***Approach for Dynamic Origin-Destination Matrices Estimation in Urban Context***

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Abstract:

The aim of this paper is to explore a new approach to obtain better traffic demand (Origin-Destination, OD matrices) in dense urban networks. From reviewing actual methods, for static and dynamic OD matrix evaluation, possible deficiencies in the approach could be identified. To improve the global process of traffic demand estimation, this paper is focussing 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 use to perform the OD estimation. The Lower level (traffic assignment) problem will determine, dynamically, the utilisation of the network by vehicles using heuristic data from traffic simulator. This simulation will be mesoscopic and a particular calibration will be done, focusing mainly on flow and route choice indicators. The Upper level (matrix adjustment) problem will precede to an OD estimation using dynamic optimization least square techniques. In this way, a full dynamic and continuous estimation of the final OD matrix could be obtained in urban context.

Keywords:

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

# Introduction

Traffic counts are the most common way to quantify traffic flows in a network. Even if this tool gives information about utilization on a specific place (location of sensor), this type of data is not sufficient for having an accurate idea of the utilization of the network by vehicles depending on mobility demand. For ATIS[[1]](#footnote-2) or detailed scenario evaluations (microsimulations for instance), demand must be determined in a global way to allow possible trips modifications in a network. Origin-Destination (OD) matrix gives the flows of vehicle between two centroids (origins and destinations in the modeled network). It informs about the volumes of traffic without fix paths choices. In this way, route choice could be an answer of the modeling and not a fixed input characteristic. For a given study period, OD matrix could be static, define equally during the whole period, or dynamic, decomposed of several time slides with its own traffic demand and the demand is evolving during the analyses period.

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. Quality and quantity must be as close as possible of real situation. 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. Due to this point, OD estimation is solved as an optimization problem, which proposes an infinite number of solutions. The adopted methodology must find the optimal one depending of 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 the 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 modify the OD matrix 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. Dynamic extension of the matrix based on traffic count could be done but adapts only the total volume and not the structure of it. Sequential (time slide) static OD estimation is also proposed but this technique does not take into account the continuity of the demand through the time.

Dynamic OD estimation presents different challenging aspects. Demand and path evaluation must be done by time slices. Total study period is divided in N equal time periods. From these time periods, OD estimation must be achieved taking into account link flows and relation between them. Indeed, depending on 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 reach 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 intervals. 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 on the network characteristics). To do that, the different stages of the OD estimation process must be adapted to catch this evolution. First, traffic assignment needs to be dynamic; DTA (Dynamic Traffic Assignment) proposes route choice solutions on time depending on traffic conditions. The OD adjustment, also, needs to take into account the evolution of trips in the network. Algorithm must be able to do a distinction between entrance time (in the network) and time period at the traffic count place. It needs this information to take into account vehicles which use more than the current time slide period to go from entrance point to the time slice they are counted.

This paper is focus on urban networks. This kind of network presents particular characteristics which influence strongly traffic flows. Laminar flows are disturbed by traffic conflicts or signalizations (Stops, give ways, signalized intersection, etc.). Platoon of vehicle are interrupted and delayed by priorities between traffic streams. This discontinuity induces great variation in flow spreading and could leads to congestion (added to high demand) and high variation 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 on focus in this paper. Current methodologies are reviewed and an innovative approach particularly adapted for dynamic urban networks is proposed. This method uses traffic simulation (mesoscopic) for traffic assignment in the network.

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. Some pretest have been done and results are encouraging, next step with larger urban network has started.

# State of the art review

Static adjustment approach is the most common method for OD estimation. In this method, the inter-dependence between OD matrices and link flows is formulated as presented in the Figure 1.

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| Figure 1 OD estimation process |
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For instance, the software EMME/2 (INRO), which is the most common used method for practitioner for static OD estimation, assigns the traffic in the network (lower level) using Wardrop equilibrium [1] based on Volume Delay functions defined for each link and junction. These functions give the relationship between the travels times needed to cross the section, and flow on it. Concerning the upper level, Spiess has particularly worked on the field of matrix adjustment and his paper [2] on Gradient approach could be considered as a reference in this domain. This paper presents a mathematical approach which formulates a convex minimization problem using the direction of the steepest descent which could be applied to large scale networks. With this process, the original OD matrix is not changed more than necessary by following the direction of the steepest descent.

This approach is 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 an evolution of a traffic peak hour (increase to 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.

