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Dynamic Urban Origin-Destination Matrix Estimation Methodology

Méthodologie pour l'estimation de matrices origine-destination dynamiques en réseau urbain

Methode zur Ermittlung dynamischer Quell-Ziel-Matrizen für städtische Netzwerke

École Polytechnique Fédérale de Lausanne (EPFL)
Laboratoire des voies de circulation (LAVOC)

Emmanuel Bert, Dr ès sciences. EPF
Edward Chung, Dr
André-Gilles Dumont, professeur EPF

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Résumé

Cette recherche vise à développer une méthodologie novatrice permettant la détermination de matrices origine destination (OD) dynamiques adaptées au trafic dans un réseau urbain. Ce type de réseau est caractérisé par un grand nombre de pôles de trafic, de choix de routes potentiellement complexes et de nombreux carrefours à feux.
L'analyse des méthodes existantes a permis d'identifier plusieurs déficiences, principalement concernant le faible niveau de détail de l'assignation du trafic mais aussi des lacunes dans l'approche dynamique.
La méthode proposée se fonde sur une approche heuristique à deux niveaux. L'assignation de la demande initiale est opérée par un simulateur mésoscopique du trafic basé sur un Equilibre Dynamique de l'Usager afin de modéliser en détail des situations de trafic dynamiques sans pour autant nécessiter de nombreux paramètres de calibrage. L'ajustement des flux OD est mis en œuvre à l'aide d'une approche aux moindres carrés efficace qui prend en compte les aspects dynamiques de la propagation des véhicules et des comptages de trafic. L'algorithme LSQR a été sélectionné pour ses aptitudes à gérer de grandes matrices et sa capacité à s'adapter aux spécificités du domaine des transports.
Une analyse comparative avec l'approche la plus couramment utilisée pour estimer les matrices OD (approche séquentielle et statique) a mené aux conclusions suivantes : premièrement, la méthode génère des flux OD proches de la demande réelle. Deuxièmement, l'utilisation de la demande obtenue avec un modèle de trafic dynamique a montré ses aptitudes à reproduire des assignations de trafic réalistes.
Finalement, l'applicabilité de la méthode a été démontrée par la résolution de deux situations de trafic complexes et concrètes à l'aide du logiciel de simulation AIMSUN dans lequel la méthodologie proposée a été implémentée en tant que plug-in: le cas d'une modification d'un parking au Flon et celui d'un incident à la gare de Lausanne.
Cette recherche a souligné l'importance des données d'entrées pour le processus d'estimation des matrices OD et plus particulièrement pour la disposition et le nombre de compteurs de trafic. Une analyse de sensibilité a montré que, dans la majorité des cas, un petit nombre de détecteurs est suffisant pour estimer de manière efficace et rapide les flux OD et ce, si ces comptages interceptent les flux de trafic les plus stratégiques.

Mots clefs:

Simulation de trafic – Demande de trafic – Estimation de matrices origine-destination – Assignation dynamique du trafic – Réseaux urbains – Télématique

Abstract

The aim of this research is to develop a new methodology to determine dynamic Origin-Destination (OD) matrices for traffic in urban networks characterized by a high number of traffic hubs, complex route choice possibilities and a high level of traffic controls.

By reviewing existing methods, from static to dynamic OD matrix evaluation, deficiencies in the approaches are identified: mainly, the low level of detail of the traffic assignment for complex urban networks and the lack in dynamic approaches.

The proposed methodology is comprised of a heuristic bi-level approach. Assignment of the initial demand is performed by mesoscopic traffic simulation based on the Dynamic User Equilibrium to model detailed dynamic traffic patterns without numerous calibration parameters. OD flow adjustment is executed by an efficient least square solution which takes into account dynamic aspects of the flow propagation and traffic counts. For this task, a LSQR algorithm has been selected for its capacities to deal with a large matrix and its ability to deal with transportation characteristics.

Parallel comparison with the most common approach for OD estimation (sequential static approach) has shown: first, the method generates OD flows close to the actual demand, compared to the common practice; second, the utilization of the obtained demand by a dynamic traffic model has established its aptitude to reproduce realistic assignment patterns.

Finally, applicability and example of utilization of the proposed method has been presented by solving two realistic and complex traffic situations using the simulation software AIMSUN in which the proposed methodology is implemented as a plug-in: the case of parking modification in Flon and an incident at the Lausanne train station.

This research has shown the importance of input data for the OD estimation process and mainly the detection layout configuration used for traffic count data. Sensitivity analysis has shown that a small number of detectors is usually sufficient for efficient OD estimation in short computation time, if the traffic detectors intercept the most critical flows.

Keywords:

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

Zusammenfassung

Die Zielsetzung dieser Forschungsarbeit ist es, eine innovative Methode zur Ermittlung dynamischer Quell-Ziel-Matrizen (QZ) für den Verkehr in städtischen Netzwerken zu entwickeln. Diese Art von Netzwerken zeichnen sich durch eine große Anzahl von Verkehrs-Zentren, komplexer Straßen-Wahl und zahlreichen Knoten mit Lichtsignalanlagen aus.
Eine Analyse der bestehenden Methoden zeigte, dass diese mehrere Schwächen besitzen. Diese Mängel betreffen hauptsächlich das geringe Niveau an Details der Verkehrs-Zuordnung, aber auch die Defizite in den dynamischen Ansätzen.
Die vorgeschlagene Methode beruht auf einem heuristischen Zweistufen-Konzept. Die Zuordnung der ursprünglichen Nachfrage wird mit Hilfe eines mesoskopischen Verkehrs-Simulator durchgeführt. Dieser beruht auf dem dynamischen Benutzer-Gleichgewicht, welches es erlaubt, detaillierte dynamische Verkehrs-Situationen mit nur wenigen Kalibrierungs-Parametern zu modellieren. Die Anpassung der QZ-Verkehrsflüsse wird mit Hilfe einer effizienten Methode der kleinsten Fehlerquadrate (LSQR) durchgeführt, welche die dynamischen Aspekte der Verkehrs-Ausbreitung und der Verkehrs-Zählungen berücksichtigt. Der LSQR Algorithmus wurde für seine spezifischen Fähigkeiten ausgewählt (Umgang mit großen Matrizen, Anpassung an den Verkehrs Bereich).
Ein Vergleich mit der am häufigsten eingesetzten Methode für die Schätzung von QZ-Matrizen (sequentiell statische Methode), hat zu folgenden Schlussfolgerungen geführt: Erstens, die innovative Methode generiert QZ-Verkehrsflüsse, welche der tatsächlichen Nachfrage sehr nahe kommen. Zweitens, die Verwendung der berechneten Nachfrage in einem dynamischen Verkehrs-Modell hat gezeigt, dass realistische Verkehrs-Zuordnungen reproduziert werden können.
Schliesslich wurde die Anwendbarkeit der Methode durch die Auflösung von zwei komplexen und konkreten Verkehrs-Situationen bewiesen: Die Umgestaltung eines Parkhauses im Quartier „Flon“ und die Simulation eines Zwischenfalls am Bahnhof Lausanne. Hierfür wurde die Simulationssoftware AIMSUN eingesetzt, in welcher die vorgeschlagene Methode als Plug-In implementiert wurde.
Diese Forschungsarbeit hat gezeigt, dass die Input-Daten für die Schätzung von QZ-Matrizen und die Anordnung und Anzahl der Verkehrs-Zählstellen, von grösster Bedeutung sind. Eine Sensitivitätsanalyse hat gezeigt, dass in den meisten Fällen eine kleine Anzahl von Sensoren für eine effiziente und schnelle Schätzung der QZ-Flüsse ausreichend ist, solange diese Zählungen die wichtigsten Verkehrsflüsse erfassen.

