Mesoscopic simulator data to perform Dynamic Origin-Destination Matrices Estimation in Urban Context

Emmanuel Bert

Edward Chung

Jaime Barcelo*

André-Gilles Dumont

Traffic Facilities Laboratory (LAVOC)
Ecole Polytechnique Fédérale de Lausanne (EPFL)
Switzerland

** Departament d'Estadística i Investigació Operativa*
Universitat Politècnica de Catalunya
Spain

emmanuel.bert@epfl.ch
Tel.: +41 21 693 06 02
Fax: +41 21 693 63 49

Submitted for the International Symposium of Transport Simulation 2008

Abstract:

The aim of this paper is to explore a new approach to obtain better traffic demand (Origin-Destination, OD matrices) for dense urban networks using traffic simulation data. From reviewing existing methods, from static to dynamic OD matrix evaluation, possible deficiencies in the approach could be identified. To improve the global process of traffic demand estimation, this paper is focusing on a new methodology to determine dynamic OD matrices for urban areas characterized by complex route choice situation and high level of traffic controls. An iterative bi-level approach will be used to perform the OD estimation. The Lower Level (traffic assignment) problem will determine, dynamically, the utilization of the network by vehicles using heuristic data from mesoscopic traffic simulator particularly adapted for urban context. The Upper Level (matrix adjustment) problem will proceed to an OD estimation using optimization least square techniques. In this way, a full dynamic and continuous estimation of the final OD matrix could be obtained. First evaluation of the proposed approach and conclusions are presented.

Keywords:

Traffic simulation – Traffic demand – Origin-destination matrices estimation – Dynamic traffic assignment – Urban Network –ITS

INTRODUCTION

OD estimation is a crucial step for transportation studies as it represents the transport demand for the network. In this way, its quality has a large influence on the results of analyses based on this traffic representation. Mathematically, this estimation is called "under-estimated" because, in most of the cases, there are more unknown parameters (OD pairs flows) than information (traffic counts data) to estimate those. The indetermination can be overcome by adding constraints providing additional information or an objective function measuring the distance between any feasible solution to the problem and a predefined target, and the OD estimation can then be solved as an optimization problem. The methodology adopted must find the optimal solution depending on the modelling constraints. To estimate an OD matrix, several inputs are needed. The network model, traffic data (traffic counts at different places) and route choice algorithms (determination of the best paths in a network depending on trip and traffic conditions), using appropriate methodology, can lead to appropriate OD matrices. OD estimation is constituted by two distinguish processes: traffic assignment, which generates the traffic distribution into the network and OD adjustment, which adapts the OD flows based on traffic counts.

Most used methods are dealing with the problem using static approaches. They are estimating a unique OD matrix for the whole period study. This limitation does not allow fluctuations of the demand through time. In this way, dynamic characteristics of the demand, particularly in urban context, could not be obtained. Different proposals have been elaborated to obtain a "dynamic" demand at the end. One approach is a heuristics time slicing of the matrix obtained using one initial static OD adjustment, which adapts OD flows from the available traffic counts for that time slice. This alternative provides a time sliced OD matrix but adapts only the volume and not the structure of the demand. Another approach is to do a sequential static OD estimation. This technique proceeds to a static OD adjustment for each time slice but does not take into account the continuity of the demand through the time (no link between different time slices).

Dynamic OD estimation presents different challenging aspects. Demand and path evaluation must be done by time slices. Global time study is divided in N equal time periods. From these time periods, OD estimation must be achieved taking into account links and relation between them. Indeed, depending of the size of the network and its complexity (speed and distance from origin to destination), part of vehicle could need more than one time period to attend their destination or counting sensor. This statement leads to the fact that counting values of one time interval could be influenced by previous one (or more). As a consequence, demand generation (OD flows) for period n must take into account action of the time period n and n+1, n+2… N (depending of the network characteristics). To do that, the different stages of the OD estimation must be adapted to catch this evolution. First, traffic assignment needs to be dynamic. DTA (Dynamic Traffic Assignment) proposes a route choice solution depending on traffic conditions. And, the OD adjustment, also, needs to take into account the evolution of trips in the network. Algorithm must be able to make a distinction between entrance time (in the network) and time period at the traffic count place.

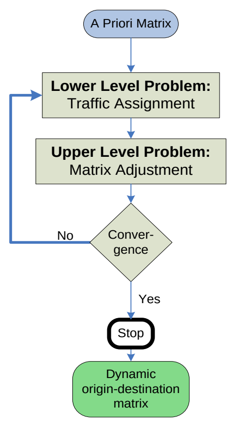
This paper is interested in urban networks. This kind of network presents particular characteristics which influence strongly on traffic flows. Laminar flows are disturbed by traffic conflicts or signalizations (Stops, give ways, signalized intersection, etc.). Platoon of vehicle are disrupted and delayed by priorities between flows. This discontinuity induces great variation in flow spreading which could leads to congestion (added to high demand) and in travel time experimented within the network. Route chose possibilities in urban areas are usually greater than in other type of network. Traffic is then spread in higher number of path from an origin to the destination. Moreover, urban networks due to high density of traffic interfaces present, in most of the case a larger number of OD pair. This heterogeneity and distribution of the traffic in a large urban network make behavior evaluation and modeling of the situation highly complex.

