A PRACTICAL PROPOSAL FOR USING ORIGIN-DESTINATION MATRICES IN THE ANALYSIS, MODELING AND SIMULATION FOR TRAFFIC MANAGEMENT

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ABSTRACT

Dealing with traffic demand trip matrices to feed models that support traffic management decisions is still a problem that deserves research into finding practical solutions in the short term horizon, before future developments become available. This paper analyzes the role of OD matrices in the framework of Analysis, Modeling and Simulation (AMS), namely when moving from static OD matrices to the time-sliced OD matrices required by (AMS) applications. The paper reviews some of the time-slicing approximations used in practice to estimate OD matrices in adjustment procedures, and it proposes an improvement to the bilevel approach by solving the lower level problem through Dynamic User Equilibrium. A practical framework is defined, where the off-line procedure is incorporated to efficiently initialize on-line Kalman filter approaches that exploit measurements from Information and Communication Technologies (ICT). The computational performance of the resulting Kalman models makes them capable of real-time applications.

INTRODUCTION

The main research and developments of traffic management has usually focused on the key role of traffic models in helping traffic managers to design and test management policies. The relevance of traffic models, the main component of traffic management systems, was especially highlighted for the case of traffic corridors. To mention a few, as early as 1993 the paper by Stephanedes and Kwon *(1)* drew attention to the effectiveness of integrated control strategies and their ability to predict diversions. They also proposed an adaptive demand-diversion, real-time predictor that combines behavioral models with an Extended Kalman Filter. A short time after that, in 1995, Papageorgiou *(2),* presented a unified approach for designing integrated control strategies for traffic corridors of arbitrary topology, including both motorways and signal-controlled urban roads. These were formulated as optimal-control problems. The list of contributions could continue almost indefinitely; however, we will end with Zhou et al. *(3),* whose more sophisticated proposal states that the "development and analysis of demand management strategies for integrated multimodal urban corridor management requires application of a new generation of demand modeling and network analysis tools". They also propose a "dynamic trip micro-assignment and (meso) simulation system that incorporates individual tripmaker choices of travel mode, departure time and route in multimodal urban transportation networks". The system includes a two-stage estimation procedure that systematically utilizes historical static demand information with time-dependent link counts. The main objective of their research was "to provide insight into the potential benefit of integrated multimodal corridor management (ICM)".

In 2008 Alexiadis *(4)* formalized Analysis, Modeling and Simulation (AMS), a methodological proposal for ICM which is conceptually described in the Figure 1 diagram (taken from the reference).
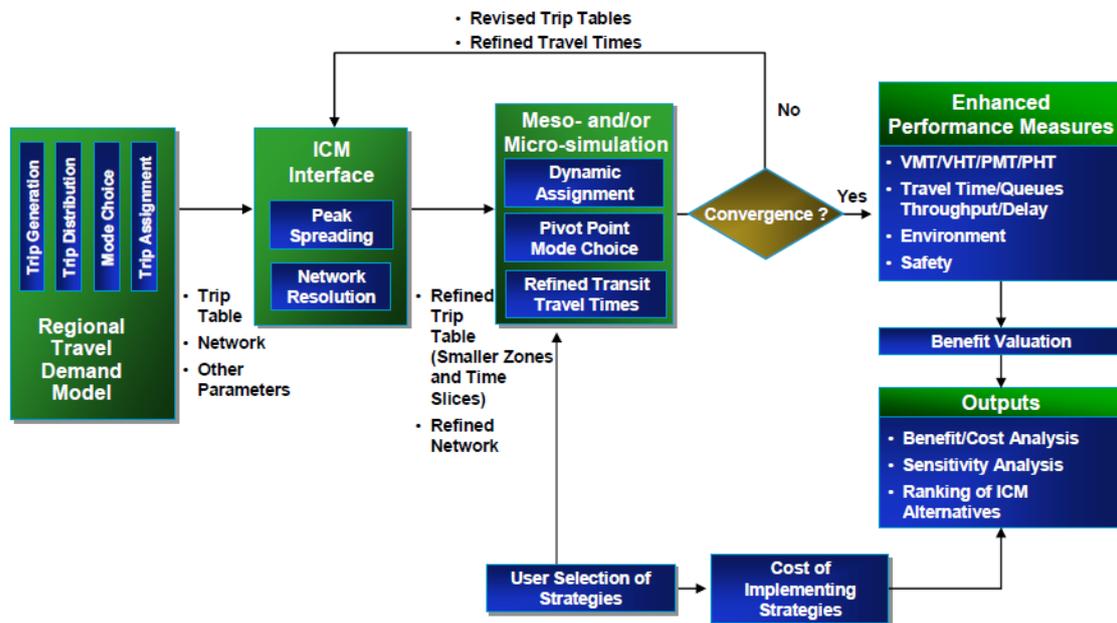

Figure 1 Test Corridor AMS framework

The proposed AMS methodology combines a variety of traffic models that are required for determining overall trip patterns, which can be refined and time sliced as far as the necessary feedback is available. It starts by manipulating a trip table that originates in a Regional Travel Demand Model. "In this AMS framework, macroscopic, mesoscopic, and microscopic traffic analysis tools can interface with each other, passing trip tables and travel times back and forth looking for natural stability within the system". Elements of this methodological framework were explicitly considered later by Cronin et al. *(5)* "Conducting analysis, modeling, and simulation tests enables corridor partners to identify the most promising strategies and informs

decisions for design of ICM systems", and they concluded that managers should integrate this methodology into ICM decision support systems to facilitate predictive, real-time, and scenario-based operational decision making. The proposed concept of decision support system is "the interactive, computer-based system that uses historical data and models to identify and solve problems as defined by Sprague and Watson" *(6)*.

They all agree that the practice of Real Time Traffic Management must be supported by Decision Support Systems to assist traffic managers in making sound decisions for avoiding --or at least alleviating—conflicting situations in traffic networks, such as those occasioned by congestion (recurrent or not) or any other potential causes. An efficient Decision Support System must help and guide the manager's decisions by quantitatively assessing the traffic conditions of the network and, if possible, predicting their likely evolution over the short term. But suitable dynamic traffic models are required for estimating the current state of the network in terms of the quantified values of the associated indicators (e.g., level of service, queues, delays, travel times etc.), as well as for short term forecasting.

