approach needs to be validated against either actual data, which was not available, or by simulation, the chosen option.

In the research undertaken within the framework of the European Union COST Action MULTITUDE, a common evaluation and benchmarking platform was developed for estimating dynamic OD trip matrices [13]. The main goal of that platform was to provide a testbed in which a number of algorithms can be linked and tested under the same conditions in a common network model.

The MULTITUDE Platform consists of a Mesoscopic Traffic Simulator (AIMSUN [14]), one dynamic OD estimation algorithm coded in MATLAB [9], and a MATLAB function (AIMSUN.m). The MATLAB function allows dynamic communication between the estimation algorithm and the Aimsun model in order to execute a traffic simulation run within the OD estimation algorithm. It does this by creating and executing a batch file, which launches the Aimsun executable and a python script with the relevant information. When the simulation is finished, the MATLAB function collects all the outputs and produces goodness of fit indicators. A case study consisting of an old AIMSUN model for Vitoria-Gasteiz, a medium-size city in Spain, was provided to MULTITUDE partners.

We chose to include the KFX3T OD transit estimation tool and Vitoria case study in the MULTITUDE platform for validation purposes. Vitoria's model contains the description of a bus network. AIMSUN does not include public transport under the scope of the *transit-assignment* to the transit network, neither under a strategy-based nor a scheduled-based behavioral hypothesis. We decided to consider EMME [12] instead of AIMSUN and we selected an EMME model that matches the MULTITUDE network. The total number of public transit trips was 47816.3 for a 2003 working day within 340 non-null cells, and an average value of 140 trips (max 1186 trips).We fixed ICT equipped transit-stops for three of the most important bus lines: L7, L8 and L13. The model and equipped transit lines are shown in **Fig.** 2**.** After selecting OD pairs with captured flows greater than 10, these lines have a total load (working day) of 20765 transit trips in 151 OD pairs (according to the additional options transit assignment results in EMME).

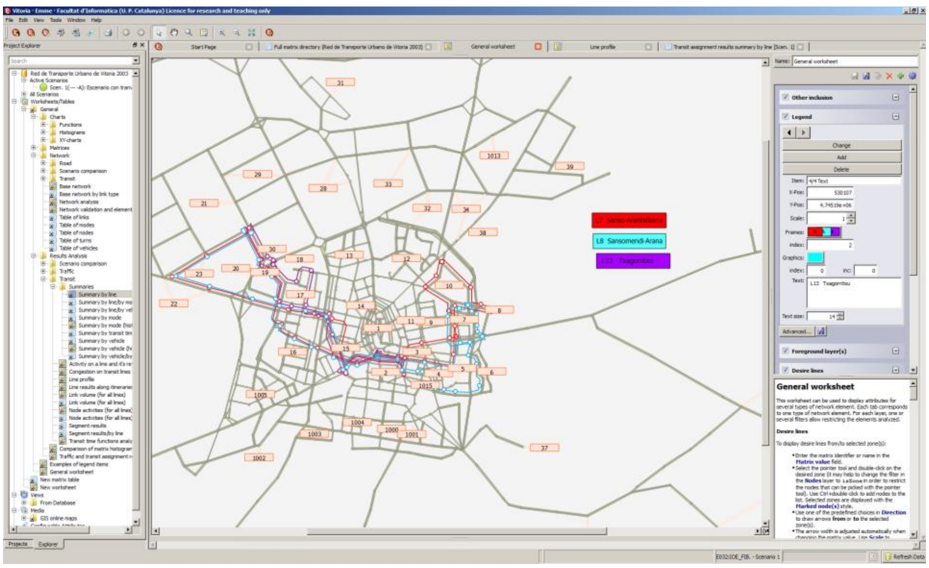

Fig. 2. Emme Model for Vitoria: BT located at transit-stops for lines L7, L8 and L13

At this point, we modified the MULTITUDE platform and substitute the AIMSUN model for EMME in order to provide:

- A graphic description (centroids, nodes, links and connectors) and transit lines (stops, headways and itineraries).
- A Transport Zoning System and historic demand matrix for the period of study.
- The location of ICT sensors at transit-stops (identified by an additional segment attribute @nBT, in EMME terminology, and an additional line attribute, @sline, to identify lines affected by BT-equipped stops, either totally or partially).
- OD paths involved in optimal strategies for the historic transit demand according to an *Extended Transit Assignment,* where OD flows are split between connectors in the origin zone using a *logit* model (scale parameter 0.5) and are subject to an OD path proportion greater than 5%.