In our case, we are going to focus on static and dynamic congested situations in urban network. Dynamicity (usually time sliced demand), route choice possibilities and traffic signals timings are challenges, which are other centre of attention in this paper. Current methodologies will be reviewed and an innovative approach particularly adapted for dynamic urban networks will be proposed. This method will use traffic simulation (mesoscopic) for traffic assignment in the network. First conclusions and results are presented. This work is part of an ongoing PhD research that started last year. The approach and methodology are explained in detail but extensive tests are still in progress.

LITERATURE REVIEW

Static adjustment approach is the most common method for OD estimation. In this method, the inter-dependence between OD matrix and link flow is formulated as a bi-level problem in most of the cases (see Figure 1) [23].

Figure 1 Bi-level process



For instance, the software EMME/2 (INRO), which is one of the most common used methods for practitioners, assigns the traffic in the network (Lower Level) using Wardrop equilibrium [31] based on Volume Delay functions defined for each link and junction. Concerning the Upper Level, Spiess developed an approach [28] dealing with the estimation of the OD flows in a static way. It means that the flow for each OD pairs is considered as constant (no variation on volume) during the analyzed period. This hypothesis is very constrained and does not take into account on the evolution of peak hour traffic (increase and then decrease of traffic demand on the network).

Dynamic approaches are indispensable to improve the process accuracy. The main contributions in the dynamic OD estimation field could be categorized based on the methodology (see Table 1). The type of network tested, the way to achieve the traffic assignment and the optimization approach for the OD estimation form different groups.

Table 1 Dynamic OD estimation in the literacy

References:	Name	Type[1]	Size[2]	Ass.[3]	Opt.[4]	RC[5]	T-S[6]
[Okutani and Stephanedes, 1984]	Nagoya	Street	Small	-	KF[7]	No	No
[Cremer and Keller, 1987]	Various	Intersection	Small	-	Varios	No	No
[Bell, 1991]	-	Street	Small	-	GLS[8]	No	No
	-	Intersection	Small			No	No
[Cascetta et al., 1993]	Brescia-Padua	Freeway	Med	Analytic	GLS	No	No
[Chang and Wu, 1994]	-	Freeway	Small	-	KF	No	No
[Chang and Tao, 1996]	-	Urban	Small	Analytic (+ cordonline)	Cordonline model	Low	Yes
[Zijpp, 1996]	Amsterdam	Freeway	Large	-	TMVN[9]	No	No
[Ashok, 1996]	Massa Turnpike	Freeway	Med	Analytic	KF	No	No
	I-880	Freeway	Small			No	No
	Amsterdam	Freeway	Large			No	No
[Sherali and Park, 2001]	-	Urban	Small	Analytic	LS[10]	Low	No
	Massa Turnpike	Freeway	Med			No	No
[Hu et al., 2001]	-	Freeway	Small	Simulator (Meso) TT	KF	No	No
[Tsekeris and Stathopoulos, 2003]	Athens	Urban	Med	Simulator (Macro)	MART, RMART, DIMAP[11]	Yes	No
[Bierlaire and Crittin, 2004]	Boston	Freeway	Med	Simulator (Meso)	KF, LSQR[12]	Low	No
	Irvine	Mid	Large			Med	No
[Balakrishna et al., 2006]	-	Intersection	Small	-	Analytic	No	No
	Los Angeles	Mid	Large			Yes	Yes

[1] Type of network test
[2] Size of the network
[3] Type of traffic assignment used in the OD estimation
[4] Method for OD optimization approach
[5] Route choice capabilities
[6] Traffic signal capabilities
[7] KF: Kalman Filtering (normal, adapted or extended)
[8] GLS: Generalised Least Squares
[9] TMVN: Truncated Multivariate Normal
[10] LS: Least Squares
[11] Multiplicative Algebraic Reconstruction Technique, (Revised), Doubly Iterative Matrix Adjustment Procedure
[12] LSQR: Spares Linear Equations and Spares Least Squares

Most literature deals with small and/or simple networks without traffic assignment (Bell [7], Okutani and Stephanedes [24] and Cremer and Keller [14]). Cremer and Keller presented different methods for the identification of OD flows dynamically. Ordinary least squares estimator involving cross-correlation matrices, constrained optimization method, simple recursive estimation formula and estimation by Kalman filtering are analysed to estimate the accuracy and convergence properties. Comparison with static approaches is carried out on small intersection networks.

Several articles (Chang and Tao [13] and Zijpp [30]) deal with freeways networks. This kind of networks offers little traffic signal and route choice capabilities. Zijpp has developed a method for estimating OD flows on freeway networks in which time interval boundaries are determined by analyzing time-space trajectories. Trajectories of the vehicles from the upstream end of the study section are computed and used to match measured link counts at various locations with correct set of OD flows. This new method is based on adopting a Truncated Multivariate Normal (TMVN) distribution for the split probabilities and updating this distribution using Bayes rule. The method has been tested on the Amsterdam freeway network. This is a large beltway (32 km) which encircled the city with 20 entrance and exit ramps. Route choice is very limited (one way or the other) and there is no signalized intersection.

The research by Cascetta et al. [11], Sherali and Park [27] and Ashok [1, 3] considered traffic assignment as an input and assignment is calculated analytically. Ashok developed a sequential OD smoothing scheme based on state-space modeling concept. He used a Kalman Filter solution approach to estimate the OD flows. He also discussed about methods to estimate the initial inputs required by the Kalman filter algorithm. The theoretical development is tested on three different networks: the Massachusetts Turnpike, the I-880 near Hayward, California and Amsterdam Beltway. These networks are different in term of scale but with minimal or no route choice and no traffic signal.