Kennwörter:

Verkehrssimulation – Verkehrsnachfrage – Schätzung von Quell-Ziel-Matrizen – Dynamische Verkehrs-Zuordnung – Städtisches Strassennetz – Telematik

Executive Summary

The aim of this research is to develop a new methodology to determine dynamic Origin-Destination (OD) matrices for urban networks characterized by a high number of traffic hubs, complex route choice possibilities and a high level of traffic controls.

By reviewing existing methods, from static to dynamic OD matrix evaluation, deficiencies in the approaches are identified: mainly, the level of detail of the traffic assignment for complex urban networks and the lack in dynamic approaches.

The proposed methodology is comprised of a heuristic bi-level approach presented in *Figure i*. Assignment of the initial demand is performed by mesoscopic simulation based on the Dynamic User Equilibrium to model detailed dynamic traffic patterns without numerous calibration parameters. OD flow adjustment is executed by an efficient least square solution which takes into account dynamic aspects of the flow propagation and traffic counts. For this task, a LSQR algorithm has been selected for its capacities to deal with a large matrix and its ability to constrain outputs.

Figure i ***Proposed methodology for OD estimation***

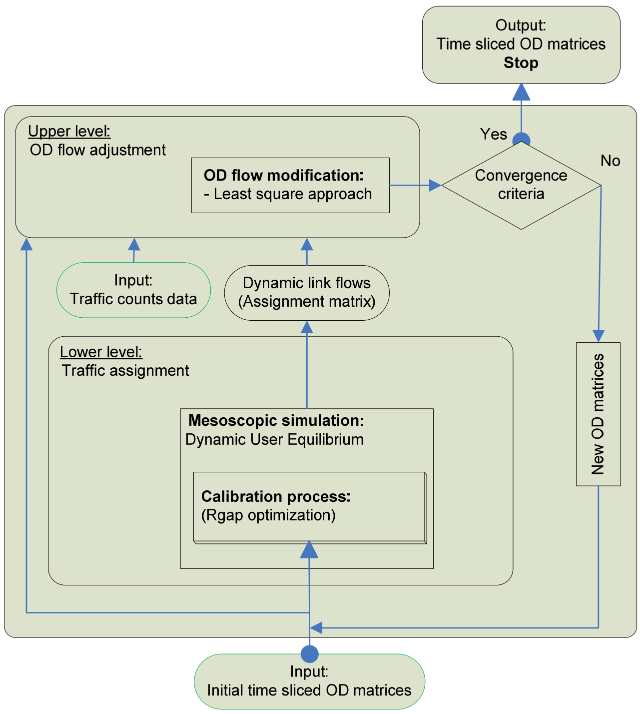
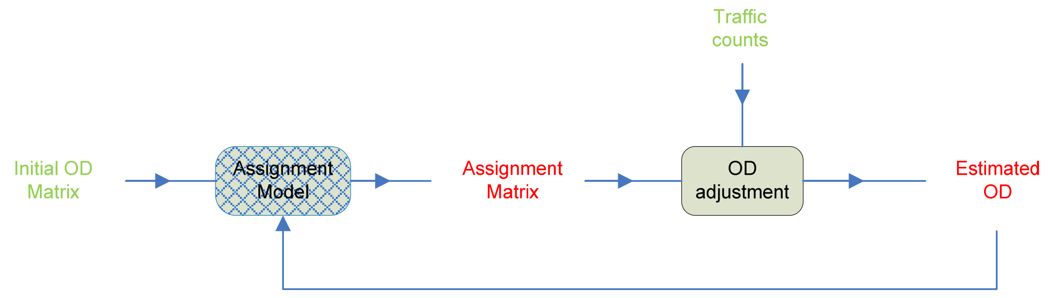


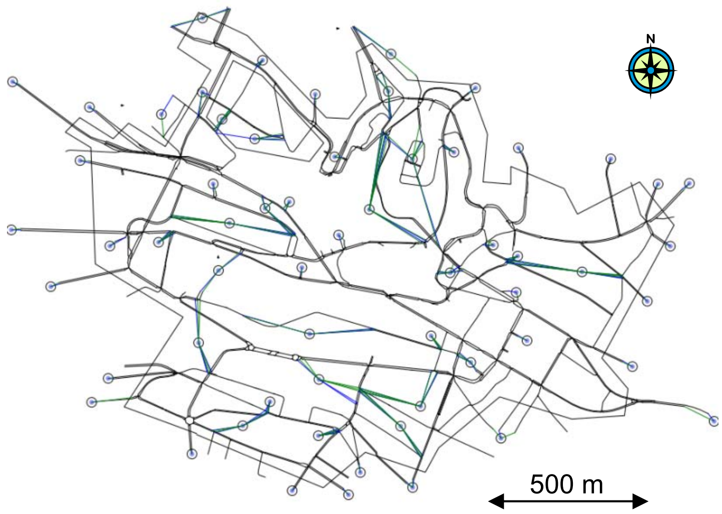
Figure ii presents a succinct description of the OD estimation process implemented in this research. Inputs are written in green, outputs in red. Dashed box is the assignment process. During this research, AMSUN Meso has been used to perform detailed and realistic assignment of the traffic. Nevertheless, any other tool could be easily employed to assess the assignment matrix needed for the OD adjustment algorithm.

Figure ii ***OD estimation process***



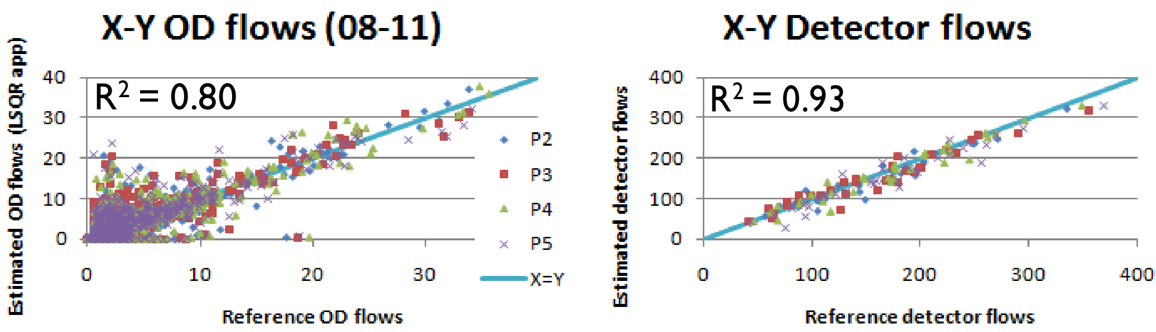
Network test is a large and complex urban network: Lausanne network (*Figure iii*) which has the typical urban characteristics needed to perform challenging demand estimation (high number of centroïds, complex route choice possibilities, high level of traffic controls, etc.).

Figure iii ***Lausanne Network***



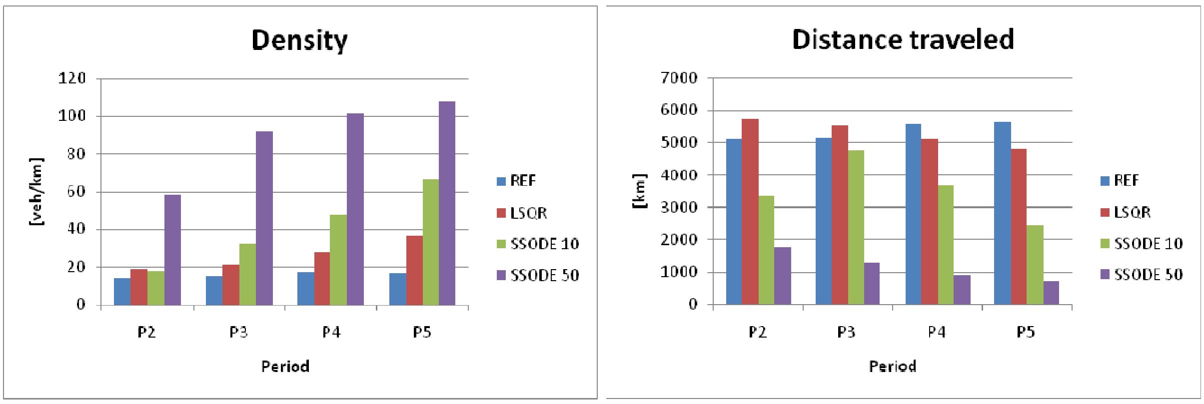
Parallel comparison with the most common approach for OD estimation used by practitioners (sequential static approach) has shown: first, the ability of the method to generate OD flows close to the actual demand (*Figure iv*), compared to the common practice.

