Dynamic Origin-Destination Matrices Estimation Method for urban networks

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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 case of dense urban networks.
To improve the global process of OD demand estimation, this paper is focussing on a new methodology to execute the dynamic OD matrices determination adapted to urban area. An iterative bi-level approach will be use to perform the OD estimation. The Lower level 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. "Design of Experiment" will be use to evaluate the influence of the parameters and to assess the best parameters combination. The Upper level problem will proceed to an OD adjustment using Kalman filtering technique.

Keywords

Traffic simulation – Origin-destination matrices – Dynamic traffic assignment – Urban Network – 7th Swiss Transport Research Conference – STRC 2007 – Monte Verità

1. Introduction

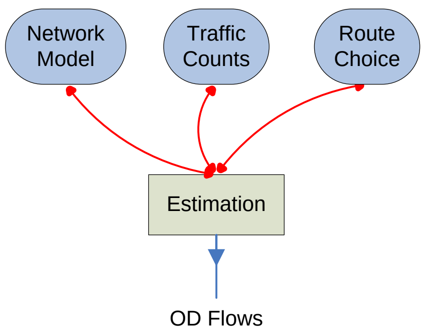
Modelling traffic simulation is becoming a more and more widely used tool in many transportation researches and studies. Road network modelling can evaluate and quantify scenarios which have been generated and help transport managers in operational and planning studies. This is a helpful decision tool for short, medium and long term studies even if it is not a perfect representation of the reality. To achieve a transportation study using modeling, supply and demand as input of the process must be known.

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. For ATIS[1] or detailed scenario evaluations (microsimulations for example), demand must be determined in a global way to allow for possible trips modifications in a network.

Origin-Destination (OD) matrix gives the flows of vehicle between two centroïds (origins or 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 characteristic.

To build 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 good OD matrices (See Figure 1).

Figure 1 OD estimation process's inputs



Based on this statement, this paper is going to analyze actual methodologies and propose an innovative approach particularly adapted for dynamic urban networks.

This method is going to use traffic simulation (mesoscopic) for traffic assignment in the network (Route Choice in Figure 1).

[1] ATIS: Advanced Traffic Information System.

Evaluation of this new method and relative improvement and comparison with the usual process will be analyzed. The benefits or issues expected must be in term of quality of the demand representation. This new demand must provide a dynamic and representative traffic modelling in urban network. The whole process for OD estimation becomes more adapted to save time in calibration and money with an increasing outputs quality ([5]).

This is an ongoing PhD research that started last year, partly explains why this paper proposes different approaches or methods without any results or final conclusion. The presented research is still in development and could change depending on the further works or investigations.

2. OD matrix estimation

OD estimation is a crucial step for a transportation study. It is representing the demand. By 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 the 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 of solutions. The methodology adopted must find the optimal one depending of the modelling constraints.

OD estimation is constituted by two distinguish processes (see Figure 2): traffic assignment and OD adjustment. Traffic assignment could be done in a congested or un-congested condition and OD adjustment could be static (flow stable during the simulation period) or dynamic (traffic volumes are changing with time), like presented in Figure 3.

Figure 2 Four cases for OD estimation

Traffic Assignment:	Un-congested	Congested
OD Adjustment:	Static	Dynamic

In the case of un-congested network, the route choice from an origin to a destination is made without consideration of the congestion. The travel time of a link is not dependent on the flow on this one (like in free flow conditions). There is no consideration of capacities for the different roads of the network. The assignment matrix which defines the path between an origin to a destination could be found using a shortest path algorithm. In this way the mathematical resolution of the problem is a minimization of the “distance” between the observed data and the real data (matrix and traffic counts).
The solution is usually obtained by using standard optimization methods, Iterative Proportional Fitting (IPF), maximum likelihood, Matrix scaling, etc.