The idea of assisting managers in making decisions with the help of this type of Decision Support System was already explored by Barceló et al. *(7)* in 2005, and a first practical implementation was described in Barceló et al. *(8)* in 2007. Key components in the architecture of these systems are the traffic models, trip tables, Origin-Destination (OD) matrices, and the critical problem of updating the times for these OD matrices.

Recently a draft report on an AMS Framework *(9)* described the predictive tools as a key component, and it raised concerns about the current approaches of Travel Demand Simulators in feeding such tools by underscoring the limitations in the usual practice of decomposing time into 24-hour trip tables.

We think that there is still room for improvement in the current practices of time-slicing OD matrices and updating them in real-time for traffic management operations. The main objective of this paper is to: review some of the current practices based on adjustments from traffic counts using static assignment; discuss the possibilities resorting to bilevel optimization models for improvement; and propose new alternatives based on replacing static with dynamic assignments. We show how these practices can produce adjusted time-sliced OD matrices to initialize real-time Kalman Filter OD estimates, whose computational performance makes them appropriate for real-time applications. The resulting computational experiment leads to the concluding methodological proposal for practical implementations of the AMS Framework, which is the main objective of this paper.

A COMMON PRACTICE: HEURISTIC APPROACHES FOR ADJUSTING OD MATRICES FROM LINK COUNTS

The methodological proposal of Alexiadis *(4)*, described by the diagram in Figure 1, proposes a practical approach to updating an OD matrix by starting with an existing OD, usually one from a demand model for a planning study. It uses a heuristic approach for time-slicing it and adjusts each time-slice with some additional information, such as link counts. A more refined proposal with a similar starting point can be found in *(3)*, and a practical application for a real life project in *(8)*.

In terms of a multiple regression model to forecast volumes and speeds in the entire network for each hour of the day, Spiess and Sutter *(10)* propose a heuristic procedure that combines hourly link counts in a subset of network links with the estimated flows from traffic assignment models of representative time periods. The combination calculates the coefficients for each hour to estimate the hourly matrices. A simplified variant of this procedure was used by Torday *(11)*. It found the most relevant link counts in a network, analyzed the hourly variability of their traffic

counts, and used it to estimate the demand percentage of the corresponding time-slice. A similar approach was used in *(8)*. The next step in this practice consists of adjusting the estimated time-slice by using the link counts for that time slice, which are acquired from a set of links with detection stations in the network.

Figure 2 illustrates how this heuristic works. The straight green line represents the constant demand g_i for the i-th OD pair, as estimated from a Travel Demand Model; and the blue line represents the within-day variability of the travel demand, which is the time dependent travel demand for the i-th OD pair $g_i(t)$ that is going to be approximated. The graphics in the bottom left of the figure depict the estimated percentage variability of traffic flows, from which coefficients α^j will be estimated. The demand for time interval j-th $g_i^j(t)$ is approximated by $g_i^j = \alpha^j g_i$. This will be repeated as many times as there are time intervals in the time horizon being considered (24 times for 1-hour intervals in the Figure 2 example). Assuming that link counts $\hat{v}_a^j$ for time interval j, are available for a subset $\hat{A} \subset A$ of links in the network, the approximated demand for time interval j can then be adjusted from these link counts to get the adjusted demand $\tilde{g}_i^j$ that will be used in what follows --for instance, as inputs to a micro- or mesoscopic simulation model. A common matrix adjustment procedure, since it is available in some of the most used professional software, is the bilevel optimization proposed by Spiess *(12)* in 1990.
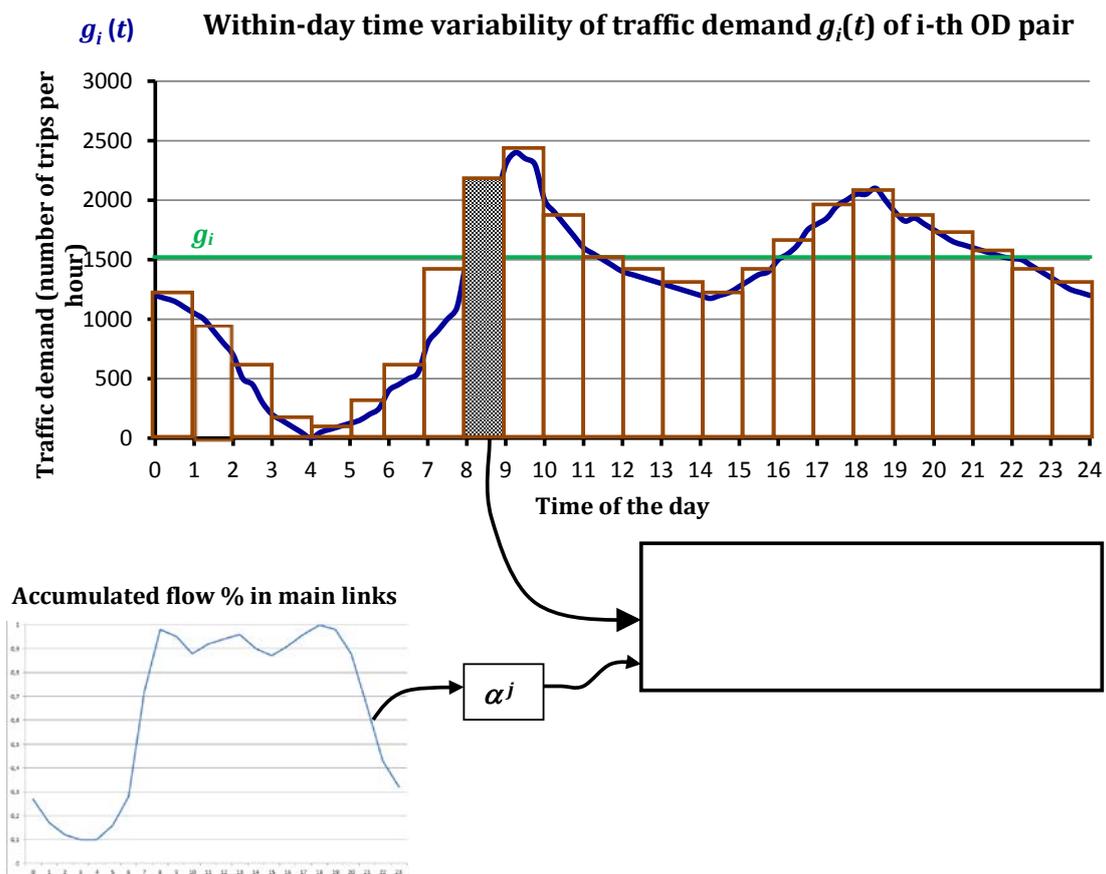