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| Table 1 Dynamic OD estimation in the literacy |
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| **References:** | **Name** | **Type[[2]](#footnote-3)** | **Size[[3]](#footnote-4)** | **Ass.[[4]](#footnote-5)** | **Opt.[[5]](#footnote-6)** | **RC[[6]](#footnote-7)** | **T-S[[7]](#footnote-8)** |
| [Okutani and Stephanedes, 1984] | Nagoya | Street | Small | - | KF[[8]](#footnote-9) | No | No |
| [Cremer and Keller, 1987] | Various | Intersection | Small | - | Varios | No | No |
| [Bell, 1991] | - | Street | Small | - | GLS[[9]](#footnote-10) | 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[[10]](#footnote-11) | 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[[11]](#footnote-12) | 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[[12]](#footnote-13) | Yes | No |
| [Bierlaire and Crittin, 2004] | Boston | Freeway | Med | Simulator (Meso) | KF, LSQR[[13]](#footnote-14) | Low | No |
| Irvine | Mid | Med | Med | No |
| [Balakrishna et al., 2006] | - | Intersection | Small | - | Analytic | No | No |
| Los Angeles | Mid | Large | Yes | Yes |

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Most literature deals with small and/or simple networks without traffic assignment (Bell [3], Okutani and Stephanedes [4] and Cremer and Keller [5]). Bell used the Generalised Least Squares procedure to estimate OD matrices. A simple algorithm is presented for this approach and the convergence is proved. This method permits the combination of survey and traffic count data in a way that allows for the relative accuracy of the two data sources. A hypothetical small network and an intersection have been tested with this method. Okutani and Stephanedes presented two models employing Kalman filtering theory for prediction of short term traffic flow. The new prediction model has been tested on a street-network in Nagoya city, Japan. This is an intersection with four links. 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 Wu [6] and Zijpp [7]) deal with freeways networks. This kind of networks offers little traffic signal and route choice capabilities. Chang and Wu presented a nonlinear dynamic system model which provides time-varying OD matrices from traffic flow measurements in freeways corridors. The methodology uses Extended Kalman Filtering algorithm and can give information without prior OD information. This model has been applied on a theoretical small freeway network. No traffic signal or route choice is possible in the example. Zijpp has developed a method for estimation 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. [8], Sherali and Park [9] and Ashok [10] considered traffic assignment as an input and assignment is calculated analytically. Cascetta, Inaudi and Marquis proposed different methods using traffic count to evaluate time varying OD flows. Combination of traffic counts information and other type of data is possible (surveys or matrices). The dynamic OD estimation technique is based on extensions to the least squares technique in the static context. They proposed two different approaches: an estimator that solves for the dynamic OD flows in multiple intervals simultaneously (OD flows for different time periods) and another one which is doing sequentially (evaluation next OD flows for a time period from the previous one). Methods are tested on the Italian Brescia-Padua freeway. The network is a 140 km freeway corridor composed of 19 centroïds, 19 nodes and 54 links. There is no route choice possible and no traffic signal. Sherali and Park presented a parametric optimization approach to estimate time-dependent path flows, or origin-destination trip tables, using available data on link traffic volumes for general road networks. A least squares model is used to determine the trip tables. Projected conjugate gradient method solves the main constrained problem, while the sub problem is a shortest path problem on an expanded time-space network. This approach has been tested on two different networks. The first one is a small theoretical corridor with one origin and three destinations. The second one is the Massachusetts Turnpike (Toll freeway stretching from the New York state border to Weston). None of them offers the possibility of route choice and traffic signal capabilities. 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. [11] and Bierlaire and Crittin [12]) used simulator for traffic assignment in the network. Hu et al. presented an adaptive Kalman Filtering algorithm for the dynamic estimation and prediction of freeways OD matrices. One particularity of this approach is the utilization of a meso simulator for travel time prediction. This methodology is particularly adapted for linear networks, such as intersections and freeway networks. It has been tested on a theoretical small freeways network without route choice and traffic light. 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, five origins and two destinations. 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 [13] and Balakrishna et al. [14] and Tsekeris and Stathopoulos [15]). Usually, OD estimation is done using data extracted from traffic measurements (traffic counts…). The model proposed by Chang and Tao offers the possibility to estimate time varying OD matrices for urban signalized networks. It is a cordon line model. Effects of traffic signal are incorporated mathematically in the calculation of the different travel time in the network. The illustrative example is a theoretical network with three origins, six destinations and six signalized intersections. There are low possibilities for route choice. 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 bof two freeways and several arterial roads. Most of the urban intersections are signalized and route choice possibilities are medium. Tsekeris and Stathopoulos analyzed dynamic OD estimation for urban networks. From a simulation-based model that enables the macroscopic consideration and deterministic control delay and variable travel time effects, they evaluated the results of coupling with three different time-dependent OD matrix estimation algorithms: MART (Multiplicative Algebraic Reconstruction Technique), RMART (Revised MART) and DIMAP (Doubly Iterative Matrix Adjustment Procedure). MART is a balancing method that provides a convergent, generalized iterative matrix scaling procedure for the recursive adjustment of the prior OD trip flows, RMART provides a diagonal search between two successive iterations to improve its convergence speed and DIMAP is a suitable combination of the aforementioned algorithms. Network tested is the greater Athens (44\*44 OD matrix) with interesting route choice possibilities and without traffic signal.