Figure iv ***OD estimation results based on the proposed approach***



Second, the utilization of the obtained demand by a dynamic traffic model has established its aptitude to reproduce realistic assignment patterns (*Figure v*, REF is used for reference OD matrices data, LSQR for matrices obtained after OD estimation process proposed and SSODE 10 and 50 for matrices obtained after static sequential OD estimation process for 10 and 50 iterations respectively).

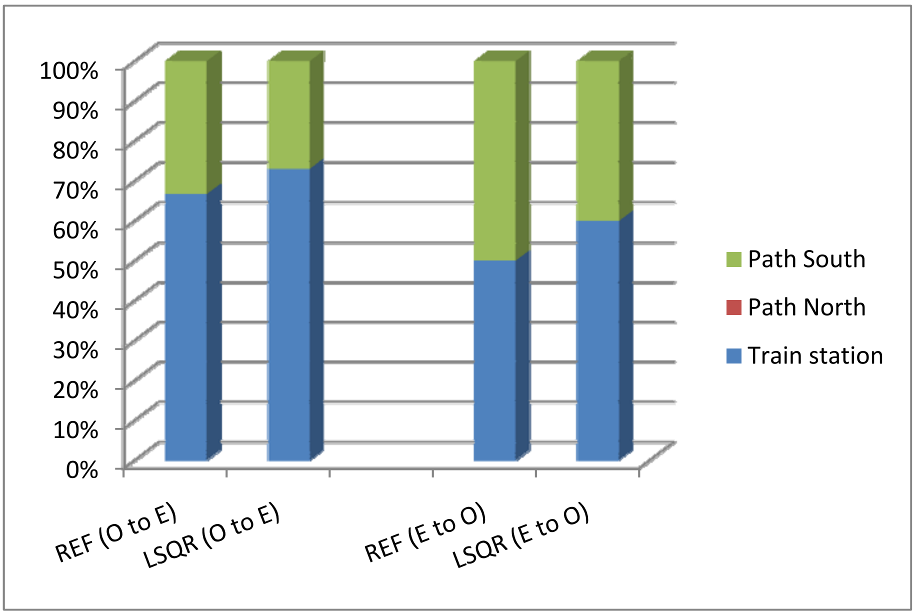
Figure v ***Demand obtained comparison***



Finally, applicability and example of utilization of the proposed method has been presented by solving realistic practical case studies using the simulation software AIMSUN in which the proposed methodology is implemented as a plug-in:

Scenario 1: Effect of a time varying attraction augmentation in a particular area is evaluated. OD matrices estimated and traffic modifications into the network are detailed to highlight benefit of the methodology.
Scenario 2: Local incident induce closing of road for 10 minutes during the evening rush hour. From that statement, reference demand and estimated demand are assigning using microscopic simulator and results are analyzed to assess reliability of the estimated demand to represent realistic traffic situations (see *Figure vi*, assignment results from reference and estimated demand).

Figure vi ***Practical case study application (assignment comparison)***



The quality (representativeness, level of detail, etc.) of the initial OD matrix obtained by studies and/or investigations could be very different depending on the cases studied. Moreover, it has been shown that detection layout configuration also has a large influence on the results. The issue is not to add extra detectors to intercept flows but to use a minimal number of traffic counts in optimal places. Therefore, the author suggests putting specific efforts in data collection to guaranty efficient computation and good results.

Finally, the proposed methodology is an iterative, bi-level process which needs several iterations to converge to an optimal solution. Different analyses performed during this research have shown that the number of iterations required to obtain satisfactory results is relatively small, usually less than 10 (dependent on the network and input data). Therefore, based on the proposed stopping criteria defined in this research, the computation time could be greatly reduced for practical application.

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Abbreviations:

DUE	Dynamic User Equilibrium
GEH	*Geoffrey E. Havers* statistic formula
HCM	Highway Capacity Manual
KF	Kalman Filtering
LSQR	OD adjustment algorithm (or process based on this formulation)
ME	Mean Error
MSE	Mean Square Error
OD	Origin-Destination
P1-6	Time period number
RC	Route Choice
REF	Reference case
Rgap	Relative Gap
R^2	Coefficient of determination
SSODE	Sequential Static OD Estimation process
SRC	Stochastic Route Choice
SUE	Static User Equilibrium
TT	Travel time
T-S	Traffic signals
UE	User Equilibrium
VDF	Volume Delay function
#Link	Number of links
#ODpair	Number of OD pairs

Units:

h	Hour
Km	Kilometer
Km^2	Square kilometer
min	Minute
s	Second
s/Km	Delay: second par kilometer
veh/h	Flow: vehicle par hour
veh/Km	Density: vehicle par kilometer

Variables:

a_i^{dn}	Proportion of the trip T_i^n traveling through detector d during time interval n
a_n^p	Fraction of the i^{th} OD flow that departed its origin during interval p and is on sensor d during interval n
B	Set of all link in the network
b	Link b
c	Index of the value evaluated (OD pair or traffic count flows)

Contents

Cap	Link capacity
d	Detector d
E_c^{sim}	Data from the simulation
E_c^{ref}	Reference data
$F_1(g,\hat{g})$	Distance between the estimated OD matrix g and the target matrix $\hat{g}$
$F_2(v,\hat{v})$	Distance between the estimated link flows v and the real or observed link flows $\hat{v}$
f_n^p	Effect of x_p on x_n
g_i^n	Demand for time period n between OD pair i
$g_i(n)$	Fraction of the demand for the i^{th} OD pair during the n^{th} time interval
$h_k^n(r)$	Flow assigned to path k during interval n at the r^{th} iteration
h_k	Flow on the k^{th} path for the i^{th} OD pair
$h_k(n)$	Space of path flow at time period n
I	Set of all Origin-Destination pairs in the network
i	i^{th} OD pair
K_i	Set of paths for the i^{th} OD pair
k	Path k
MM	Number of value included in the average mobile for stopping criteria of the bi-level approach
N	Total number of time intervals
n	Time interval
p'	Maximum number of time intervals taken to travel between any OD pair of the network
q'	Number of lagged OD flow assumed to affect the OD flow in interval $n+1$
R	Total number of iterations
r	Iteration
S_b	Function which defines the delay depending on the flow for the link $b \in B$
$S_k(n)$	Path travel time on path k during the time interval n determined by the dynamic network loading
$s_k^n(r)$	Experienced travel time of path k at interval n in the iteration r
TC	Total number of traffic counts
TOD	Total number of OD pairs
T_i^n	Number of vehicle during time interval n for OD pair i
t	Link travel time on Volume Delay function
t_0	Link free flow travel time on Volume Delay function
$u_i^n(r)$	Cost of the shortest path of OD pair i at interval n in the r^{th} iteration
V	Link flow
V_d	Flow for the detector d
$v(g)$	Flow on link b with the trip matrix g
v_n	Vector of random variable capturing the error measurement on traffic count data during time period n

w_n	Vector of random variables capturing the error during time period n
x	OD flows vector for Fixed-point formulation
x_n	Actual OD table capturing all trips departing during time interval n
x_n^H	Associated historical OD table with x_n
y_n	Vector gathering all traffic counts flows
α, β	Empirical coefficient for Volume Delay function calibration
γ	Fixed limit based on requirement for stopping criteria of the bi-level approach
ϵ	Minimum Rgap as stopping criteria for DUE
$\#E$	Number of measurements
Ω	Feasible region for DUE

1 Introduction

The end of the last century has seen a fast and big change in the transportation world, among other things. The growth of urban automobile traffic has led to serious and worsening traffic problems (congestion, pollution, accidents, etc.) in most cities around the planet. In this world, the importance of a better utilization of space and infrastructure is universally accepted.