Figure 3 Demand representation

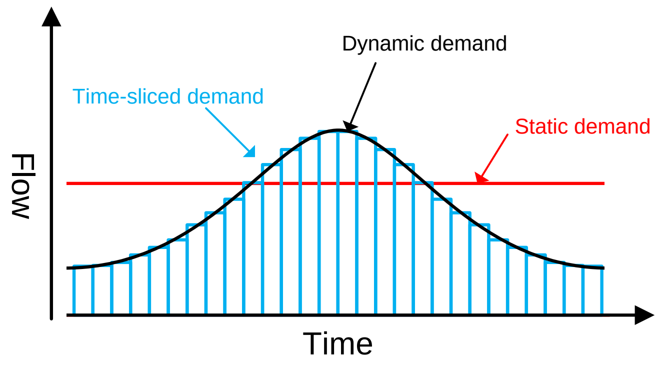


Figure 3 shows the different ways to represent traffic demand. Real and continue dynamic demand is represented in black. From this curve, traffic volume could be modeled by a time sliced approximation, in blue or in a very simplistic way, using a constant (static) demand during the whole period (in red).

In our case, we are going to focus on static and dynamic congested situation in urban network. Dynamicity (usually time sliced demand), route choice possibilities and traffic signals timings are difficulties which are taking our attention in this paper.

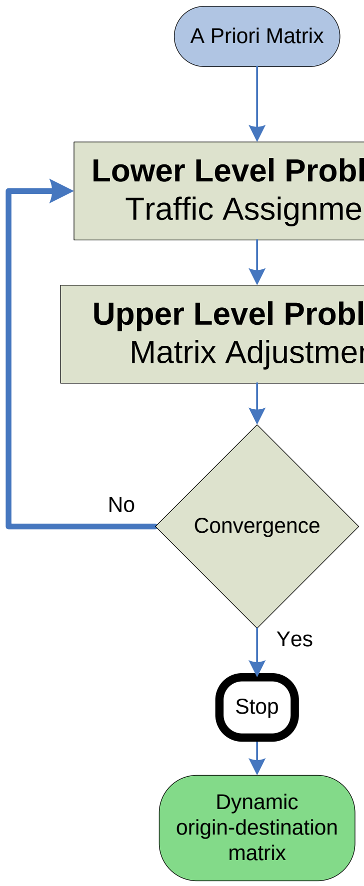
2.1 State of the art

Static adjustment approach is the most common method for OD estimation. It is based on works of several main contributors. Few of them are presented here with their works.
To begin, the Wardrop equilibrium [25] is the first hypotheses of this process. It says “Under equilibrium conditions traffic arranges itself in congested network in such a way that no individual trip maker can reduce his path cost by switching routes”. An alternative way of assigning traffic onto a network is expressed in the second principle “Under social equilibrium conditions traffic should be arranged in congested networks in such a way that the average (or total) travel cost is minimized" [18]. The static equilibrium is based on this principle and lead to a user’s equilibrium or selfish.
To evaluate this travel cost, different factors (tolls, fuel…) could be considered but, usually, the main part of this cost is constituted by travel time. From this statement and to allow assignment, the relationship between the speed on a link to its flow has been studied and established. Highway Capacity Manual (HCM) determines different volume delay functions for numerous different roads or intersections. This handbook gives these formulas depending of the road types (freeways, rural, suburban highways and urban streets), the conditions (roadway, traffic and control conditions), etc. Several groups of function have been developed to improve the accuracy and to match better with the traffic and the infrastructure. We can site 1985 HCM, 1994 HCM [22], BPR (Bureau Public Road), Akcelik or Spiess (conical) curves.

Finding the shortest path in road network is done using algorithms. The two basics ones have been developed by Moore (1957) and by Dijkstra (1959) to allow efficient process and computing.
For OD adjustment, traffic assignment is combined with the observed flows (traffic counts). Spiess developed a method to minimize the "distance" between observed and real flows ([21]).
Evaluation of the obtained matrix is important to provide a representative demand. Bierlaire [6] worked on testing the quality of OD matrix. His paper proposes a new method for measure the quality for OD trip tables estimated from link counts. This method, called the Total Demand Scale, is based on the assignment matrix used to determine the estimated OD trip table and this OD matrix itself. It measures the under-determination related to the OD estimation problem, considering only the underlying route choice model and the network topology.