# Weakness of existing OD estimation methods

All approaches presented previously propose a solution to the OD estimation problem, but 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, using Wardrop equilibrium approach, depending of the complexity of the network (intersections), parameterization of Volume Delay functions is very difficult and seldom done in detail by practitioners.

Usually, to use a statically determined OD matrix in a dynamic simulation (microsimulation with time dependant demand), it is common to modify the demand based on traffic counts. The shape of traffic counts curves from main arterials is used to reproduce the volume time variation of the demand. This method helps to represent the global variation in time but omit structure modifications of the matrix (commuter traffic or non-uniform modifications changes on matrix values for instance).

Another approach to evaluate variation of the demand in time is to do a sequential static OD estimation. The results are a matrix for each period of the time. This method could be considered as dynamic but it does not take into account previous time period in the calculation of the actual one; there is not link between different time periods. Using macroscopic simulator does not give disaggregated information in sections; therefore, it is impossible to get information about vehicles, which enter the network in a different time interval than the actual traffic count. From these points, an integrated and global approach must be developed to take into account these limitations.

**- 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 is very few tools adapted for medium to large urban network with real route choice possibilities and signalized intersections.

Papers from Balakrishna [14] and Chang & Tao [13] are the most relevant papers for urban characteristics but we can see that the first one use 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 one takes into account only freeways and main arterials. Bierlaire and Crittin [12] 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 is 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 of 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 for traffic engineers. An innovative approach must allow efficient assessment in various types of networks and not limited to specific cases.

Based on deficiencies identified above, the proposed methodology is focusing on several improvements of the current solutions. First, the approach 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 for this step to provide an assignment really representative of the actual one whatever the traffic situations. Moreover, this assignment and also the OD matrix adjustment must be done dynamically. The methodology is going to tackle the major problems of the time dependant formulation (travel time in the network, constraints on OD modification, etc.).

# Methodology proposed

To improve the demand modeling, this study focuses on the distribution of the traffic in the network, particularly in urban area. 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 approaches (see Figure 2).

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| Figure 2 Detailed methodology proposed |
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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. In the first approach, Kalman filtering is computed for its capabilities to find the optimal solution of the least square problem.

## Traffic assignment problem

Based on preliminary 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 or counting location are established for the whole time study.

The simulator "AIMSUN NG" [16, 17] developed by the Polytechnical University of Catalunya in Spain has been used for this task because it offers three different kind of simulators (microscopic, mesoscopic and macroscopic), useful for process evaluation and API[[14]](#footnote-15) which allows possibilities to export/import all the needed information. Initially, it was proposed to use microsimulator for its dynamic and detailed capabilities, however it has been replaced by a mesoscopic simulator in the process. Mesosimulation offers almost the same level of detail (dynamic demand, queuing, traffic lights, signalized intersections…) but due to a lower number of parameters (meanly concerning car behavior modeling); the calibration of this kind of tool is much easier. Moreover, this kind of simulator is particularly adapted for large urban network simulations. This is an interesting particularity in our case; this simulation must be included in an automatic 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; the better the equilibrium could be obtained.

Initial time dependent OD matrix is the important input of the system. This matrix must be as close as possible to the researched one. Historical data (OD tables), observations (real time…), surveys, investigations, determination of the mobility attraction poles are tools to evaluate the best initial OD matrix. First OD matrix from first OD estimation could also be obtained using gradient approach [2] and extended to a time sliced OD matrix using observed flows in main arterials.

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**

At this step, the aim is to determine the assignment matrix which gives the different paths choices depending of origin and destination and traffic conditions. AIMSUN mesoscopic simulator is looking to Dynamic User Optimal (DUO) by iteration ([18]). The simulator is minimizing the Rgap value using Method of Successive Averages techniques (MSA, [16]).



Where  are the travel times on the shortest paths for the i-th OD pair at time interval $t$,  is the travel time on path $K$ connecting the i-th OD pair at time interval $t$, 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.

A small value of Rgap expresses equilibrium in the network close to the Dynamic User Optimal.

Using the AIMSUN Mesoscopic simulator allows accurate and realistic distribution of the traffic in the network. Its Rgap minimization using MSA provide 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.