The following papers (Hu et al. [18] and Bierlaire and Crittin [8]) used simulator for traffic assignment in the network. In their paper, Bierlaire and Crittin compared the Kalman filter algorithm to LSQR algorithm (algorithm for sparse linear equations and sparse least squares). They showed the fact that for large scale problems; the LSQR presents better performance in comparison to the other approach. The authors used a very simple network for a numerical comparison and two other networks as case studies. The first one is the Central Artery/Third Harbor Tunnel. It is a medium size network with low route choice possibilities, with five origins and two destinations and nodes are unsignalized. The second one contains the major highways I-5, I-405, and CA-133 around Irvine, California. This is a medium scale network with 625 OD pairs (25*25 OD matrix), without signalized intersection. This network could also be considered close to an urban network but even if the geographical size of the network is large, the complexity of the model (number of route possibilities and the size of the matrix is medium.

Finally, urban networks are analyzed by few researchers. Traffic assignment could be known (input) or calculated analytically (Chang and Tao [12] and Balakrishna et al. [4] and Tsekeris and Stathopoulos [29]). Usually, OD estimation is done using data extracted from traffic measurements (traffic counts…). Paper by Balakrishna et al. presented a new method which allows estimating the complex link between OD flows and traffic counts. The relationship between flows and traffic measurements are captured using an optimization approach which considers the assignment model as a black box. Assignment matrix and dynamic OD estimation are estimated mathematically. Two practical cases have been analyzed. The first one is a small network constituted by four simple intersections (unsignalized) with three origins and one destination (no route choice). The second one is named South Park, Los Angeles Network. It is a medium size network composed of two freeways and several arterial roads. Most of the urban intersections are signalized and route choice possibilities are medium.

Many people have been interested in the field of OD estimation for many years. These development have followed mathematic and computers capabilities evolution. From the static estimation on basic networks to complex algorithm on large networks, different approaches have been explored. Assignment problem has been explored using different approaches: from inputs data, analytically or using traffic simulation.

WEAKNESS OF EXISTING OD ESTIMATION METHODS

All approaches presented previously propose a solution to the OD estimation problem, but the following disadvantages can be identified.

- Static/Dynamic approach:
Disadvantages or lacks of the static method can lead to outputs not adapted or incompatible for an exploitation of the data for detailed analyses. The static equilibrium does not allow a time dependant traffic variation adapted for dynamic flows modifications (essential for short-term microscopic studies). Moreover, in case of utilisation of the Wardrop equilibrium, depending on the complexity of the network (intersections), parameterization of Volume Delay functions is very difficult and seldom done in detail by practitioners. Several approaches have been developed to deduct dynamic demand for static one (see Introduction) but quality of the obtained matrix is not satisfactory due to weaknesses in the approach.

- Network equilibrium research approach:
In the literature, we can find very little consideration about complex traffic route choice possibilities in the Lower Level problem (assignment matrix). It could be done by observation, analytically or by simulation. In papers about dynamic estimation (see Table 1), there are very few tools adapted for medium to large urban network with real route choice possibilities and signalized intersections. Papers from Balakrishna [4] and Chang & Tao [12] are relevant papers for urban characteristics but we can see that the first uses a small and theoretical network ("much remains to be done to have a reliable dynamic OD system for efficient use in practice") and an analytic approach for the assignment matrix whereas the second takes into account only freeways and main arterials. Bierlaire and Crittin [8] dealt with KF in the Irvine network (urban). This network is quite large in area and offer route choice capabilities, however in terms of link density (number of road per unit area) and OD matrix size, it is not large. Moreover it does not consider traffic signals. In addition, this paper does not explain in detail how the assignment matrix is obtained.

- Urban applications:
As we can see in the Table 1, there is very little consideration for urban network and for rare cases which are dealing with this kind of typography, usually they are small ones with low route choice and signalized capabilities. This lack could be problematic for most traffic studies in city areas with congested and dense networks and signalized junctions. Majority of the traffic problematic are observed in urban area and present more challenging and interesting task for traffic engineers. An innovative approach must allow efficient assessment in various types of networks and not limited to specific cases.

Based on the deficiencies identified above, the proposed methodology is focusing on several improvements of the current solutions. First, the approach is formulated as a Bi-level problem and uses a tool for demand assignment particularly adapted for the large and complex urban networks, i.e. mesoscopic simulator. Quality of the equilibrium, route choice and level of detail of the network signals settings are important features to provide an assignment really representative of the actual one for all the traffic situations. Moreover, this assignment and also the OD matrix adjustment must be done dynamically. The proposed methodology is going to tackle the major problems of the time dependant formulation e.g. travel time in the network, constraints on OD modification, negative flows, etc.

METHODOLOGY PROPOSED

To improve the demand modeling, this study focuses on the distribution of the traffic in the network. This distribution has a strong influence on the utilization of the different roads depending on origins and destinations paths and congestion level. The utilization of a simulation tool can allow an accurate and realistic modeling of the route choice in the road network. In the Upper Level problem, this repartition will be an input for OD matrix estimation algorithms. Innovative approach (e.g. by a heuristic way using traffic simulation) could be applied to solve the Lower Level of the bi-level problem. Upper Level will be solved using least square approach (see Figure 2).