Nowadays, the current situation in transportation makes traffic management very difficult without advanced techniques and tools. Intelligent Transport Systems (ITS) is an umbrella term that embraces a variety of advanced technologies in the areas of traffic detection, communication, information provision, intelligent road infrastructure, and traffic control systems. For ITS systems, novel tools are required to take into account whole phenomenon of the transport domain.

In this context, modeling traffic simulation is becoming a more and more widely used tool in transportation research. Road network and demand modeling can evaluate and quantify scenarios that have been generated based on actual data; it helps transport managers in operational and planning studies. This modeling is a helpful decision tool for short, medium and long-term studies. To achieve a transportation study using simulators, supply and demand must be known as inputs of the process. This research is focusing on ways to estimate demand inputs for traffic analysis and in particular for traffic simulation use.

1.1 Road traffic's background

Road traffic can be defined as the actual utilization of a specific road network. It is characterized and defined by supply and demand. These two concepts are dependent on the perimeter area studied, the road network and the mobility observed between places. Stabilization of traffic flows can be observed based on constant supply and demand and define transportation patterns. Diverse information defining these situations must be estimated to analyze traffic transportation scenarios for study. From the transport planner to the traffic operator, this kind of information is used as input to observe, compare and evaluate problems for on-line (in real time) or off-line applications and for short, medium and long-term studies. Additional assessments or processes could also use outputs of these evaluations.
The main road traffic analyses difficulty is to quantify and represent as accurately as possible the supply and demand because they must be identified over both space and time. It is difficult to capture the total spatial vision of traffic situations through

time. More information and details about general theory of transportation systems can be found in [26, 78].

1.1.1 Traffic demand

Usually people are making a trip for a particular purpose, to satisfy a need (work, leisure, etc.). Moving is not a means to an end. Keeping this in mind, the cause of these human or industrial needs and its repartition in space and time must be understood and measured to analyze traffic demand. Road traffic demand is the entirety of the trips (moving from point A to point B) made on a specific road network for a particular area in a defined period of time. Departure and arrival time, day of the week, week of the year, the purpose of the journey, type of cargo, trip frequency, traffic volume, etc. are data for qualifying and quantifying traffic demand. Types of vehicles making the trip are also a characteristic of the demand (heavy vehicle, light vehicle, buses, motorcycles, etc.).

Space is an important aspect of transportation and is strongly linked with the time necessary to travel from an origin to a destination (as presented in 1.1.3). Study perimeter is commonly divided into space zones to aggregate the mobility per area. Centroïds, which are entrance and exit of vehicles into the network, are positioned on each of these zones. For dynamic analyses, study period is usually divided in different time intervals to model dynamic variation of the demand (or supply). Dynamicity is one of the main aspects of the traffic demand. This characteristic makes traffic demand very difficult to define and quantify. Usually, the majority of the demand is concentrated around a few hours of the day; indeed, most congestion is observed during morning and/or evening peak hours, particularly in urban areas. Nevertheless, traffic variations are observed all day long.

- **How to collect traffic data**

Depending on the output needed, different methods can be used to quantify traffic demand. They consist of estimating or observing different effects of the demand (i.e. number of vehicles at particular places during one hour, number of vehicles moving from one point to another, etc.) with a focus placed on the typology (what is the cargo, the type of vehicle, etc.), space (measurements for certain time at a particular place in the network) or time (space situation for a particular time). Most commonly used techniques to measure different types of traffic data are induction loop detectors in the pavement, ultrasonic or infrared sensors, video monitoring, floating cars, etc. for on-line data and Origin-Destination (OD) questionnaires, travel or mobility surveys, etc. for off-line information. The reader can find more information concerning the ways to collect traffic data in [15].

The most common technique to collect traffic data is using loop detectors for traffic counts. Nevertheless, even though this tool can give time dependant information about utilization at specific places, in most of the applications, this type of data (at various places) does not sufficiently produce an accurate idea of the utilization of the network by vehicles. Several tools must be used and combined to obtain relevant traffic information for the whole network and then evaluate more accurately demand.

- **How to represent traffic demand data**

As is done for collection of data, information which must be presented determines the way to represent it. Depending on the issue of the representation, different aspects of the demand could be represented: percentage of special types of vehicle, flows at one point for a period of time, total trips in a network, flows between two points (Origin-Destination matrix), percentage of turning in junctions, etc.
Figure 1-1 shows one way to represent the demand using traffic flow value at a particular point (at the location of the traffic detector) for a certain period of time. It represents the sum of the proportion of the different OD pairs for all the time periods passing through detector *a* as presented in Equation 1.

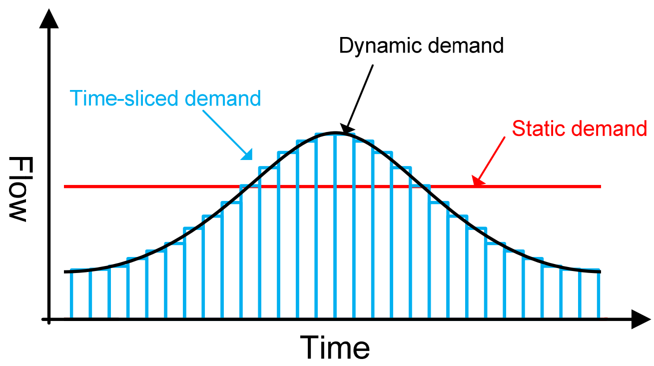
Equation 1 ***Traffic counts***

$$V_d = \sum_N \sum_I T_i^n a_i^{dn}, \qquad 0 \leq a_i^{dn} \leq 1$$

Where n is the time interval, N is the total of time interval, a_i^{dn} is the proportion of the trip T_i^n for the OD pair i (from Origin to Destination) traveling through d. V_d is the flow for the detector d.

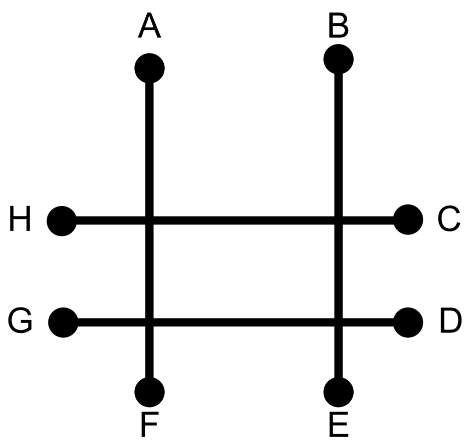
We can see three different demand curves shown in Figure 1-1, depending on the data frequency and the period. Actual and continuous dynamic demand is represented in black. When the data frequency is lower than the period represented or if the measurements are not dependent on the time (only aggregate data collected), there is only one average flow value for this period: the static demand case (shown in red). In another case (time sliced curve), the data are collected at high frequency and are observed on the graph (shown in blue).