A strategy file is saved by EMME and the *Extended Analysis tool* reports path-based details on paths extracted from strategies in a text file. This text file contains the path description included in the optimal strategies restricted to OD pairs and whose OD flow could be captured by some ICT sensors in accordance with historic demand and transit assignment. The path file has a complex format and is post-processed using python script to generate the desired information in the data model of KFX3T. For each ICT-equipped transit-stop, the captured optimal transit OD paths are identified. For each pair of ICT transit-stops, the paths and subpaths connecting both sensors are identified. Report files related to OD pairs, nodes, links, etc. were converted to worksheet and *.csv* format files, in order to be read by the KFX3T model building procedures. This led to:

- A network workbook containing worksheets for: centroids, nodes and links.
- A demand workbook containing worksheets for: OD pairs, Entrances, Exits and OD paths involved in optimal strategies.
- A measurement workbook containing worksheets: Measures, SODMeasures, ActiveMeas, CapODPaths and Global (parameters).

The KFX3T internal data model is divided into MAT files that are loaded as needed into the program. They are: *Global.mat, Tuning.mat, Graph.mat, Demand.mat* and *Measures.mat*. Additionally, two additional MAT files have been included for internal use in order to simplify the access to some critical structures. These two files are: *AccDem.mat* (related to accessing OD pairs and paths) and *AccMes.mat* (related to OD paths captured by each defined sensor and pairs of ICT sensors).

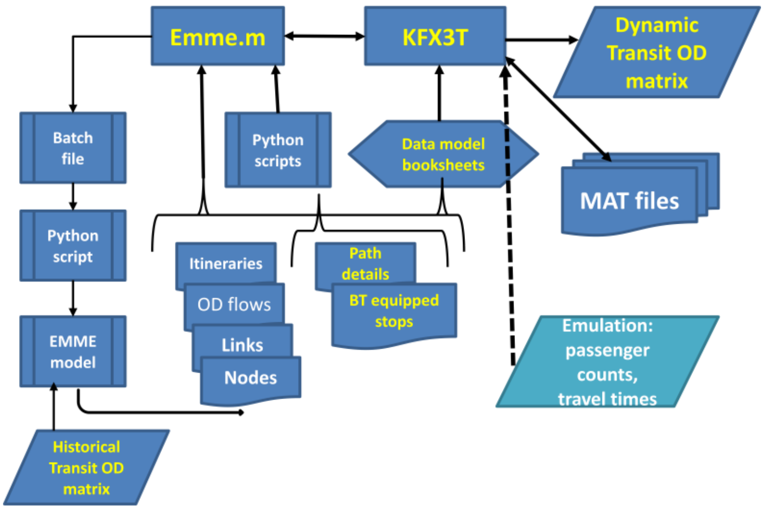

Fig. 3. Flowchart with the main elements of KFX3T in the MATLAB application

Fig. 3 shows the flowcharts between the dynamic transit estimation KFX3F tool and the source of data for model building (MAT files). We have completed development of all software pieces, except for the simulation tool that emulates passenger counts at stops and travel times between pairs of ICT sensors. Once available, the estimation and forecasting tool (KFX3F) could be validated using Vitoria's network.