Figure 2 Detailed methodology proposed

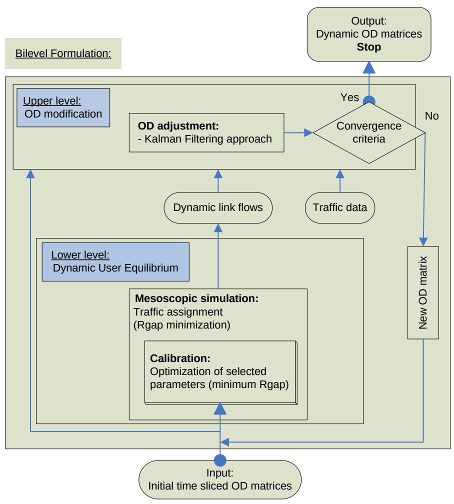


Figure 2 shows the details of the bi-level mechanism in the new approach. Let's see in more details the different parts of this bi-level process.

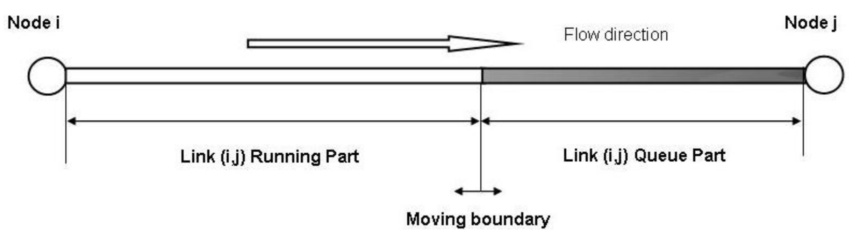
Solving Lower Level problem using Mesosimulation

Based on remarks on urban networks and OD estimation in a dynamic context presented in the Introduction, the aim of the Lower Level is to assign the demand in the network; to know how it influences traffic sensors. Using an appropriate simulator in the Lower Level allows performing dynamic assignment on urban network and extracting all the needed information useful for the process. It must achieve paths estimation from origin to destination depending on urban constraints (signalization, congestions, etc.). From the dynamic best paths evaluation, we need to extract useful information for the further step (Upper Level). Entrance time period, counted time period, proportion of the global flows of the OD pair concerned and counting location are established for the whole time study.

Macroscopic or microscopic simulators could be use to assess the demand in the network. Macroscopic models use an aggregate user equilibrium approach and provide low detail information on vehicle (particularly in urban context due to discontinuous flows) and are usually static (constant demand in time). These characteristics do not match with our objectives. Then, initially, it was proposed to use a fully disaggregated microsimulator for its dynamic and detailed capabilities. This kind of tool is adapted for detailed analysis of small networks but is limited for large networks. From these statements, mesoscopic simulators which are situated between macrosimulator and microscopic models seem to be the most adapted tool. Mesoscopic simulator focuses on essential behaviour without unnecessary details. The aim is to achieve the same level of analyses as microsimulation but with greater computation efficiency. Although mesoscopic simulator offers almost the same level of detail of a microsimulator (dynamic demand, queuing, traffic lights, signalized intersections, etc.) but due to a lower number of parameters (meanly concerning car behaviour modelling); the calibration of this kind of tool is much easier. Moreover, mesoscopic simulator allows simulation of large urban network. This is an interesting feature in our case because this simulation must be included in an automated process (total OD estimation process, see Figure 2). Reaching a representative equilibrium is dependent on the setting of these calibration parameters. The lesser, the parameters to calibrate; the better the equilibrium could be obtained. Different mesoscopic simulators have been developed (DYNASMART, DYNAMIT or DTASQ) and experiences show that there are well adapted for large urban network studies.

The simulator "AIMSUN NG" [6] developed by the Polytechnical University of Catalunya in Spain has been chosen for this task because it offers the three different kind of simulators (microscopic, mesoscopic and macroscopic), useful for process evaluation and API (Application Programming Interface) which allows possibilities to export/import all the needed information. However, AIMSUN Mesoscopic simulator is used in the methodology ([5]). AIMSUN Mesoscopic model is based on the event scheduling approach (as [10]). It means, instead of focusing on the trajectory of each vehicle, this model is interested in different particular events in the network (generation of new vehicle, entrance into a link, transfer from one link to another one, etc.). Individual vehicles are not taken into account but grouped in platoon. Links are splits in two parts i.e. running and queuing and each part has proper rules. The boundary between the two parts is moving depending on the entrance and exit conditions (see figure 3). The running part is a free flow space using simplified car following model and the queuing part is following the queue server approach taking into account the signalization and their effect on the flows (delays).