## OD adjustment problem

The proposed approach must find the best way to solve the upper level problem depending on inputs. Mathematic algorithms are going to minimize the gap between simulated data and observed data by modification of the OD matrix used in the lower level problem to fit to the real counting values. Inputs are initial time sliced OD matrix (obtained from surveys observations or previous demand) and actual time varying counting values at different point of the network. OD estimation could use existing method, of course adapted to the new constraints of the new approach: Gradient, Least square, Kalman filtering, etc.

* **Least square formulation**

Based on the work of Ashok and Ben-Akiva [19], they computed the upper level using Kalman filtering. To adjust the OD matrix dynamically, with white and Gaussian errors in the measurements and state equations ($ω\_{n}$, $v\_{n}$), and if these equation are linear, Kalman Filtering [20] propose the optimal solution to the problem [21]. This process allows generating flow of the OD matrix at state (t + 1) depending of 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). Kalman filtering is defined by two equations which model the evolution of the OD flows (solving as in [12]):

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 $∂x\_{h}= x\_{h}- x\_{h}^{H}$. $y\_{lh}$ is the number of vehicles crossing sensor $l$ during time interval $h$ and $y\_{h}$ the vector gattering all such counts.

Transition Equation: $∂x\_{h}= \sum\_{p=h-q'}^{h-1}f\_{h}^{p}.∂x\_{p}+ w\_{h}$

With $f\_{h}^{p}$describes the effect of $x\_{p}$ on $x\_{h}$ and $w\_{h}$ is a random error. $q'$is the number of lagged OD flow assumed to affect the OD flow in interval $h+1$h+1.

Measurement Equation: $y\_{h}= \sum\_{p=h-p'}^{h}a\_{h}^{p}.x\_{p}+ v\_{h}$

Or $ ∂y\_{h}= \sum\_{p=h-p'}^{h}a\_{h}^{p}.∂x\_{p}+ v\_{h}$

Where $∂y\_{h}=y\_{h}- \sum\_{p=h-p'}^{h}a\_{h}^{p}.x\_{p}^{H}$

$a\_{h }^{p}$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 [12], 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 (impossibility 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 realistic solution of the problem but it is not consistent in term of traffic demand. For all these reasons, it is important to evaluate an alternative to achieve the upper level. LSQR presented in [22, 23] has been chosen for the smaller size of the variables and for its possibilities of constrained on the OD flows (non negative or boundary constraints).

* **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 comparing to inputs and the results of the previous iteration. Criteria must be developed to evaluate if the OD matrices are converging to a stable value with iteration. First of all, iteration must be done until the correspondence of the counting's values, inputs of the process must be reach before having a look at the stabilization of the OD flows.

If stabilization is not observed, the process goes back to the lower level problem (iteration loop) 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 OD matrix. The result or output of the upper level problem is a 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 very first tests 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 a 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 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 test, adapted network must be use with urban characteristics. Route choices, traffic signals and high density of road are researched particularities needed to evaluate the dynamic and urban capabilities of the methodology. For this, the city center of Lausanne city (Switzerland) will be use. This is a 2 km x 2 km (4 Km2) 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 loaded (particularly on the city centre exits and entrances). OD matrix size is 80\*80.

# Evaluations and results expected

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 increase 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 matrixes 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. Dynamic quality of the outputs of different approaches will be tested and evaluated by microsimulations using actual networks. Several networks (Section 5) 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 investigate 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’s 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. It is reason why we are going to focus on specified examples and using a relative approach.

# 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 modeling 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 haves 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 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 intersection, traffic signals, high route choice possibilities…) is used to assign traffic in the network. Moreover, matrix adjustment is done using least square techniques (LSQR) 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.

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1. ATIS: Advanced Traffic Information System. [↑](#footnote-ref-2)
2. Type of network test [↑](#footnote-ref-3)
3. Size of the network [↑](#footnote-ref-4)
4. Type of traffic assignment used in the OD estimation [↑](#footnote-ref-5)
5. Method for OD optimization approach [↑](#footnote-ref-6)
6. Route choice capabilities [↑](#footnote-ref-7)
7. Traffic signal capabilities [↑](#footnote-ref-8)
8. KF: Kalman Filtering (normal, adapted or extended) [↑](#footnote-ref-9)
9. GLS: Generalised Least Squares [↑](#footnote-ref-10)
10. TMVN: Truncated Multivariate Normal [↑](#footnote-ref-11)
11. LS: Least Squares [↑](#footnote-ref-12)
12. Multiplicative Algebraic Reconstruction Technique, (Revised), Doubly Iterative Matrix Adjustment Procedure [↑](#footnote-ref-13)
13. LSQR: Spares Linear Equations and Spares Least Squares [↑](#footnote-ref-14)
14. API: Application Programming Interface. [↑](#footnote-ref-15)