Figure 2 Conceptual diagram of the heuristic approach for adjusting time sliced OD matrices

The bilevel approach in *(12)*, although computationally efficient and relatively easy to implement, has practical drawbacks that can be overcome using formulations that include constraints on the adjusted variables and objective functions that also account for distances

between the seed matrix g_i^j and the adjusted $\tilde{g}_i^j$. A good example is the formulation proposed by Lundgren and Anderson *(13),* which solves the optimization problem at the upper level:

$$\underset{g}{MIN}\, F(g,v) = \gamma_1 F_1(g,\hat{g}) + \gamma_2 F_2(v,\hat{v})$$

$$s.t.\, g \in G = \{g \,|\, g_i \geq 0, \forall i \in I\} \qquad (1)$$

Where F_1 and F_2 are the suitable distance functions between, respectively, the seed and adjusted matrices, and the observed and estimated link counts; and γ_1 and γ_2 are the corresponding weighting coefficients that express the analyst's confidence in the related observations. The lower level optimization problem is the user equilibrium traffic assignment:

$$v(g) = arg\, min \left\{ \sum_{a \in A} \int_0^{v_a} s_a(x)dx \right\}$$

$$s.t.\, \sum_{k \in K_i} h_k = g_i, \forall i \in I$$

$$\sum_{i \in I} \sum_{k \in K_i} \delta_{ak} h_k = v_a, \forall a \in A \qquad (2)$$

$$h_k \geq 0, \forall k \in K_i, \forall i \in I$$

This ensures consistency at each iteration between the estimated OD matrix $\hat{g}$ and the corresponding link flows $\hat{v}$, and it accounts for the variability of link and path usage when congestion grows. h_k is the flow in paths k of K_i, the set of paths for the i-th OD pair; I is the set of all OD pairs; v_a is the flow in link a; and δ_{ak} is the link-path incidence matrix. The algorithm to solve the problem is an adaptation of the projected gradient method and includes a second order approximation of the involved subgradients of the objective function. The method is able to accelerate the convergence more than the heuristic of Spiess *(12)* and without significantly affecting computing times. The reported practical experiment is rather good for large networks *(13), (14).*

PERSPECTIVES OPENED BY THE AVAILABILY OF ICT MEASUREMENTS

The penetration of ICT applications provides accurate measurements of new traffic variables collected continuously in time. A key example could be the measurement of travel times between detection stations located at different points A and B in a network. This occurs when the technology captures the vehicle at A, either by reading the license plate or by detecting an associated device (e.g., a Bluetooth), and then re-captures it again sometime later at point B downstream. It soon became evident that these new types of measurements could be successfully exploited for estimating time-dependent Origin destination matrices.

The research reported in *(15)* presents the results obtained for the real-time estimation and short term prediction of dynamic OD matrices in urban networks with a linear state-space formulation. These explicitly exploit travel times (collected by Information and Communication Technologies (ICT)) and counts (collected by loop detectors). State variables are defined as deviations of OD path flows in a subset, which itself is defined as a limited number of the most likely OD path flows. This is a design parameter identified from a Dynamic User Equilibrium (DUE) assignment (based on the historic time-sliced OD matrix for the modeling period). A formulation based on deviations was selected because they incorporate more historical data as *a priori* structural information for the model. A linear relationship between state-variables and measurements was proposed, since –compared to other state space models—it is computationally advantageous and reduces the number of state variables in the KF formulation. Time-varying dependencies between measurements (sensor counts) and state variables (deviations of equipped vehicles in the most likely OD path flows) are modeled by updating

discrete approximations of travel time distributions, based on the travel time measurements obtained from ICT-equipped vehicles. This allows a linear formulation, since the corresponding measurements can replace the estimated travel times of nonlinear models, which would otherwise require an Extended KF.

The computational results reported in *(16)* prove the general robustness of the state-space approach to reconstructing a known OD matrix in synthetic experiments. The consistency of the estimated OD was explored by conducting a set of simulation experiments in Barcelona's CBD network, which consists of 2111 sections, 1227 nodes, 120/130 generation/attraction centroids and 877 non-zero OD pairs. The performance and robustness was also tested in another set of simulation experiments designed in terms of what were considered controllable design factors, that is, factors whose design level could be the consequence of the analyst's decision. The penetration rate of ICT is a critical factor, but not controllable, which was also considered. The two key design factors taken into account were:

- 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 this factor was related to the quality of the detection measured in terms of: the percentage of the total number of trips captured by the detectors, the proportion of OD pairs covered by the detectors, and the proportion of paths intercepted by the detectors. For further details see Barceló et al. *(17)*.
- The quality of the historic time-sliced OD matrix used to initialize the KF algorithm. The approach, as reported in *(16)*, is robust in achieving convergence but the convergence speed is highly sensitive to low volume OD pairs when we consider the quality of the initialization.

The computational experiments were conducted on a Windows 7 – 64 bit – 8 GB RAM -Intel Core i7-2600 (8M, 3.40 GHz) 4C/8T. After tuning and selecting the most suitable levels for performance factors, each Kalman iteration took 7.6 to 10.2 CPU sec, depending on the number of Bluetooth Sensors and percentage of equipped vehicles. In half–hour forecasting, CPU time would range from 1 to 2 min and, thus, it made the procedure suitable for real-time applications if an appropriate initialization is used.

A PROPOSAL FOR THE OFF-LINE GENERATION OF TIME SLICED TARGET MATRICES

From the previous discussions about the computational performance of the Kalman Filter approach for real-time estimation of the OD matrices, an open research question naturally arises: After having determined how the detection layout is kept under control *(17)* as well as its use *(16),* what can be done to improve the quality of the historic time-sliced OD matrices and to initialize the Kalman Filter procedure at each time interval.