Figure 1-1 ***Traffic demand representation by traffic count***



Another solution to represent trips in a network are Origin-Destination (OD) matrices (illustrated in Figure 1-2). The OD matrix quantifies the flows (number of vehicles per time unit) between two points of the considered network (at the limit or into). It informs of the origin and destination of the journeys and the number of trips, but does not contain any information about the route used in the network (i.e. no route choice information). Keeping this in mind, a description of the demand is objective and not dependant on traffic assignment and measurement location.

Figure 1-2 Example of network and Origin-Destination Matrix



From \ To	A	B	C	D	E	F	G	H
A	-	20						14
B		-		125		1600		10
C			-					20
D		546		-		48		
E					-			450
F	50	287				-		
G			123		25		-	12
H	22							-

- **Traffic management: information, prediction, evaluation**

Even if mobility is motivated by external factors (trip generators, people and goods needs, etc.), demand and effect of this demand can be influenced via different methods. Traffic management using pre-trip and on-route road information (via Variable Message Signs (VMS), radio, internet, etc.) could also modify the utilization of the roads.

One motivation for conducting traffic monitoring is to forecast and control the evolution of traffic over time. To apply traffic management measures, it is important to evaluate the evolution of traffic and then to predict, based on the current situation, what will be the situation in 5, 10, 30 minutes or more. For instance, traffic based measures for congestion management are designed to reduce car flows on the system (or at particular places) by distributing the travel demand over time and the traffic more uniformly on the network (increasing vehicle occupancy and public transit share). Numerous prediction models have been developed and can be found in the literature.

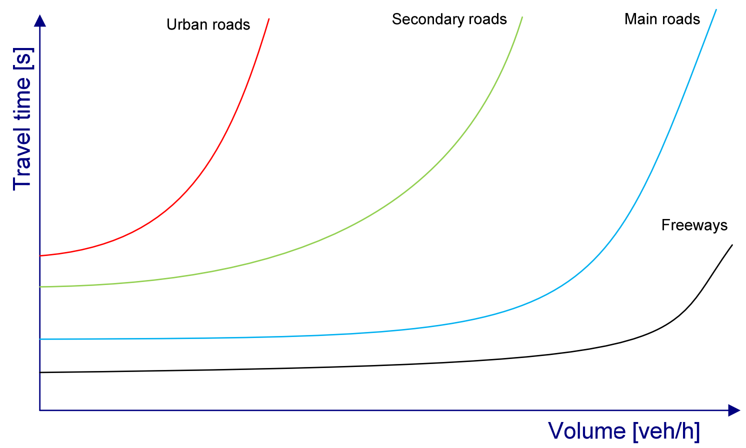
1.1.2 Traffic supply

A network is modeled using links and nodes. Each link is defined by its position, altitude, length, orientation, number of lanes, bus stops, free flow speed, maximum speed, etc. Turning movements and maximum turning speed are defined for each node by the lanes on its upstream (incoming) and downstream (outgoing) links that are permitted for the movement. Nodes start and end each link network and complete the needed information useful for network modeling.

In comparison to demand, supply is a service. It must be used at the defined place and time. In this way, it is crucial to have an accurate estimation[1] of demand to obtain a correct representation of the traffic flow behavior, particularly in road design field. Supply is defined as the capacity of a link (section of road between two intersections), route or network. It is the capability of a specific place at a certain time to deal with traffic flows. Capacity of each link changes constantly through time based on weather conditions, link curvature, traffic conditions, type of vehicle, etc.. It is influenced by various characteristics: for example, the number of lanes, the length of the section, the number and the type of intersections, the type of control (give ways, traffic signals, roundabout, etc.), etc.. One definition could be: "The maximum traffic flow obtainable on a given roadway using all available lanes; usually expressed in vehicles per hour or vehicles per day" (see [91])

Supply could be highly influenced by congested conditions. Congestion is observed when traffic levels approach the capacity of the road/link. In these cases, capacity could be greatly modified (decreasing) by the increase of traffic. As shown in Figure 1-3, the curve representing the travel time (which is dependent on capacity of links) on the link is a non-linear, monotonous, increasing function of the traffic volume. Increase of the traffic volume in the link decrease its capacity and therefore greatly increases the time to cross it (travel time). In this case, the delay increases. As you can see, position of the exponential increasing point (point between constant part and heavy enhance of the slope of the curve) is dependent on the type of road.

Figure 1-3 ***Example of travel times observed depending on volume of traffic***



Decrease of the capacity (and/or increase of the delay) could have large effects in case of dynamic study. Indeed, if the time period is divided into several intervals, large travel times could lead to an increase in the number of vehicles which need more than one interval to cross the network and in this way, the propagation of the traffic through time periods will change.
Supply could also decrease due to exceptional causes. Accidents, roadwork or blocked roads can completely crash a network and decrease its capacity to zero.

[1] Global process of estimation new OD matrix based on initial OD matrix and traffic counts, including traffic assignment and OD flow adjustment (see 2.1)

Due to differences presented and, as can be observed in the previous figure, supply is very different depending on the road context. Freeways and urban supply are differently influenced by network characteristics, users, and the environment (space and items surrounding the road).

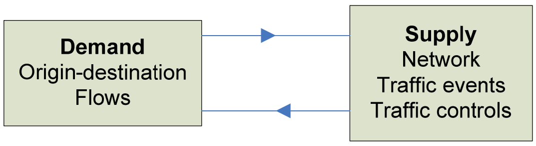
- **Supply management**

Supply based measures try to increase the actual capacity of links or network in order to improve the traffic flows. For different reasons (safety, vehicle priority, network efficiency, policy, etc.) supply can be controlled using tools: traffic controls, roundabout, speed bumps, incident management, etc.

1.1.3 Supply and demand interactions

In a majority of the networks, users have different possibilities when traveling to his destination. The set of feasible paths from an origin to a destination at time *t* is the path choice. This choice is mainly made by the user depending on his destination (traffic demand definition) and traffic conditions (traffic supply conditions). An interaction between supply and demand exists, which defines the transportation conditions of utilization of the network for a certain time interval. Route choices and supply conditions lead to travel time (TT) on the network. Figure 1-4 illustrates the interaction between Demand and Supply.

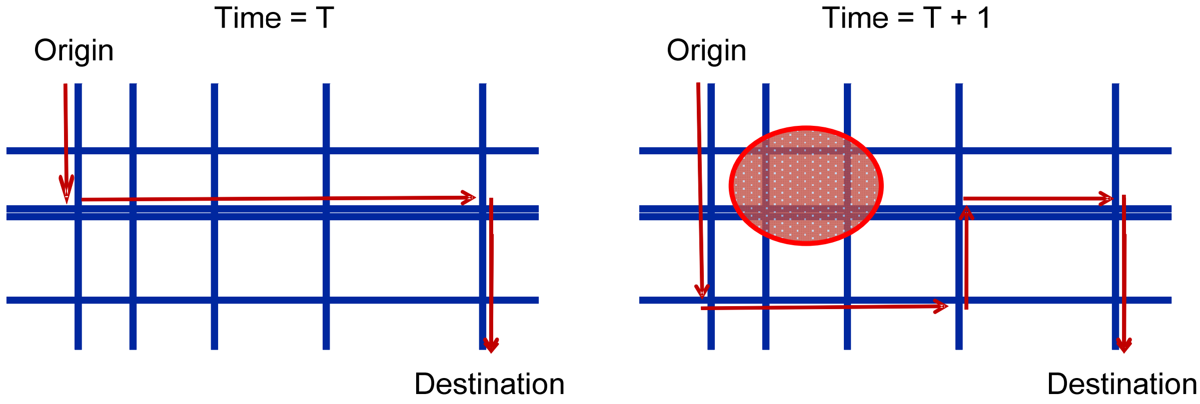
Figure 1-4 Demand - Supply interactions



Path flow estimation (assignment) is a critical point for traffic studies. Indeed, a good representation of the route used by vehicles guarantees realistic reproduction of real phenomenon and efficient calibration and validation of traffic models.