In these methods, the inter-dependence between OD matrix and link flow is formulated as a bi-level problem[2] in most of the cases (see Figure 4).

Figure 4 Bi-level process



[2] [15]. **A. Migdalas**, (1995), *Bilevel programming in traffic planning: Models, Methods and Challenge.* Journal of Global Optimization. **7**: p. 381-405.

Upper level problem:
The matrix adjustment problem ("It minimizes the sum of distance measurements")

$$MinF(g,v) = F_1(g,\hat{g}) + F_2(v,\hat{v})$$

Functions $F_1(g,\hat{g})$ and $F_2(v,\hat{v})$ represent the distance between the estimated OD matrix g and the target matrix $\hat{g}$, and between the estimated link flows v and the real or observed link flows $\hat{v}$, respectively.

Lower level problem:
The traffic assignment ("It defines a user optimal assignment which guarantees that the estimated OD matrix and corresponding link flows satisfy the user equilibrium conditions")

$$\begin{aligned}
&v(g) = \arg\min \sum_{a \in A} \int_0^{V_a} s_a(X).dx \\
&s.t \sum_{k \in K_i} h_k = g_i, \forall i \in l \\
&h_k \geq 0, \forall k \in K_i, \forall i \in l \\
&v_a = \sum_{i \in l} \sum_{k \in K_i} \delta_{ak} h_k
\end{aligned}$$

Where $v(g)$ is the flow on link a with the trip matrix g. h_k is the flow on the k-th path for the i-th OD pair. l is the set of all Origin-Destination pairs in the network, and K_i is the set of paths connecting the i-th OD pair. S_a is the function which defines the delay depending on the flow for the link $a \in A$.

In the literature, generally, people describe in detail the resolution of the upper level problem, which represents a bigger mathematical challenge (OD adjustment).
Spiess has particularly worked on the field of matrix adjustment and his paper [21] 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 using static assignment and is applied in the software EMME/2 (INRO).
The paper of Yang, Sasaki, Yasunori and Asakura [27] presents utilization of existing methods such as the generalized least squares technique with an equilibrium traffic assignment in the form of a convex bi-level optimization problem. This is a heuristic approach based on Stackelberg leader-follower structure.
Yang presents two new heuristic algorithms [26]. The first one is a heuristic iterative algorithm between traffic assignment and OD matrix estimation (estimation-assignment) and the second one is a sensitivity analysis based on heuristic algorithm. Small networks are used to test the two approaches theoretically and numerically.
Florian proposes a Gauss-Seidel type coordinate decent method for solving the matrix adjustment problem [12]. A main feature of the method is to solve two one-level optimization problems at each iteration by fixing the upper and lower variable in turn such that the path information may not need to be used directly. It is a static and analytic approach.

Figure 5 Dynamic OD estimation in the literacy

References:	Name	Type[3]	Size[4]	Ass.[5]	Opt.[6]	RC[7]	T-S[8]
[Okutani and Stephanedes, 1984]	Nagoya	Street	Small	-	KF[9]	No	No
[Cremer and Keller, 1987]	Various	Intersection	Small	-	Varios	No	No
[Bell, 1991]	-	Street	Small	-	GLS[10]	No	No
	-	Intersection	Small			No	No
[Cascetta, Inaudi 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
[Zipp, 1996]	Amsterdam	Freeway	Large	-	TMVN[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[12]	Low	No
	Massa Turnpike	Freeway	Med			No	No
[Hu, Madanat et al., 2001]	-	Freeway	Small	Simulator (Meso) TT	KF	No	No
[Bierlaire and Crittin, 2004]	Boston	Freeway	Med	Simulator (Meso)	KF, LSQR[13]	Low	No
	Irvine	Mid	Large			Low	No
[Balakrishna, Ben-Akiva et al., 2006]	-	Intersection	Small	-	Analytic	No	No
	Los Angeles	Mid	Large			Yes	Yes

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

Previous papers (before Figure 5) were 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 (see Figure 3). This hypothesis is very constrained and does not into account an evolution of a traffic peak hour (load and unload of 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 Figure 5). The type of network tested, the way to achieve the traffic assignment and the optimization approach for the OD estimation form different groups.