To answer this question we focused our on the methodological framework *(5)*, the practice reported in *(8),* and the improvements proposed in *(13),* which were computationally tested in *(14).* We took into account that the primary objective was to achieve a good estimate of the time variability of the OD matrix, and that this is the natural cause of congestion for a network with a predefined capacity in the absence of incidents. Therefore, it was logical to wonder what could happen in the estimation process if we avoided the static point of view and instead approximated flow dynamics that can acceptably reproduce the dynamic approach ((1) and (2)) and solve the lower level problem (2) with a Dynamic User Equilibrium model (DUE).

From a practical point of view the straightforward possibilities were to employ any of the available tools, like Dynameq *(18)* or Aimsun Meso *(19)*, among others, and instead implement a DUE *(20), (21),* whose Dynamic Network Loading *(22)* mechanism is based on traffic

simulation. Solving the lower level problem heuristically through simulation raises a new computational problem, since the objective function cannot be evaluated analytically and it requires other types of numerical methods. In *(23)* Cipriani et al. proposed an algorithmic approach combining Dynameq (for the DUE assignments) and Spall's *(24)* Stochastic Perturbation Stochastic Approximation (SPSA) method, (for the optimization problem with a derivative free procedure). In this formulation of the adjustment problem, it is assumed that link counts and point speeds are available for a subset of links in the network.

The approach that we explore in this paper is based on an adaptation and extension of the method proposed by Cipriani et al. *(23)*. We have additionally assumed that travel times between Bluetooth sensors are available along the main paths that connect them in the network. The research reported in *(17)* proved that a suitable Bluetooth sensor layout allows the identification of the paths between sensors and, therefore, the measurement of the associated travel times. Consequently, to implement the proposed approach, we needed the lower level DUE to generate not only the simulated flows and speeds at detection stations (as in Cipriani et al. *(23))*, but also the simulated travel time estimates between Bluetooth antennas along the corresponding paths. The dynamic O-D adjustment problem is formulated in *(23)* as dynamic optimization problem aimed at minimizing: 1) the discrepancy between actual and estimated observations, and 2) the "distance" between estimated and a-priori O-D demand flows (seed matrix).

Given: A network B = [N, A], where N are nodes and A are links; the period of analysis T, is divided into n_h intervals, and a subset of links S={1… n_s} ∈ A equipped with sensors. The problem lies in finding an optimal demand vector $\left(d_1^* … d_{n_h}^*\right)$, such that:

$$\left(d_1^* … d_{n_h}^*\right) = arg \quad min_{(x_1…x_{n_h})\geq 0}[f_1\left(x_1 … x_{n_h}, \hat{d}_1 … \hat{d}_{n_h}\right) + f_2\left(v_1 … v_{n_h}, \hat{v}_1 … \hat{v}_{n_h}\right) +$$
$$f_3\left(s_1 … s_{n_h}, \hat{s}_1 … \hat{s}_{n_h}\right)] \tag{3}$$

Where for each time interval

x_i estimated matrix i, i = 1… n_h
v_i simulated volumes on links ∈ S at i, i = 1… n_h
s_i simulated speeds on links ∈ S at i, i = 1… n_h
$\hat{d}_i$ seed matrix at i, i = 1… n_h
$\hat{v}_i$ traffic volumes on links ∈ S at i, i = 1… n_h
$\hat{s}_i$ measured speeds on links ∈ S at i, i = 1… n_h

The three terms objective function takes the "distance" between observations/simulations of flows/speeds and combines it with the "distance" between the seed matrix and the resulting estimated demand.

We propose a reformulation that incorporates a new term in the objective function, one which corresponds to the travel times in the predefined paths between Bluetooth sensors. The objective function then becomes the sum of four distances:

$$\left(d_1^* … d_{n_h}^*\right) = arg \quad min_{(x_1…x_{n_h})\geq 0}[f_1\left(x_1 … x_{n_h}, \hat{d}_1 … \hat{d}_{n_h}\right) + f_2\left(v_1 … v_{n_h}, \hat{v}_1 … \hat{v}_{n_h}\right)$$
$$+ f_3\left(s_1 … s_{n_h}, \hat{s}_1 … \hat{s}_{n_h}\right) + f_4\left(t_1 … t_{n_h}, \hat{t}_1 … \hat{t}_{n_h}\right)] \tag{4}$$

where the components of the fourth distance term for each time interval are:

t_i travel times in specified routes at i, i = 1… n_h

$\hat{t}_i$ measured travel times in specified routes at i, i = $1...n_h$

The distance functions f_1, f_2, f_3 and f_4 used in this paper are the Normalized Mean Error distance (NME), selected as the most significant among the alternatives tested in the MULTITUDE project (24).

Consequently, the SPSA gradient calculations must be modified accordingly. The simulated travel times are computed as follows:

1. The complete underlying graph of the urban network is extracted from the microscopic simulation model, including all turnings and their associated penalties.
2. The simulation model is run for an estimated OD matrix $\hat{\mathbf{g}}(\mathbf{t_i})$ for a given time interval $\mathbf{t_i}$ to generate a database with the estimated link travel times for that time interval.
3. The data from the link travel times, the graph of the urban network, the detection layout and the defined paths between pairs of Bluetooth antennas are used to calculate the measured path travel times **tt.**

As detailed in Spall *(25),* choosing the gain sequences (a_k and c_k) and simultaneous perturbation vector (SPV) is critical for SPSA performance. We use an Asymmetrical Design (AD) to halve the number of objective function evaluations required in any simultaneous perturbation. First we do a simulation (Due-Simulation function call) using the iteration's initial matrix. From this, we get the value of the objective function as follows:

gradient = ((objectiveplus - objective)/ck)*Simultaneous_perturbation_vector;

The objective value remains unchanged throughout the iteration, but the *objectiveplus* value varies in each of the "m" gradient approximations because we have an inner loop where "m" perturbations of the initial matrix are created. The procedure consists schematically of the following inner and outer loops:

Iteration k
Matrix
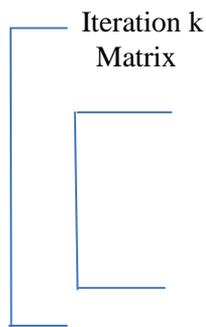
Computational Testing

The first computational testing of the proposed approach was conducted using a scenario from the common evaluation and benchmarking platform developed within the framework of the EU COST Action MULTITUDE TU903. The main goal of this platform *(24)* was to provide a test bed in which a number of algorithms could be implemented and tested under the same conditions. Our algorithm was one of them.