Figure 3 Link model in AIMSUN Mesoscopic



The approach taken in AIMSUN Mesoscopic to solve the dynamic equilibrium problem assumes that according to Friesz et al. (1993) [17], it can be formulated in the space of path flows $h_k(t)$, for all paths $k\in K_i$, where K_i is the set of feasible paths for the i-th OD pair at time t. The path flow rates in the feasible region Ω satisfy at any time $t\in(0,T)$ the flow conservation and non-negativity constraints [15, 16]:

$$\Omega = \left\{ h(t) \mid \sum_{k\in K_i} h_k(t) = g_i(t), i \in I; h_k(t) \geq 0 \right\} \text{ for almost all } t \in (0, t) \quad (1)$$

where I is the set of all OD pairs in the network, T is the time horizon, and $g_i(t)$ is the fraction of the demand for the i-th OD pair during the time interval t. The approach assumes that the optimal user equilibrium conditions can be defined as a temporal version of the static Wardrop user optimal equilibrium conditions, which can be formulated as:

$$s_k(t)\begin{cases} = u_i(t) \text{ if } h_k(t) > 0 \\ \geq u_i(t) \text{ Otherwise} \end{cases} \qquad u(t) = \underset{k\in K_i}{\text{Min}} \left\{ s_k(t) \right\}$$
$$\text{for } \forall k \in K_i, \forall i \in I, \text{ for almost all } t \in (0, t) \quad h_k(t) \in \Omega \qquad (2)$$

Where $s_k(t)$ is the path travel time on path k determined by the dynamic network loading. Friesz et al. (1993), show that these conditions are equivalent to the variational inequality problem consisting on finding $h^*\in\Omega$ such that:

$$\left[S\left(h^*\right), h - h^* \right] \geq 0, \forall h \in \Omega \qquad (3)$$

This problem is usually solved numerically discretizing the time horizon T into discrete time periods $t = 1,2,\ldots,\left|\frac{T}{\Delta t}\right|$ of length Δt, corresponding to equilibrium flows according to (1) and (2) where the feasible flows $h_k(t)$ are the solution of the discretization of (3):

$$\sum_t \sum_{k\in K} s_k(t)\left[h_k(t) - h_k^*(t)\right] \geq 0 \qquad (4)$$

Where $K = \bigcup_{i\in I} K_i$ is the set of all paths for all OD pairs. The approach taken in AIMSUN Mesoscopic solves analytically this problem at each time interval by the Method of Successive Averages (MSA) [15, 21]. Once the paths and the paths flows for the current time interval have been calculated the dynamics of the flows in the link is simulated according with the approach described above.

Initial time dependent OD matrix is the important input of the system. This matrix must be as close as possible to the targeted one. Historical OD tables, observations (real time…), surveys, investigations, determination of the trips attracters are tools to evaluate the best initial OD matrix. Moreover, time dependent traffic counts are indispensable for the matrix adjustment. This set of data is the only point which reflects the real traffic conditions in the network and represents the matching point of the process.

- **Mesoscopic simulation for dynamic user equilibrium**

The aim of this step is to determine the assignment matrix which gives the different paths choices depending on origin and destination and traffic conditions. AIMSUN Mesoscopic simulator is searching for Dynamic User Optimal (DUO) by iteration (see [26]). Given that the network loading is based on a heuristic simulation approach, analytical proof of convergence to a user equilibrium cannot be provided, but empirically convergence to an equilibrium solution can be provided by the Rgap function, measuring the distance between the current solution and an ideal equilibrium solution [16, 19]. A small value of Rgap expresses equilibrium in the network close to the Dynamic User Optimal.

$$Rgap(t) = \frac{\sum_{i \in I} \sum_{K \in K_i} F_K(t).[S_K(t) - U_i(t)]}{\sum_{i \in I} G_i(t).U_i(t)}$$

Where $U_i(t)$ are the travel times on the shortest paths for the i-th OD pair at time interval t, $S_K(t)$ is the travel time on path K connecting the i-th OD pair at time interval t, $F_K(t)$ is the flow on path K at time t, $G_i(t)$ is the demand for the i-th OD pair at time interval t, K_i, is the set of paths for the i-th OD pair, and I is the set of all OD pairs.

Using the AIMSUN Mesoscopic simulator allows accurate and realistic distribution of the traffic in the network. Its Rgap minimization using MSA provides a dynamic user equilibrium indispensable for the traffic assignment. Moreover, urban characteristics are fully modeled and route choose is obtain in the same way as detailed microscopic simulation. As explained above, assignment of the traffic is particularly adapted for complex and large urban networks.

<u>Solving Upper Level problem using Least Square formulation</u>

The proposed approach must find the best way to solve the Upper Level problem depending on inputs. Optimisation algorithms are going to try to minimize the gap between simulated data and observed data by modification of the OD flows used in the Lower Level. A particular attention should be given to the quality of the actual traffic counts inputs (traffic and OD flows interception). OD adjustment is a least square problem and could be solved using existing methods (e.g. Gradient, Kalman Filtering, etc.), of course adapted to the new constraints of the new approach.

- **OD adjustment**

In the first approach, Kalman Filtering (KF, [20]) is computed for its capabilities to find solution of the least square problem (See Ashok and Ben-Akiva [2]). To adjust the OD matrix dynamically, with white and Gaussian errors in the measurements and state equations (ω_n, v_n), and if these equations are linear, KF propose the optimal solution to the problem [22]. This process allows generating flow of the OD matrix at state (t + 1) depending on the state (t) and an assignment matrix (which defines influences of OD flow on the different links). This approach takes into account dynamically the traffic evolution in the network. The filter does an estimation of a solution depending on a first "block" (time slice) of data and updates it using new data (next time slice). KF is defined by two equations which model the evolution of the OD flows (solving as in [8]):

Analysis period is divided into equal intervals h = 1,…,N. x_h is the actual OD table capturing all trips departing during time interval h and x_h^H is the associated historical OD table. The vector of deviations is denoted by $\partial x_h = x_h - x_h^H$. y_{lh} is the number of vehicles crossing sensor l during time interval h and y_h the vector gatering all such counts.