First, the following papers are dealing with small and/or simple networks without traffic assignment:
Okutani and Stephanedes presented two models employing Kalman filtering theory for prediction of short term traffic flow [17]. The new prediction model has been tested on a street-network in Nagoya city. This is an intersection with four links.
Cremer and Keller presented different methods for the identification of OD flows dynamically [11]. 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.
Bell used the Generalised Least Squares procedure to estimate OD matrices [4]. 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.

Several articles are treating freeways networks. This kind of networks offers low 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 [10]. 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 [24]. 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.
This two first works considered traffic assignment as an input. In the three next papers, assignment is calculated analytically:
Ashok developed a sequential OD smoothing scheme based on state-space modeling concept [1]. 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.
Cascetta, Inaudi and Marquis proposed different methods using traffic count to evaluate time varying OD flows [8]. 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 [20]. 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.
The following two papers 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 [13]. 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) [7]. They showed the fact that for large scale problems; the LSQR presents better performance in comparison to the other approach. 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 large scale network with more than 600 OD pairs, without signalized intersection. This network could be also considerate as an urban network.

Finally, urban networks are analyzed by few publications. Traffic assignment could be known (input) or calculated analytically:
The model proposed by Chang and Tao offers the possibility to estimate time varying OD matrices for urban signalized networks [9]. It is a cordon line model. Effects of traffic signal are incorporates 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.
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 [2]. 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 by two freeways and several arterial roads. Most of the urban intersections are signalized and route choice possibilities are medium.

2.2 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).
To use this OD matrix as an input of a microsimulator and then do a dynamic traffic evaluation with a time dependant demand, it must be extrapolated base on measurements in the network. Nevertheless, depending on the measured data, this technique does not allow representing the possible variations of the matrix structure by time (non uniform modifications changes on matrix values).

Equilibrium research approach:
In the literature, we can find very little consideration about the traffic route choice in the lower level problem (assignment matrix). It could be done by observation or analytically. For example, Ashok computes the assignment fractions from simulated travel time. In papers about dynamic estimation (see Figure 5), there are no really tools and tests for medium to large urban network with real route choice possibilities and signalized intersection.
Papers from Balakrishna and Chang & Tao [2, 9] 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 freeways and main arterials.

2.3 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. 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 with automatic calibration of route choice parameters) could be applied to solve the lower level of the bi-level problem. Upper level will be solved using Kalman filtering (see Figure 6).