The selected scenario was a microscopic Aimsun simulation model of the Vitoria network in the Basque Country. TSS provided it to the MULTITUDE project. Vitoria's network has 57

centroids and 2800 intersections (see Figure 3). Traffic data are collected from 389 loop detectors and 50 ICT detectors, which were distributed according to the layout models in *(17)*. Almost 90% of the trips are collected at least twice in the peak-afternoon, 1-hour long demand scenario, which accounts for 95% of the number of OD pairs and 86% of the most likely used paths identified by the 'true' historic OD matrix in a DUE assignment.

Figure 3. Vitoria's network and subnetwork covered by ICT sensor layout.

When we talk about travel times, what do we mean exactly? In the Vitoria network we have chosen 50 pairs of antennas and we calculate the most likely routes between them. The procedure returns simulated travel times on these predefined and stored routes.

The level of demand is a key element affecting the performance of OD estimations, since the problem becomes more difficult under congestion. The experimental design in MULTITUDE *(24)* for Vitoria's network consists of three different demand levels that are grounded in the 'true' historic demand level *D* for the 1h peak-afternoon period. In constructing the three demand levels, demand entries were perturbed randomly according to:

1. Low demand (denoted as D7): D*[0.7+0.3*rand( )].
2. Medium demand (D8): D*[0.8+0.3*rand( )]
3. High demand (D9): D*[0.9+0.3*rand( )]

Results for Bilevel-DUE in Vitoria's network

Because the MULTITUDE platform uses Aimsun, the DUE-Function uses Aimsun Meso *(22)* to perform the DUE assignment. In Figure 4, the progress in the objective function is shown, with the three demand levels (D7, D8 and D9) depicted. The objective function decreases in all instances, although the best value is obtained for D8, with a reduction of 55% (from 1.38 to

0.68) in 20 iterations. For D7 and D9, reductions are 24% and 32%, respectively. Figure 5 shows normalized mean error reductions in flow term discrepancy as the algorithm progresses.

$$f_2\left(v_1 \dots v_{n_h}, \hat{v}_1 \dots \hat{v}_{n_h}\right) = \frac{4 \cdot 389 \sum_{k=1:4} \sum_{i=1:n_h} \left(v_{i,k} - \hat{v}_{i,k}\right)}{\sum_{k=1:4} \sum_{i=1:n_h} \hat{v}_{i,k}} \qquad (5)$$
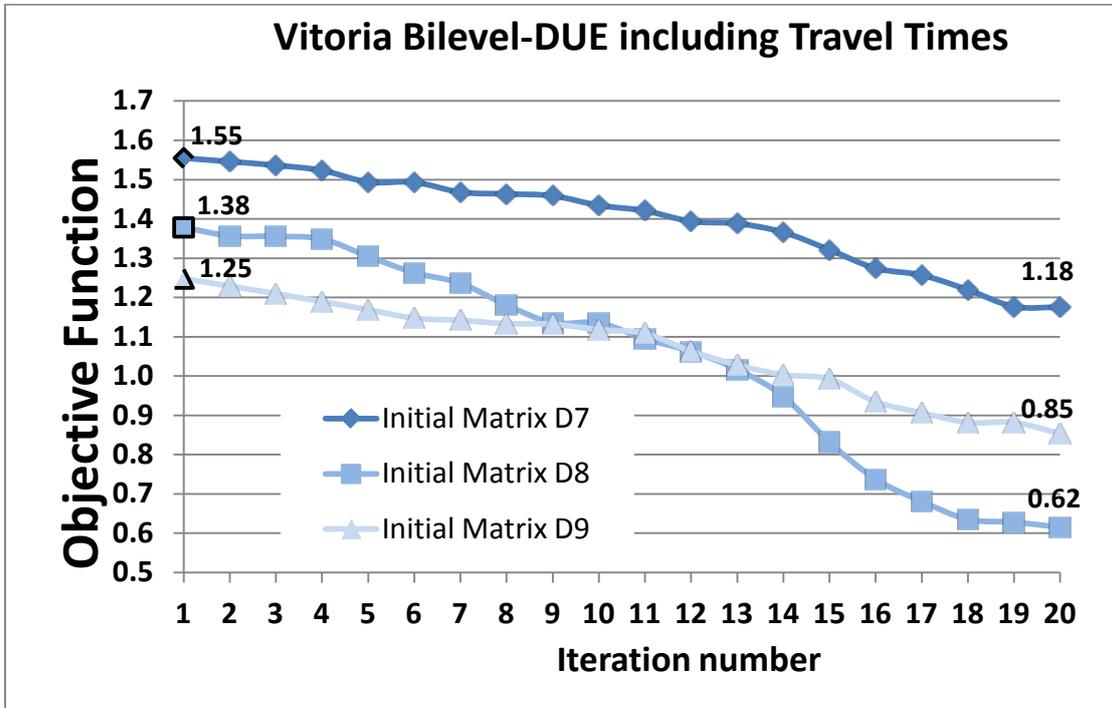

Figure 4. Vitoria network- Bilevel-DUE off line OD matrix estimation: objective function progress (including travel times)

The reduction in the NME (Normalized Mean Error) is 36%, 69% and 28%, depending on the initializations D7, D8 or D9 when travel times are considered. This influences its progress. But in the D7 initialization, when the travel time term is not used, the flow term is reduced by up to 21%, which is lower than that obtained when travel times are considered (36%).
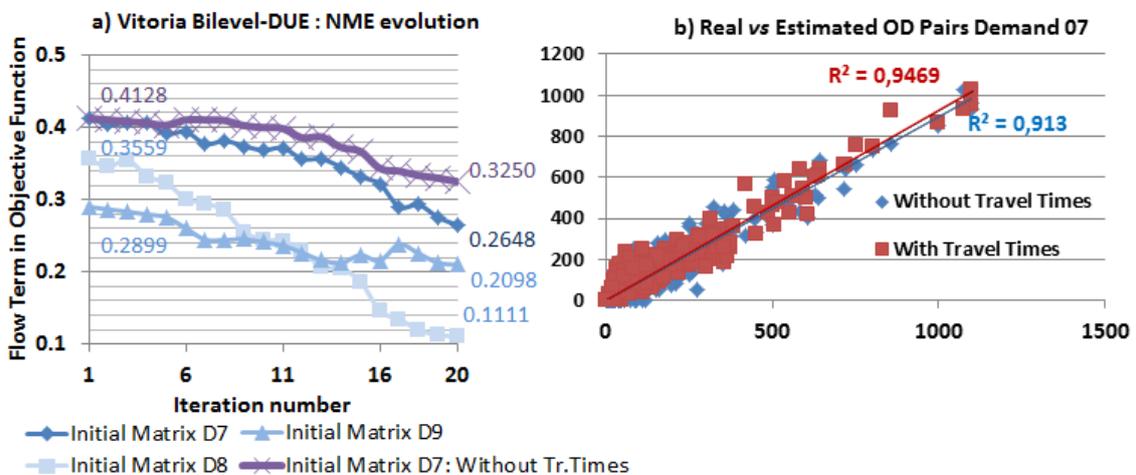
Figure 5. Vitoria network: a) Bilevel-DUE off line OD matrix estimation: flow term evolution, b) Bilevel-DUE real vs. estimated total OD flows (1h period).