$$\text{Transition Equation:} \quad \partial x_h = \sum_{p=h-q'}^{h-1} f_h^p . \partial x_p + w_h$$

With f_h^p describes the effect of x_p on x_h and w_h is a random error. q' q'is the number of lagged OD flow assumed to affect the OD flow in interval $h+1$h+1.

$$\text{Measurement Equation:} \quad y_h = \sum_{p=h-p'}^{h} a_h^p . x_p + v_h$$
$$\text{Or} \quad \partial y_h = \sum_{p=h-p'}^{h} a_h^p . \partial x_p + v_h$$

Where $\partial y_h = y_h - \sum_{p=h-p'}^{h} a_h^p . x_p^H$

a_h^p is the fraction of the rth OD flow that departed its origin during interval p and is on sensor l during interval h. v_h is the measurement error. p' is the maximum number of time intervals taken to travel between any OD pair of the network.

This method proposes interesting results but presents several limitations in our case (urban applications). Indeed, as explained partially in [8], the size of the problem increase with the number of OD pair and time periods in the network. For medium to large networks, the mathematical resolution of the different steps of the algorithm becomes complex or even impossible (to find a feasible solution). Moreover, the computation efficiency decreases proportionally to the size of the OD matrix. In addition, Kalman Filtering allows no possibilities of controlling the outputs. Thus, mathematically, negative flow of an OD pair is a possible solution of the problem but it is not realistic in term of traffic demand. For all these reasons, it is important to evaluate an alternative to achieve the Upper Level. LSQR presented in [9, 25] has been chosen for the smaller size of the variables inside the process and for its ability to constrain OD flows.

- **Stopping criteria of the process loop**

An evaluation of the convergence (stabilization of the results) of this OD matrix and traffic counts during iterations must be done. Criteria must be developed to evaluate if the OD matrices are converging to a stable value with iteration. Firstly, iteration is carried out until traffic counts from the mesosimulation matches with observed traffic counts, before considering the stabilization of the OD flows.
If stabilization is not observed, the process goes back to the Lower Level problem (see Figure 2) with the new matrix computed in the Upper Level to do a new iteration (Lower and Upper Level steps) and improve the process output based on the new inputs. If convergence criteria are satisfied, output of the Upper Level problem is the adjusted time sliced OD matrix.
Process loops are done using heuristics information from mesosimulation, thus, analytic prove of the convergence could not be obtained. Particular attention must be observed to verify the consistence of the results. Only the quality and the robustness of the methodology can lead to converge to a solution.

TEST NETWORKS

After the theoretical approach, methodology has been coded as a plug-in of the AIMSUN NG software. In this way, dynamic OD estimation using mesosimulation and OD adjustment are fully integrated in the package. After the initial test with simple networks to assess the reliability of the plug-in developed to execute automatically the different points presented in the previous chapter, full evaluation is done. In the first step, the different phases of the process are going to be tested with a small urban network (Dublin city network, 5*5 OD matrix). These first batch of runs (several scenario elaborated) will allow seeing influences of the different inputs of the bi-level approach and the quality of the outputs.

After this validation, adapted network must be used to assess urban characteristics. Dynamic traffic demand, route choices, traffic signals and high density road are researched particularities needed to evaluate the time varying and urban capabilities of the methodology proposed. The assignment part of the approach will be analyzed in detail in the Lower Level (Rgap value convergence, calibration parameters, queuing, etc.). In the Upper Level, estimation of OD cells based on algorithm will be followed during time periods and iterations. For this, the city centre of Lausanne city (Switzerland) will be use. This is a 2.5 km x 2.5 km (6.25 Km^2) perimeter area representing a dense network where all the roads and signals have been considered. Congestion during evening rush hours can be considered as moderate even if, some arterials are over saturated (particularly on the city centre exits and entrances). OD matrix size is 80*80. Initial OD matrices have been obtained using a static approach (using common approach) and about twenty to thirty traffic counts are going to be used to adjust the demand.