For instance, Figure 1-5 presents two different paths for the same OD pair at different times. Variation of the supply in the network (decrease of the capacity in the circle, due to an accident at time T+1) leads to a modification of the utilization of the network. More details about demand and supply interactions can be found in [43].

Figure 1-5 ***Paths flow***



From the definition of supply presented previously, traffic flow induces travel time (TT) for each link. This time to travel from A to B is commonly used by models to assign demand on network. In this way, model equilibrium is reached by finding a compromise between two competing mechanisms: volume increase due to link utilization and minimization of the travel time of travelers. An equilibrium point presents the optimal global solution of the assignment of the demand into the network.

1.1.4 Urban and Freeway traffic

A distinction must be made between different topologies of a network. Traffic demand and supply characteristics of urban areas and freeways are very different, for instance. In a majority of the cases, reflections based on one type of traffic could not necessarily be directly translated to another one. Meyer and Miller [73] explains in more detail urban and transportation system characteristics.

The first difference between these two main types of traffic conditions is the number of the modes of transportation present. In urban areas, several modes coexist and interact (pedestrians, bicycles, cars, buses, trucks, etc.). On highways, users are mainly cars and trucks. This diversity can, for instance, lead to a relatively large disparity in travel speed and density. Moreover, the number of intersection (conflict points between several traffic flows) are high in an urban network and lower on freeways. These junctions interrupt flow and thus modify the travel time of users. Due to the high number of crossroads in urban network, feasible path choices increase between origins and destinations. Moreover, the cause of the trip is usually different, expect in the case of ring roads comparable to freeways in a city context. Short work trips are mainly concentrated in urban areas whereas freeway users are traveling for medium to large distances (longer trips). In this way, distance between off/on ramp is larger. Therefore, the number of OD pairs is much greater in an urban area and OD flows are lower.

1.1.5 Conclusions

Road traffic is a complex and varying phenomena. It is crucial to develop tools and methodologies that allow a model representation of its various components to understand, represent and analyze it. These evaluations are starting points to qualify and analyze road traffic conditions.

1.2 Context

From this short introduction on road traffic, a problem statement can be presented to contextualize this work into the transportation field. Research objectives, scope and limitation of the study are presented.

This report is inspired from a recent PhD thesis work [16][2]. Whereas, the PhD report is proposing academic and scientific contributions, the present report is focusing on practical aspects of the urban OD estimation methodology.

1.2.1 Problem Statement

More and more traffic engineers are using models to understand and solve complex traffic situations. These new tools are very efficient for analyzing various phenomena and provide complete and detailed solutions. Nevertheless, quality of the data used to model the reality has a very strong influence on outputs of the assessment. Then, a representative value of the data (adequate and actual information) is indispensable requirement for these inputs. A real lack of traffic data collection, particularly in Switzerland penalizes an efficient observation of the traffic. In majority of the case, it is very difficult to access good quality input data. It could be due to a lack of data (actual data measured on the network) or a loss of quality due to processing of non-adequate raw data. From that statement, it is important to place particular attention on the measurements. Indeed, the best model cannot provide interesting results without accurate and detailed information about the actual situation. Keeping this in mind, measurement campaigns and processes that treat this raw data are very important. It is essential for the quality of the demand (OD matrices, for instance) to be close to reality. This research focuses on the current situation (State Of the Art and Practice) and proposes practical solutions and tools for traffic engineers.

Based on the "Four Step" planning process presented in 8.1 in annex, demand generation proposed will focus on a dynamic approach (with time sliced demand and dynamic assignment) for urban areas. Indeed, as presented in Figure 8-14 in chapter 8.2.4, dynamic cases present more challenging aspect as traffic flow propagation or realistic time sliced urban assignment. Then, it represents a step further for demand estimation. Nevertheless, the main steps can be compared. We can say that our approach is going to focus mainly on step 2 "Trip distribution" and step 4 "Trip assignment". Indeed, we are going to deal with assignment[3] of demand into a

[2] http://library.epfl.ch/en/theses/?nr=4417
[3] Assignment of the demand used in the demand estimation process (see 2.1.3)

network and with the adjustment[4] or modification of trips based on input traffic data (traffic counts).

1.2.2 Research objectives

The main goal of this research is to develop a way to estimate dynamic OD matrices for complex and large urban networks. During this process, focus will be placed on paths flow estimation. Indeed, this information is critical for the calibration and validation of traffic models.

The first objective is to analyze and evaluate the need for traffic demand estimation[5], particularly in a dynamic context and for urban networks. State of the Art and State of Practice will be analyzed, followed by the identification of the needs and deficiencies of current methods.

The second objective is to propose an efficient matrix estimation methodology for dynamic urban networks, taking into account the results of the first objective.

The third objective is to apply this methodology on different real networks and particularly on dense urban ones. The first part consists of validating the methodology in terms of OD estimation (quality and robustness of output OD matrices). The second part consists of applying the methodology on a complex and signalized urban network in the Lausanne centre. Focus will be put on practical applications and limitations of the proposed methodology. Moreover, outputs of OD estimations (demand) will be evaluated to assess their capabilities to reproduce observed traffic behavior using traffic models. Finally, several realistic applications will be considered to demonstrate the benefit of the methodology in practical context.

1.2.3 Scope and limitations

The scope of the research described in this report is limited as follows. First, it focuses on movements of motorized traffic. The term, motorized traffic refers to all traffic that uses the road network and can be observed by traffic detectors. It means cars, trucks, buses, motorbikes. Furthermore, no distinction is made between these different types of motorized vehicle. This research does not take into account variations in public transport use.

Second, the research is focusing mainly on the urban environment. As discussed previously, urban traffic differs from freeway traffic in several ways and so freeway patterns cannot be easily applied to urban context. The approach is focusing on networks with urban characteristics: dense road networks, traffic signal controls, high paths choice alternatives, etc.

[4] Adjustment modifies OD flows based on assignment matrix and traffic counts in the OD estimation process (see 2.1.4)
[5] As presented in 2.1

When we speak about dynamic or time sliced aspects (OD flows, traffic counts, etc.), we only consider intraday variation (as defined in [43]).

1.3 Scientific and practical relevance

1.3.1 Scientific relevance

The aim of this study is to develop a methodology for complex urban and congested urban conditions with the influence of intersections and traffic signal controls (characteristics of European cities). This method uses a mesoscopic simulator for traffic assignment and least square solutions for a dynamic OD flow adjustment (detailed in chapter 3).
The main contributions of this work are:

- The development of a new methodology to improve dynamic assignment and OD adjustment processes in urban context addressing weaknesses of current approaches

- The evaluation of the proposed approach against the state of practice

- The assessment of the effect of the detection layout configuration on the OD estimation process outputs

- The analysis of simulation outputs (i.e. network performance) based on the estimated demand using the innovative proposed methodology

- The demonstration and evaluation of the applicability of the proposed method on realistic scenarios facing practitioners

Secondary contributions of this research are:

- Detailed State of the Art of OD estimation and particularly on dynamic OD estimation
- Utilization of a Bi-level approach for OD estimation
- Utilization of DUE for traffic assignment
- Implementation and limitations of the Kalman Filtering algorithm
- Implementation of a constrained LSQR algorithm
- Applications on urban large network

1.3.2 Practical relevance

Throughout the study, focus has been placed on the practical aspects of the process. Indeed, problems in the study come from limitations of the common methods experienced by the author. One important aspect of the work is the exploitation of a practical utilization of the methodology proposed. For all these reasons, choice of the best methodology, results presented, implementation of the algorithm, and the evaluation method have been produced as close as possible to user's considerations and point of view. Limitations and the development of the method have been make taking into account the lack of traffic data, compatibility with commercial tools, computer limitations or input needed, and outputs.