Figure 6 Detailed methodology proposed

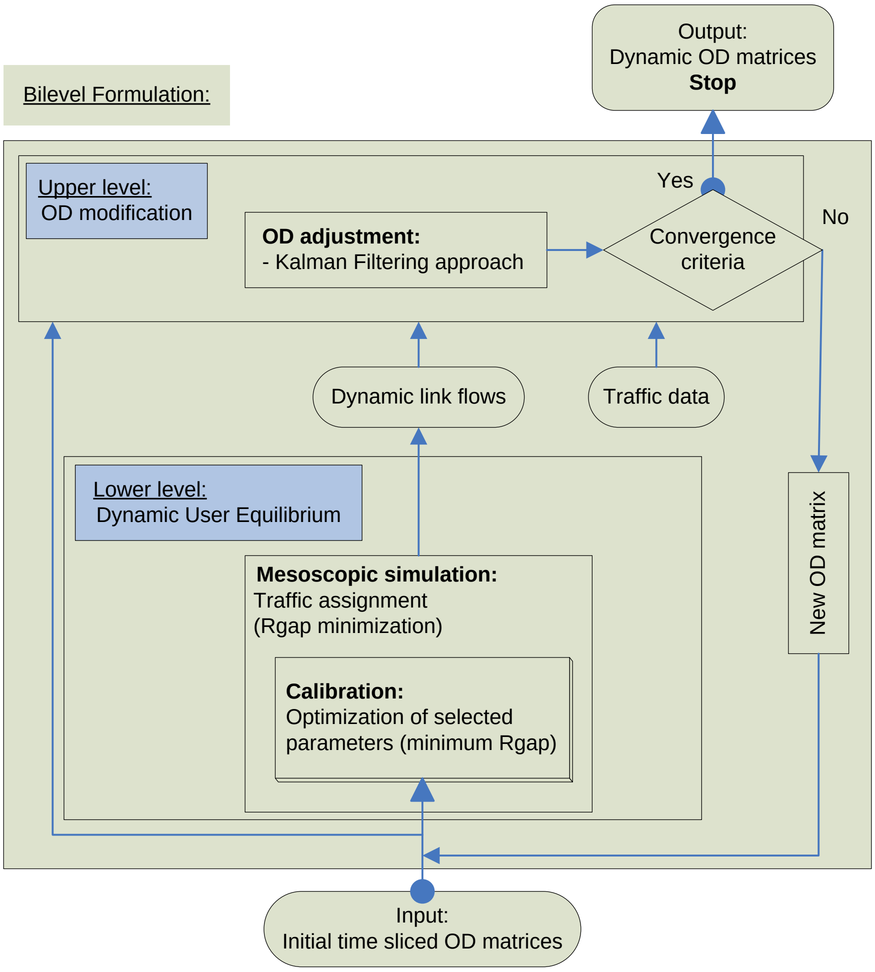


Figure 6 shows the details of the bi-level mechanism in the new approach. Let's see in more details the different parts of this bi-level process.

2.3.1 Lower Level problem

The aim of the lower level is to assign the demand in the network, to know how it influences traffic counts used in the upper level (see Figure 1 and 6)
Using a simulator in the lower level allows extracting all the needed information useful for the process. Travel times, turn proportions, shortest paths, flows… could be known for each places and for each time interval.

The simulator "AIMSUN NG" [3, 23] 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, needed for process evaluation) and API[14] allows possibilities to export 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.
This is an interesting particularity in our case; this simulation must be included in an automatic process (total OD estimation process, see Figure 6). 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[15] 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.
AIMSUN mesoscopic simulator is looking to Dynamic User Equilibrium (DUE) by iteration [19]. DUE will spread the demand generated by the input matrix through the network. Mesosimulator is minimizing the Rgap value [3].

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

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, Ki, is the set of paths for the i-th OD pair, and I is the set of all OD pairs.

- **Parameter calibration**

The problem of traffic simulator calibration is the fact that there is no representation or analytic formulation which allows finding the optimal combination of the different parameters which influence the results of the simulation. An "automatic" approach will be developed using Design of Experiment (DEO, [16]) to find how to set the values. The automatic process has also to determine the most critical parameters.

[14] API: Application Programming Interface.
[15] [21]. **H. Spiess**, (1990), *A gradient approach for the o-d matrix adjustment problem*, Centre de Recherche sur les Transports de Montréal. Montréal, Canada. Publication # 693.

This calibration is indispensable to obtain a good behavior of the car in the network. In our case, principally, route choice parameters will have a strong influence on the results of the lower level problem.

- **Outputs of the Lower level problem**

The simulation step results are clearly the utilization (car spraying) of the modeled road network by the traffic demand. This utilization represents the equilibrium with minimized global Rgap in the network. The path choice of OD pairs (assignment matrix) will be the input of the next step, the upper level problem.

2.3.2 Upper level problem

The proposed approach must find the best way to solve the upper level problem depending on inputs. Algorithms are going to try 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 values. OD estimation could use existing method, of course adapted to the new constraints of the new approach: Gradient, Least square, fixed point, Kalman Filtering, etc.