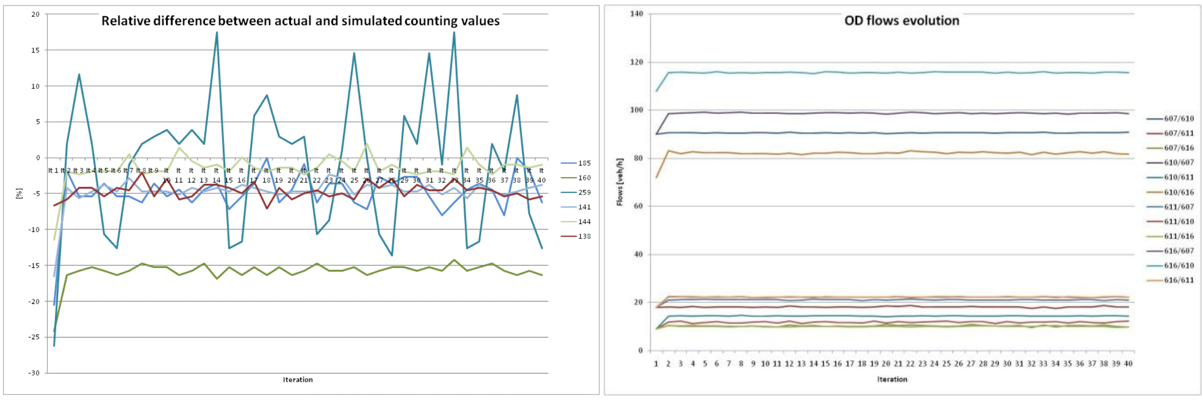
EVALUATIONS AND FIRST RESULTS

The benefits expected must be in term of robustness of the demand representation. This new OD demand must provide a dynamic and reliable traffic modelling in urban networks. The whole process for OD estimation becomes more streamlined and thus save time in calibration with an increasing outputs quality. The aim is to highlight the different advantages (and the disadvantages) of the implementation of a dynamic OD matrix in the process.
One particularity of the OD estimation problem is the under estimation. It means that the process is looking for a solution which satisfies the given conditions, but the number of conditions is smaller than unknown values. In our case traffic counts and initial OD flows are the inputs. From these, a lot of different OD matrix can satisfy constraints defined by them. All those solutions are consistent with the problem. Moreover, as explained in the Introduction, real OD matrices are usually unknown. Therefore, it is difficult to discuss about the absolute quality of the outputs obtained. These results have to be evaluated in a relative way. Robustness and consistency of the approach are important aspects of the evaluation and can lead to favorable outcomes. Nevertheless, the proposed approach could be compared to the static approach followed by the dynamic extension based on traffic counts (heuristics time slicing of the static matrix, see Introduction). Dynamic quality of the outputs of different approaches will be tested and evaluated by microsimulations using actual networks. Several networks and scenarios will be developed to test if the demand is representative, well defined and adapted for detailed study. Dynamic properties are going to be investigated by analyzing the built up and distribution of congestion on the network during rush hours, the behavior of the traffic in front of an accident, the creation of a traffic jam due to an accident and the dissipation of the queue, creation, variation and evolution of length of queues, etc, compared with observed behavior.

One important aspect of this method is the stochasticity. AIMSUN Mesoscopic simulator presents for each experiment a daily simulation (by seed, each day is different). Variations are due to the random generator internal of the simulator for variables setting (maximum speed desired, gap acceptance, etc.) and the heterogeneous of the flow inside the network due to urban constraint. Results of the process and evaluations have to take into account this characteristic to achieve analyzes as relevant as possible. It is important to note that the different issues of the process are linked with the inputs used. The quality and the quantity of the initial OD matrix (obtained by studies and investigations) could be very different depending on the origin of the data. Data used to determine this matrix could have different structures or shapes. Depending on these data, dynamic aspects (structural variation of the matrix depending on the hour) could be relatively included in the input. The dynamic matrix extension based on traffic counts could be more or less precise depending on this data quality.

Figure 4 shows first outputs of the process using Kalman Filtering approach on Dublin network. Relative errors on counting values are presented and evolution of the OD flows through the iteration. Stabilisation of the results is obtained after few iterations.

Figure 4 First results of KF application on Dublin network



CONCLUSION

Traffic simulation is more and more widely used tool for planners and managers in the ITS arena. This tool allows scenario evaluation and also online traffic assessment. Demand modelling is one of the important inputs of simulators. In this way, OD estimation is a crucial step for any transportation studies. Demand quality influences strongly the results of detailed analyses. Quality and quantity must be as close as possible to the real demand. Due to the complexity of the mathematical solving of this problem, OD estimation is an optimization problem which have an infinite of solutions. The methodology adopted must find the optimal one depending on the network constraints.

This paper presents a critique of existing methods and proposes an innovative dynamic OD matrix estimation process developed for urban area. The bi-level approach is innovative, principally for its capabilities to deal with complex and dense urban network. Using AIMSUN Mesoscopic traffic simulator allows accurate determination of the traffic assignment. It fully models the urban characteristics and provides a detailed and realistic route choice for each OD pair and then the whole data needed for OD adjustment. Dynamic user equilibrium based on urban constraints (signalized intersections, traffic signals, high route choice possibilities…) is used to assign traffic in the network. Moreover, matrix adjustment is done using least square techniques to allow full consideration of dynamic particularities of urban networks and the mathematical method is adapted for this task e.g. avoiding negative flow and taking into account the computation limitations.

REFERENCES

[1]. Ashok, K., *Estimation and Prediction of Time Dependent Origin-Destination Flows*, in *Transportation systems*. 1996, MIT: Boston.

[2]. Ashok, K. and M.-E. Ben-Akiva, *Dynamic Origin-Destination Matrix Estimation and Prediction for Real-Time Traffic Management Systems*, in *International Symposium on Transportation and Traffic Theory*, C.F. Daganzo, Editor. 1993, Elsevier Science Publishing Company. p. 465-484.

[3]. Ashok, K. and M.E. Ben-Akiva, *Estimation and Prediction of Time-Dependent Origin-Destination Flows with a Stochastic Mapping to Path Flows and Link Flows.* Transportation Science, 2002. **36**(2): p. 184-198.

[4]. Balakrishna, R., M. Ben-Akiva, and H.-N. Koutsopoulos. *Time-Dependent Origin-Destination Estimation without Assignment Matrices*. in *ISTS*. 2006. Lausanne, Switzerland.

[5]. Barcelo, J., *Dynamic Network Simulation with Aimsun*. R. Kitamura and M. Kuwahara ed. Simulation Approaches in Transportation Analysis: Recent Advances and Challenges. 2005.

[6]. Barcelo, J., et al. *A Hybrid Simulation Framework for Advanced Transportation Analysis*. in *ISTS*. 2006. Lausanne, Switzerland.