In Figure 5.b, the total OD flows for the 1h peak-afternoon period are shown (real versus estimated) for both versions of the Bilevel-DUE scheme that estimates the off-line matrix: the original one, without travel times; and the modification proposed by the authors. The coefficient of determination is almost 95% when times are included, which is higher than the 91% obtained without travel times.

A second set of computational experiments

Since we obtained interesting results for the Vitoria network in the experiment on the off-line Bilevel-DUE that was modified with the times term, we conducted a different set of experiments on Barcelona's CBD network, the same network used in references *(15)* and *(16)*. The OD pattern is common for all 5 slices, but intensities are slice-varying with a total number of 59774 trips. The 'real' OD matrix has five different time slices, accounting for 20%, 27%, 20%, 13% and 20% of the total flow, and it corresponds to a synthetic time-sliced matrix of 1h 15min. This was obtained to represent a point of heightened congestion, in accordance with the network's MFD (Macro Fundamental Diagram), by Danganzo and Geronimilis *(26)*. 50 ICTs were located at intersections following *(17)*. There are 116 loop detectors (see Figure 6). For Barcelona's network, the objective function in equation (3) is decomposed into terms of flow, density and speed.

The initial time-sliced OD matrix was 75% of the real OD matrix, and the OD Pattern perturbed for the most important centroid. Both Bilevel-DUE approaches are able to converge. However, as in Vitoria, the regression between real and observed total OD flows for the study period shows a 92% coefficient of determination when travel times are included, but just 85% when they are not considered (see Figure 7.a). In Figure 7.b, progress to reduction of flow term is faster when travel times are included in the upper level objective function of the proposed Bilevel-DUE scheme. These results are consistent with those found in the Vitoria test network. Convergence of the density term does not progress better once travel times are included, thus the conclusions are not so clear in this case.
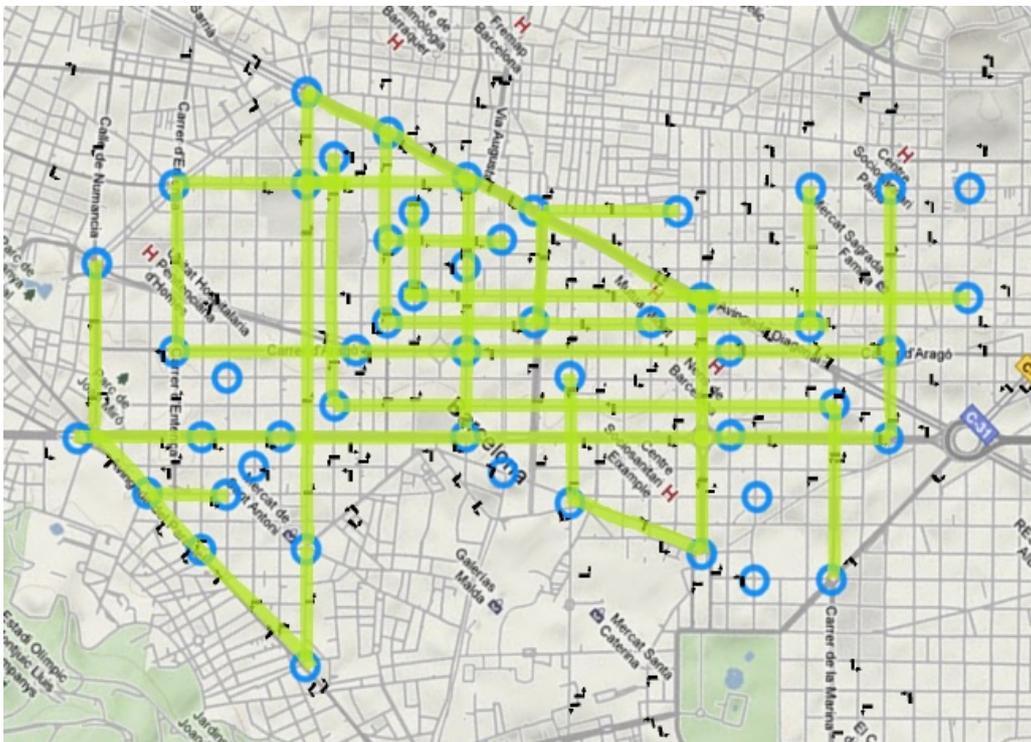