5 Conclusions

This paper has given an account of how to estimate Dynamic OD matrices for passengers in a real-time context, since they constitute the basic input for dynamic models involved in Advanced Traffic Management and Information Systems. The purpose of the present paper is to show the model-building process for a linear Kalman filter formulation developed by the authors. The framework implements a MATLAB program (KFX3T) which takes advantage of the EMME transportation planning environment through the definition of paths related to optimal strategy-based transit assignment.

Finally, the software prototype, KFX3T, has been validated in a limited way. Firstly, using a toy network and simulated data. Secondly, the mean squared error (MSE), which summarizes accuracy on average; is the default goodness of fit for testing the convergence. However, it would be interesting to assess the performance results of different measures in the future. Further experimental evidence is needed with a medium-size network. Computational results of a similar approach applied to private transport networks by the authors support the on-line applicability.

6 Acknowledgments

The research was funded by TRA2011-27791-C03-02 of the Spanish R+D National Programs, and it benefited from EU COST Action TU0903 MULTITUDE.

7 References

1. Florian, M. Hearn, D.: Network Equilibrium Models and Algorithms. In: Chapter 6 in M.O. Ball et al., Eds. Handbooks in OR and MS, Vol.8, Elsevier Science B.V (1995).
2. Ashok, K. Ben-Akiva, M.: Alternative Approaches for Real-Time Estimation and Prediction of Time-Dependent Origin-Destination Flows. In: Transportation Science vol.34 no.1, pp. 21-36 (2000).
3. Kostakos, V., Camacho, T., Mantero, C. Wireless detection of end-to-end passenger trips on public transport buses. In Proceedings of the IEEE Conference on Intelligent Transportation Systems, Funchal, Portugal pp. 1795-1800 (2010).
4. Wang, W., Attanucci, J. P. and Wilson, N.H.M., Bus *Passenger Origin-Destination Estimation and Related Analyses Using Automated Data Collection Systems*. In: Journal of Public Transportation, vol.14, no.4, pp.131-150 (2011).
5. Wong, S.C., Tong, C.O. Estimation of time-dependent Origin-Destination matrices for Transit networks. In: Transportation Research B vol.32, no.1, pp.35-48 (1998). Elsevier Science Ltd.
6. Ren, H.L. Origin-Destination Demands Estimation in Congested Dynamic Transit Networks. In Proceeding 14th International Conference on Management Science and Engineering, Harbin (2007).
7. Wu, J. In: A real-time origin-destination matrix updating algorithm for on-line applications. In: Transportation Research B vol. 31-5 pp.381-396 (1997).
8. Barceló, J., Montero, L., Bullejos, M., Serch, O., Carmona, C.: A Kalman Filter Approach for the Estimation of Time Dependent OD Matrices Exploiting Bluetooth Traffic Data Collection. In: GITS Journal of Intelligent Transportation Systems, vol. 17(2) pp.123-141 (2013).
9. MatLab (R2012a) by MathWorks, Inc. (www.mathworks.com) (2012).
10. Barceló, J., Montero, L., Bullejos, M., Linares, M.P., Serch, O. : Robustness And Computational Efficiency Of A Kalman Filter Estimator of Time Dependent OD Matrices. Transportation Research Record 2344-04 pp.31-39 (2013).
11. Lin, P., Chang, G. A generalized model and solution algorithm for estimation of the dynamic freeway origin-destination matrix. In: Transportation Research B vol.41 (2007) pp.554-572.
12. EMME 4.0.8: User's Manual. INRO, Montreal (www.inrosoftware.com) (2013).
13. Antoniou, C., Ciuffo, B., Montero, L., Casas, J., Barceló, J., Cipriani, E., Djukic, T., Marzano, V., Nigro, M., Bullejos, M., Perarnau, J., Breen, M., Punzo, V. and Toledo, T. A framework for the benchmarking of OD estimation and prediction algorithms. Presented at 93rd Transportation Research Board Annual Meeting (2014), Washingtong, D.C.
14. AIMSUN 7.0.4 Microscopic Simulator, TSS- Transport Simulation Systems, Barcelona (www.aimsun.com) (2013).