[7]. Bell, M., *The Estimation of Origin-Destination Matrices by Constrained Generalised Least Squares.* Transpn. Res:B, 1991. **25 B**(1): p. 13-22.

[8]. Bierlaire, M. and F. Crittin, *An Efficient Algorithm for Real-Time Estimation and Prediction of Dynamic Od Tables.* Operations Research, 2004. **52**(1): p. 116-127.

[9]. Bierlaire, M., P.L. Toint, and D. Tuyttens, *On Iterative Algorithms for Linear Least Squares Problems with Bound Constraints.* Linear Algebra and its Applications, 1991. **143**: p. 111-143.

[10]. Burghout, W., H. Kotsopoulos, and I. Andréasson. *Hybrid Mesoscopic-Microscopic Traffic Simulation*. in *83rd TRB Annual Meeting*. 2005. Washington.

[11]. Cascetta, E., D. Inaudi, and G. Marquis, *Dynamic Estimators of Origin-Destination Matrices Using Traffic Counts.* Transportation Science 1993. **24**(4): p. 363-373.

[12]. Chang, G.-L. and X. Tao. *Estimation of Dynamic O-D Distributions for Urban Networks*. in *International Symposium on Transportation and Traffic Theory*. 1996. Lyon, France.

[13]. Chang, G.-L. and J. Wu, *Recursive Estimation of Time-Varying Origin-Destination Flows from Traffic Counts in Freeway Corridors*. Transportation Research Part B: Methodological, 1994. **28**(2): p. 141-160.

[14]. Cremer, M. and H. Keller, *A New Class of Dynamic Methods for the Identification of Origin-Destination Flows.* Transportation Research B, 1987. **21 B**(2): p. 117-132.

[15]. Florian, M., M. Mahut, and N. Tremblay. *Application of a Simulation-Based Dynamic Traffic Assignment Model*. in *International Symposium on Transport Simulation, Yokohama (also in: Simulation Approaches in Transportation Analysis, Edited by R. Kitamura and M. Kuwahara, Kluwer, 2005 pp 1-21)*. 2002.

[16]. Florian, M., M. Mahut, and N. Tremblay. *A Hybrid Optimization-Mesoscopic Simulation Dynamic Traffic Assignment Model*. in *IEEE Intelligent Transport Systems Conference*. 2001. Oakland.

[17]. Friesz, T., et al., *A Variational Inequality Formulation of the Dynamic Network User Equilibrium Problem.* Operations Research, 1993. **41**: p. 179-191.

[18]. Hu, S.R., et al., *Estimation of Dynamic Assignment Matrices and Od Demands Using Adaptive Kalman Filtering.* ITS Journal, 2001. **6**(3): p. 281-300.

[19]. Janson, B.N., *Dynamic Assignment for Urban Road Networks.* Transpn. Res. B, 1991. **25**(2/3): p. 143-161.

[20]. Kalman, R.-E., *A New Approach to Linear Filtering and Prediction Problems.* Transactions of the ASME - Journal of Basic Engineering 1960. **82**(D): p. 35-45.

[21]. Mahut, M., M. Florian, and N. Tremblay. *Traffic Simulation and Dynamic Assignment for Off-Line Applications*. in *10th World Congress on Intelligent Transportation Systems*. 2003. Madrid.

[22]. Maybeck, P.S., *Stochastic Models, Estimation, and Control*. Department of Electrcal Engineering Air Force Institutre of Technology Wright-Patterson Air Force Base Ohio. Vol. 1. 1979: Academic Press Inc. 442.

[23]. Migdalas, A., *Bilevel Programming in Traffic Planning: Models, Methods and Challenge.* Journal of Global Optimization, 1995. **7**: p. 381-405.

[24]. Okutani, I. and Y.J. Stephanedes, *Dynamic Prediction of Traffic Volume through Kalman Filtering Theory.* Transportation Research Part B: Methodological, 1984. **18**(1): p. 1-11.

[25]. Paige, C.C. and M.A. Saunders, *Lsqr: An Algorithm for Sparse Linear Equations and Sparse Least Squares.* ACM Trans. Math. Softw., 1982. **8**(1): p. 43-71.

[26]. Perakis, G. and G. Roels, *An Analytical Model for Traffic Delays and the Dynamic User Equilibrium Problem.* Operations Research, 2006. **54**(6): p. 1151-1171.

[27]. Sherali, H.D. and T. Park, *Estimation of Dynamic Origin-Destination Trip Tables for a General Network.* Transportation Research Part B: Methodological, 2001. **35**(3): p. 217-235.

[28]. Spiess, H., *A Gradient Approach for the O-D Matrix Adjustment Problem*. 1990, Centre de Recherche sur les Transports de Montréal: Montréal, Canada.

[29]. Tsekeris, T. and A. Stathopoulos, *Real-Time Dynamic Origin-Destination Matrix Adjustment with Simulated and Actual Link Flows in Urban Networks.* Transportation Research Record, 2003. **1857**(-1): p. 117-127.

[30]. van der Zijpp, N.J., *Dynamic Origin-Destination Matrix Estimation on Motorway Networks*. 1996, Delft University of technology: Delft.

[31]. Wardrop, J.-G., *Some Theoretical Aspects of Road Traffic Research.* Institute of Civil Engineers II, 1952. **1**: p. 325-378.