Figure 6. Barcelona's CBD network and subnetwork covered by ICT sensor layout

The starting time-sliced OD matrix was 75% of the real OD matrix in all slices, and the OD Pattern perturbed for the most important origin centroids in the network. As previously with Vitoria, the regression between real and estimated total OD flows for the study period (1h15min) shows a 92% coefficient of determination when travel times are included, but just 85% when they are not considered (see Figure 7).
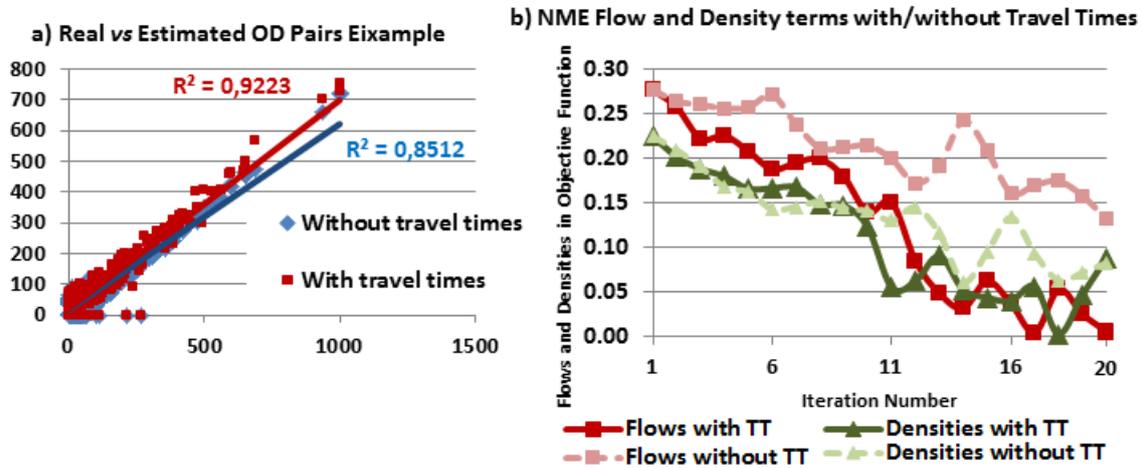

Figure 7. Barcelona's CBD network: a) Real vs. Estimated total OD flows (1h15 min), b) Flow and Density terms progress along Bilevel-DUE iterations with and without travel times in the objective function

The concluding remarks about computational times are: the algorithm performs 15 dynamic equilibrium assignments for each iteration. Each DUE assignment in the Vitoria network takes about 7.50 min of elapsed time, which means a total amount of 2 hours per iteration (40 hours for 20 iterations). In Barcelona's network each DUE assignment takes about 9 min of elapsed time, which means 2.25 hours per iteration (45 hours for 20 iterations). Experiments were conducted on a Windows 7 - 64 bit - Intel i7-3770 8 CORES 3.4GHz RAM 16GB.

CONCLUSIONS AND A METHODOLOGICAL PROPOSAL

We gained some practical experience in *(8)* by considering the approximated time-sliced OD matrices; the computational results of the proposed Bilevel adjustment based on DUE assignment, which used link counts and ICT measurements; and the computational performance of the Kalman Filter approach *(15), (16),* which also used ICT measurements. This experience led us to the following conclusions:

a. The computational performance of the Kalman Filter *(15), (16)* makes it useful for real-time applications. But this is true only when we require the detection layout, the level of ICT penetration and initialization quality.
b. ICT measures can be exploited by the modified bilevel, which heuristically solves the lower level optimization with a DUE using a mesoscopic simulation for the DNL. It also provides a quite good time-sliced OD that is suitable for the initialization. However, the computational times make the measures useful only for off-line applications.

These conclusions prompted the idea of combining both methods to propose the methodological component for practical implementations of the AMS Framework, described conceptually in the diagram in Figure 8.
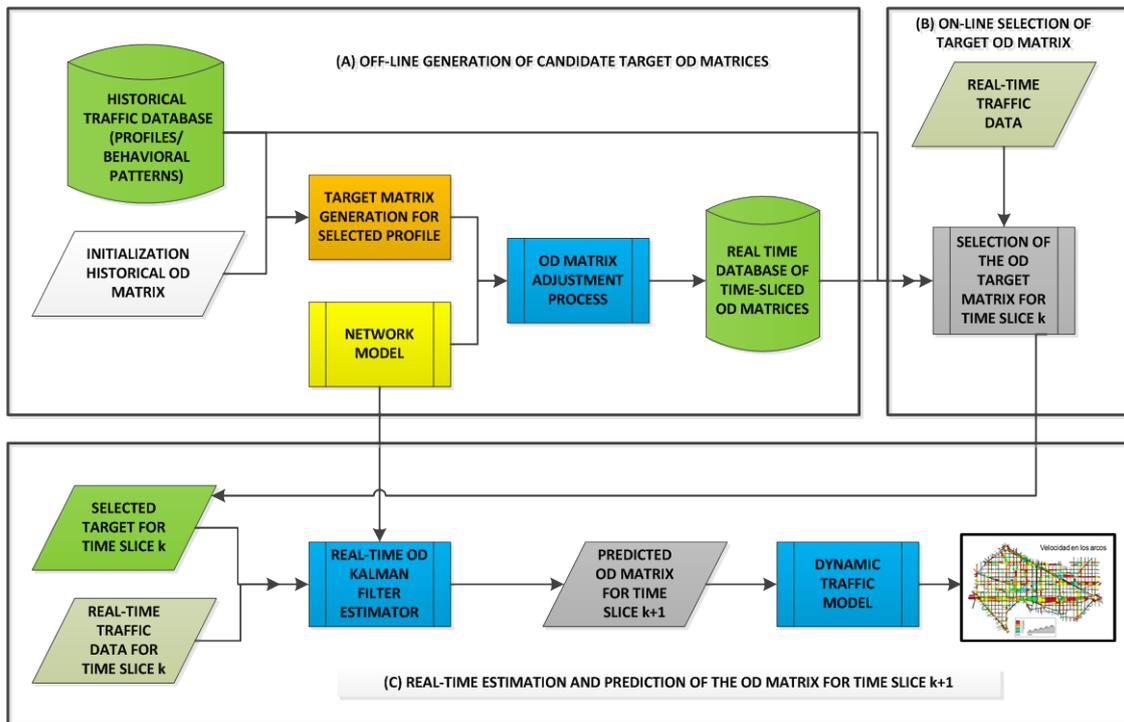
Figure 8 Methodological diagram for the use of OD matrices in an AMS Framework

The process is split into three components:

A. An off-line generation of candidate target matrices for the initialization of the on-line procedure.

   It combines an initial OD matrix or similar practical applications with the historical traffic data clustered in profiles for different times of the day (e.g., raining Tuesday from 6:00 am until 8:00 am, and so on). This likely comes from a Travel Demand Model as in (4), (8). The heuristic procedure described in Figure 2 time slices the initial OD in terms of the profiles. These time slices, along with a network model, are the input to the Bilevel-Due proposed in this paper. The repetitions of the process for the different time intervals generate a database of candidate target matrices off-line.

B. An on-line selection of the most likely OD matrix for the initialization, given the current traffic conditions

   The real-time traffic data from the traffic monitoring system provides the input for a process to identify the profile that fits the current situation better, and it then selects the select most likely OD matrix for that time interval.