- **OD adjustment**

To adjust the OD matrix dynamically, the most intuitive and efficient approach is actually the Kalman Filtering[16]. 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.

$$\text{Transition Equation: } x_{r,h+1} = \sum_{p=h-q'}^{h} \sum_{r'=1}^{n_{OD}} F_{rh}^{r'p}(x_{r'p}) + w_{rh}$$

Whit $F_{rh}^{r'p}$ describes the effect of $x_{r'p}$ on $x_{r,h+1}$ and w_{rh} is a random error. q' is the number of lagged OD flow assumed to affect the OD flow in interval h+1.

$$\text{Measurement Equation: } y_{th} = \sum_{p=h-p'}^{h} \sum_{r=1}^{n_{OD}} a_{th}^{rp}.x_{rp} + v_{th}$$

a_{th}^{rp} is the fraction of the rth OD flow that departed its origin during interval p and is on link l during interval h. v_{th} is the measurement error. p' is the maximum number of time intervals taken to travel between any OD pair of the network.

- **Convergence**

An evaluation of the convergence of this OD matrix during iterations must be done comparing to the results of the previous iteration.

Criteria must be developed to evaluate if the OD matrices are converging with each iteration. Different statistical performance tests could be used: Mean Square Error (MSE), RMSE…. "Distance" between real and simulated data must be analyzed but

[16] [14]. **R.-E. Kalman**, (1960), *A New Approach to Linear Filtering and Prediction Problems.* Transactions of the ASME - Journal of Basic Engineering **82**: p. 35-45.

also between OD matrix at time (t) and at time (t+1). An evaluation of the obtain matrix must be done to know if the quality of the OD flows are sufficient.

If convergence is not observed, the process goes back to the lower level problem (iteration loop) with the new matrix to do another iteration (Lower and Upper level problems) and improve the process output based on the new inputs.
If convergence criteria are satisfied, output of the upper level problem is an adjusted OD matrix. The result or output of the upper level problem is time sliced OD matrix.

3. Issues

After developing these steps, an evaluation method must be done to judge the quality of the new method and to see the contributions of this research in the traffic simulation field.

The actual and the new OD matrices estimation have to be compared in term of quality and representativeness. OD matrices must model as close as possible the real demand in the network. The aim is to highlight the different advantages (and eventually the disadvantages) of the implementation of a dynamic OD matrix in the process and not adjusted at posteriori and of the process itself. To do, a new OD matrix evaluation tool has to be developed for these two methods. For adjustment by static equilibrium, several tools exist but these have been created for static assignment. Therefore, a unified method needs to be developed to evaluate the OD matrices from both approaches.

Several applications could be done to estimate the benefit of the new OD determination method. Dynamic quality of the outputs of different approach will be tested and evaluated by microsimulations. 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 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.

The OD matrix obtained by dynamic adjustment could be used as input of a microscopic simulation. With this test, the behavior of the demand could be analyzed and the gain in calibration time could be quantified. This evaluation could be done with a simulator using the same Traffic Assignment (TA) process (use simulator X for the TA and test the matrix with the microsimulator X) or not (X and Y). Both results could give information about the compatibilities of the approach depending of the different tools used.

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.

4. Conclusion

Traffic simulation is more and more widely used tool for planer and managers. 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 study with an innovative dynamic approach of the OD matrix determination process in urban area instead of the usual static approach. Evaluation and tests of the proposed method are presented to quantify the improvement.

Different steps and developments of this approach constitute new contributions to the simulation domain and particularly the traffic demand estimation and modeling.

The approach is innovative, principally by the repartition of traffic through the network. The idea of using this dynamic process to find the distribution of the traffic depending on the initial demand represents the advantage of meeting the needs of the next step, i.e. microsimulation studies. This approach is particularly adapted to complex and dense urban network. Using mesoscopic traffic simulator allows the determination of the whole needed data for OD adjustment. DUE based on urban constraints (signalized intersection, traffic signals, high route choice possibilities…) is used to assignment traffic in the network.

The last contribution of this work is the development of new evaluation and comparison processes to test the matrices obtained with the different approaches. A methodology has to be established to highlight and analyze the different qualities needed for a good utilization of the data.

5. References

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