The proposed methodology has been designed based on constraints related to application in real, complex, urban networks: the importance of the structure of the network, link density, number of alternative between OD pairs, density of traffic lights, congested roads, etc.

The result of this research is a "friendly" implementation of an efficient process for dynamic OD estimation. It is presented as plugins of well-known commercial software. This is a first prototype of the implementation but only few modifications (mainly optimizations) are needed to allow an integration of the approach for a commercial application. It represents a link between academic and theoretical approach and practical application for practitioners.

1.4 Report outlines

The focus of this research is to investigate an innovative approach for dynamic OD estimation in an urban context. To that effect, the following steps are followed:

The *second chapter* is dealing with the OD estimation process. All steps of this process are described and analyzed to understand issues of each part. From the initial OD matrix through assignment and adjustment processes and inputs, the possible tools are presented to tackle these tasks. The OD estimation State of the Art and particularly in a dynamic context, is presented. Weaknesses of current methods are identified.

Chapter three describes the innovative method proposed for OD estimation. Each part of the methodology is presented (mesosimulation DUE based traffic assignment, least square flow adjustment, etc.). Two different adjustment algorithms are presented and evaluated: Kalman Filtering and LSQR.

Networks tested and methodologies used for evaluation of the proposed method are presented in detail in *chapter four*.

Chapter five presents results obtained and highlights improvements and contributions of the new approach.

Conclusions, recommendations and further researches are presented in *chapter six*.

References used in this research are presented in *chapter seven*.

Chapter height groups different Annexes of this work.

2 Origin-Destination matrix estimation

To achieve traffic studies in the most accurate way, a definition of the road traffic demand is indispensable (as presented in Figure 2-1). This is one of the first types of data needed for transport evaluations. In this way, traffic engineers have to develop tools, which allow demand estimation as close as possible to the actual one.

Figure 2-1 Traffic study inputs

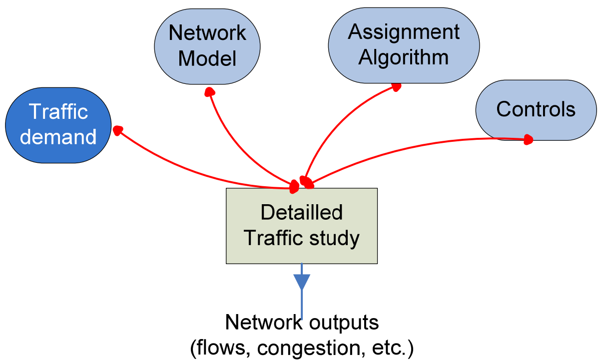
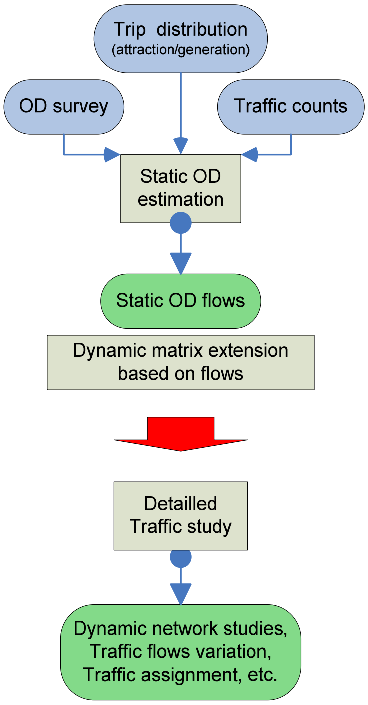


Figure 2-2 presents the process, commonly used in practice from trip generation modeling to dynamic analyses via OD matrix estimation. Due to costly and time-consuming data collection campaigns, initial OD matrix estimation is often conducted using aggregate data and therefore based on macroscopic assignment, even if the final goal is to perform a dynamic and detailed study. From the road network, demand centers (centroïds) modeled and the measured traffic counts, macroscopic simulator can be used to statically assign demand to determine the flows corresponding to measured traffic counts. This demand is required for microscopic simulation studies. Hence, from this OD matrix (extended to several time sliced OD matrices), microsimulators evaluate dynamic traffic variations in the network. Microsimulation outputs could be traffic assignment, traffic flow variations, etc. depending on the needs of the study. Keeping this in mind, we can note that inputs of the detailed traffic study are not well adapted for this task (global time sliced extension of a static OD matrix estimation, see Figure 8-10).

Figure 2-2 Common traffic study process



An origin-Destination matrix gives the trips of vehicle between two centroïds (origins and destinations in the modeled network). It informs about the volumes of traffic without fixing path choices. In this way, route choice could be an answer of the modeling and not an input characteristic. For a given study period, the OD matrix could be static, defined constants during the whole period, or dynamic, composed of several time slices with its own traffic demand.

Origin Destination estimation is a critical step for transportation studies as it represents the transport demand. 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 to the real demand to allow a realistic behavior of the model. In the case of dynamic OD estimation, time demand variation must be evaluated. Different stages of the OD estimation must be adapted to capture this evolution. Traffic assignment proposes a route choice solution depending on time and traffic conditions. The OD adjustment process needs to take into account the evolution of trips in the network. Algorithms must be able to make a distinction between entrance time (in the network) and the detection time (time interval at the traffic counts location). It needs this information to take into account vehicles which use more than the current time slide period to cross the network (traffic propagation). In our case, we are going to focus on static and dynamic congested situations in urban networks. Dynamicity (usually time sliced demand), route choice possibilities and traffic signal timings are challenges that are focused on in this research.

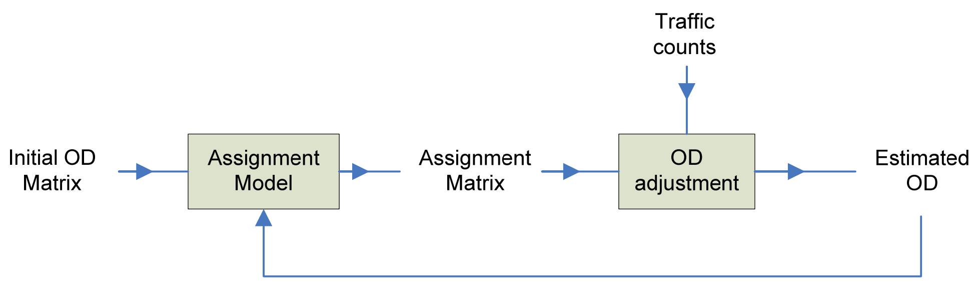
In this chapter, different steps of the OD matrix estimation tasks are presented to understand goals and challenges of each part. Afterward, the State of the Art demand estimation field is detailed to evaluate weaknesses of current methodologies.

2.1 OD matrix estimation process

In a majority of traffic studies using a model, traffic demand is one of the first requirements. In this way, an OD matrix estimation is an essential step even if, practically, it is complex to achieve. As presented in [22], an OD estimation is the inverse problem of the traffic assignment. Indeed, the later is looking for link flows based on demand, and an OD estimation consists of finding the demand that generates measured link flows. Then, the estimation aim is to propose a consistent OD matrix (or time sliced OD matrices), which is not directly measurable in-situ. It consists of solving systems where objectives are the minimization of the deviation between estimation link flows and observed link counts on the one hand and estimated demand and target (or reference) demand on the other.