C. The real-time estimation and prediction of the OD matrix

   The selected OD is the initial matrix used by the ad hoc Kalman Filter model to estimate and predict the expected OD for the next time period. This OD will be the inputs for the traffic model to estimate the network state and to predict its short-term evolution.

The proposed approach can be considered a further refinement of those proposed and experimented in *(4)*, *(8)* and similar projects. With respect to others that have similar objectives, such as Zhou and Mahmassani *(27)*, what is different in our approach is that we propose a

decoupled process to determine off-line the most likely OD pattern for initializing the Kalman Filter model. In this way, we provide an a priori estimate of the real-time estimation instead of including it as part of the Kalman Filter process, which would therefore increase the computational burden and make it difficult to apply in real-time operations. The off-line bilevel adjustment using a DUE assignment in the lower level accounts for time variability, and it is an initialization that puts the method on a path for real-time applications, as shown in Barcelo et al. (17).

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REFERENCES

(1) Y. J. Stephanedes, E. Kwon (1993), Adaptive demand-diversion prediction for integrated control of freeway corridors, Transp. Res.C, Vol.1, Issue 1, 23–42.
(2) M. Papageorgiou (1995), An integrated control approach for traffic corridors, Trans. Res. C, Vol.3, Issue 1, 19–30
(3) X. Zhou, H. S. Mahmassani, K. Zhang (2008), Dynamic micro-assignment modeling approach for integrated multimodal urban corridor management, Trans. Res. C, Volume 16, Issue 2, 167–186
(4) V. Alexiadis, (2008) Integrated Corridor Management Analysis, Modeling, and Simulation Experimental Plan for the Test Corridor, USDOT Integrated Corridor Management (ICM) Initiative, FHWA-JPO-08-035, EDL 14415
(5) B. Cronin, S. Mortensen, R. Sheehan, and D. Thompson (2010), Integrated Corridor Management - Vol. 74 · No. 3 - Public Roads
(6) Sprague, R.H. and H.J. Watson, (1986) Decision Support Systems: Putting Theory into Practice, Prentice- Hall.
(7) J. Barcelo, H. Kirschfink, A. Torday (2005) An integrated software platform to assist advanced traffic management decisions, Modeling and Simulation Workshop, Sedona.
(8) J. Barceló, M. Delgado, G. Funes, D. García and A. Torday (2007), An on-line approach based on microscopic traffic simulation to assist real time traffic management, 14th World Congress onITS, Beijing.
(9) AMS Framework for DMA and ATDM Programs. Draft report Version 1.4, May 2013, USDOT.
(10) H. Spiess and D. Sutter (1990), Modeling the daily traffic flows on an hourly basis, Proceedings of the 18th Summer Annual Meeting of PTRC.
(11) Torday A. (2005), Elaboration d'un système de navigation auto-alimenté (SNA) et évaluation de ses performances.Ph D Thesis, Num. 3147, EPFL Switzerland (in French)
(12) H. Spiess (1990), A gradient approach for the OD matrix adjustment problem, Publication 693 Centre de Recherche sur les Transports, Univ. Montréal.
(13) Lundgren, J.T., Peterson, A. A Heuristic for the Bilevel Origen-Destination-Matrix Estimation Problem. Trans.Res.B 42, 2008, pp.339-354.
(14) B. Moya (2013), Heuristic procedures for the stimation of OD matrices from traffic counts, M. Sc. Thesis (in Catalan), Department of Statistics and Operations Research, UPC-BarcelonaTech.
(15) J.Barceló, L.Montero, M.Bullejos, O. Serch and C. Carmona (2013), A Kalman Filter Approach for the Estimation of Time Dependent OD Matrices Exploiting Bluetooth Traffic Data Collection. JITS Journal of Intelligent Transportation Systems, 17(2):1-19.
(16) J.Barceló, L.Montero, M.Bullejos, M.P. Linares, O. Serch (2013), Robustness and computational efficiency of a Kalman Filter estimator of time dependent OD matrices

exploiting ICT traffic measurements. Paper 13-3919, accepted for publication in Transportation Research Records

(17) J.Barceló, F. Gilliéron, M.P. Linares, O. Serch, L.Montero (2012), Exploring Link Covering and Node Covering Formulations of Detection Layout Problem. Transportation Research Records2308, pp.17-26.

(18) INRO (2010) Dynameq User's Manual, INRO, Montréal, Canada

(19) TSS-Transport Simulation Systems (2013). Aimsun 7 Dynamic Simulator User's Manual, TSS, Barcelona, Spain

(20) Mahmassani, H.S. Dynamic network traffic assignment and simulation methodology for advanced system management applications. *Networks and Spatial Economics*, 1(3-4):267-292, 2001.

(21) S. Peeta and A. K. Ziliaskopoulos. Foundations of dynamic traffic assignment: The past, the present and the future. *Networks and Spatial Economics*, 1(3-4):233-265, 2001.

(22) Chiu, Y.C., Bottom, J., Mahut, M., Paz, A., Balakrishna, R., Waller, T. and Hicks, J. (2010) A primer for dynamic traffic assignment. Transportation Research Board.

(23) Cipriani, E., Florian, M., Mahut, M. and Nigro, M. (2011) A gradient approximation approach for adjusting temporal origin–destination matrices. Trans. Res. C 19 pp.270-282.

(24) Antoniou, C., Ciuffo B., Montero, L., Casas, J., Barceló, J., Cipriani, E., Djukic, T., Marzano, V., Nigro, M., Bullejos, M., Perarnau, J., Breen, M. and Toledo, T., (2013), A framework for the benchmarking of OD estimation and prediction algorithms, Submitted at IEEE transactions on ITS.

(25) Spall, J.C (1998) An overview of the simultaneous perturbation method for efficient optimization. Johns Hopkins APL Technical Digest, 19 (4) (1998), pp.482–492

(26) Daganzo, C.F. and Geroliminis, N. (2008) An analytical approximation for the macroscopic fundamental diagram of urban traffic. Trans. Res.B 42, 2008.

(27) X. Zhou and H. S. Mahmassani (2007) A structural state space model for real-time traffic origin-destination demand estimation and prediction in a day-to-day learning framework. Transportation Research B: Methodological Vol41,Iss.8 pp823-840.