An OD estimation is mainly composed of two distinguished processes: traffic assignment, which generates the traffic distribution into the network and OD adjustment, which modifies the OD matrix based on traffic counts. Figure 2-3 illustrates the sequences of this process. Assignment of the estimated demand into the network is an input of the OD adjustment process. One particularity of the problem is its under-determination. Indeed, in most of the cases, there are more unknown variables (OD flows) than equations to find them (traffic information).

Figure 2-3 OD matrix estimation process



From an initial reference OD matrix, the assignment model is performing the traffic assignment. Resulting is the assignment matrix, which is used by the OD adjustment process (least square algorithm) to estimate new OD flows based on traffic count values. These new OD matrices are assigned at another time into the network to provide a new assignment matrix. It is an iterative process to take into account the modification of the demand at each adjustment and, therefore, a modification in the assignment.

As presented in the introduction, common traffic studies use demand estimated in a static way, by lack of detailed and accurate data to perform a better OD estimation. In our case, focus is put on improving this input for detailed dynamic traffic studies.

2.1.1 Network model

To perform a traffic assignment during the OD estimation process, the perimeter area must be modeled with all the characteristics needed by the model used (it could be traffic simulators or analytic models). This perimeter area must be large enough to include all route paths possibility needed for scenario evaluation (taking into account the possible modification of the affectation based on supply changes for instance) and as small as possible to avoid unnecessary and time consuming coding and data collection. Links, nodes, centroïds, junctions, etc. must be placed as well as signalizations, vehicle properties and capacity of paths. Based on the level of detail of the model, the number of inputs could vary.

2.1.2 Initial traffic demand information

The reference OD matrix is the starting point of the OD matrix estimation. To reduce the under-determination of the problem, this input provides various kinds of information: structures, volumes, evolutions or limits of the target matrix. Thus, differences between this matrix and the estimated one provide relevant information about the value of estimation. This matrix must be as close as possible to the targeted one. Historical OD tables, observations (in real time or off-line), previous surveys, investigations, determination of the trips attracters, etc. are tools to evaluate a good initial OD matrix.

This initial OD matrix provides a basis for which the content information is related to the network area (associated with the actual assignment). Dependent on the type of network, information could vary significantly. Indeed, each kind of network has its own characteristics. Table 2-1 summarizes the main particularities of urban and freeway networks:

Table 2-1 ***Urban vs. freeway network characteristics***

	Urban	Freeway
# of traffic lights	High	Low
# of intersections	High	Low
OD flows	Low	High
Network length (Km)	Med	High
Mode of transportation	Various	1-2
Type of trips	Local	Long distance
Length of trips	Short	Long
Route choice possibilities	High	Low
Average speed	Low	High

Each type of network presents great differences. They are mainly due to the aim of the trip. Usually, journeys in cities are short and numerous, cut by other flows of the various paths possible between numerous origins and destinations (houses, parking, working places, etc.). On freeways, trips are usually for longer distances (between cities), with high and constant speeds (low perturbations except in case of congestion). Entrances and exits of the network are distant from each other and then the number of OD pairs is quite low. In this way, OD flows could be high and route choice possibilities are usually small or null.

Various studies have been carried out concerning OD estimations for freeway networks, [34, 55] for instance, but only a few for urban areas. Therefore, this work focuses on the later, which represents a big challenge to analyze, understand and decrease congestion in cities.
Heterogeneity and distribution of traffic in a large urban network makes behavior evaluation and modeling of the situation highly complex. Indeed, this kind of network presents particular characteristics that strongly influence traffic flow. Traffic conflicts or signalizations (stops, give ways, signalized intersection: adapted, coordinated or not, etc.) disturb and delay laminar flows by platoon. This discontinuity induces great variation in flow spreading and could leads to congestion (added to high demand volume) and high variation in travel time experimented within the network. Moreover, urban networks, due to a high density of traffic interfaces (centroïds), present in most of the cases a larger number of origins and destinations and therefore OD pairs. This particularity leads to low flows for each OD pair (and then, difficulties to intercept all OD pairs using detectors, see section 2.1.5) and to the definition of a large problem (Least square problem for OD adjustment) in case of OD estimation. Route choice possibilities are usually greater than in other types of network. Traffic is then spread in higher numbers of paths from an origin to the destination.

Initial OD matrix is the results of previous OD matrix estimation process, therefore, number of OD pair, number of paths, initial volume of flows, etc. are already identified. More, based on assignment used, information about travel time experimented, influence of traffic lights, queues, etc. are also included in this initial demand. All these characteristics are important issues for demand estimation. In this way, a particular attention must be paid to develop a tool adapted for OD estimation to a city context.

2.1.3 Traffic assignment process

The aim of this step is to determine the assignment matrix that gives the different paths choices depending on the origin, destination, time interval and traffic conditions. Different approaches could be envisaged to perform this task: analytical (based on analytic formulation of the path choice problem) or heuristic, using simulation models are the most common approaches.

To be the most realistic and flexible possible, this work is focusing on heuristic approaches concerning the traffic assignment. Indeed, simulation tools are more flexible in term of utilization (commercial software with advanced graphical interface, etc.), customization (network or route choice for instance using API or SDK) and validate as representative for an assignment task by the scientific community. Moreover, these models deal better with complex dynamic situation and high level of network detail than analytic models. In this way, different current simulation models and processes used by them are presented to choose the most adapted one for traffic assignment for OD estimation.

- **Traffic assignment methods**

Given a modeled network (defined by links and nodes) and a demand (number of trips for each OD pair), usually, a cost for each link is evaluated depending on distance, free-flow speed, volume of traffic, capacities, speed-flow relationship, monetary cost, comfort, etc. These costs are used to evaluate the best (or optimal) path for users from their origin to their destination. It is commonly assumed that users will try to minimize their personal travel time or cost during a trip. A particularity of the assignment in congested networks (taking into account capacities of links) is the fact that the assignment is based on cost and this assignment influences and modifies cost. Indeed, if all users are taking the same path between an origin and a destination, the travel times on the concerned links are going to increase due to congestion. This statement induces an interaction between cost and assignment, which could be tackled using different approaches (dynamic equilibrium, user equilibrium, dynamic user equilibrium, etc.)

Based on cost for each link, finding shortest paths in a road network is done using algorithms. The two basic ones have been developed by Moore (1957) and Dijkstra (1959) to allow efficient processing and computing. Route choice spreads vehicles on these shortest paths. Different methods could be used for this task, from all-or-nothing assignment to assignment in congested networks (Wardrop's equilibrium, incremental assignment, method of successive averages, etc.). The paths for each OD pair are the result of the assignment of the demand into the network.

Different approaches for route choice based on the shortest paths are presented here. One used by microscopic models is a reactive affectation called Stochastic Route Choice (SRC). It estimates performance, predicts the future conditions, and generates route guidance based on current conditions (see more detail in [6, 9, 10, 19, 27, 62, 90, 93]). Routes are assigned to the vehicles entering the network according to the current traffic conditions. Traffic conditions are represented by a cost for each link of the network that is calculated on the basis of the average travel time experienced by the vehicles that covered the link in the previous time periods. In this way, the cost represents a type of current attractiveness of the link. Route choice models determine the distribution of the traffic demand on the chosen shortest itineraries. Logit and C-Logit models are the most used ([30]); the latter is an extension of the first, but penalizing overlapping situations. Nevertheless, a dynamic traffic assignment does not guarantee the equilibrium of traffic into the network.

Other models are using equilibrium to tackle the interaction between assignment and cost, presented previously. Different kinds of equilibrium could be modeled. By iterations, equilibrium allows the decrease of dispersion in the results. The first used is the static equilibrium of Wardrop [99]. It says “Under equilibrium conditions traffic arranges itself in congested networks 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" [78]. The static equilibrium is based on this principle and leads to a user’s equilibrium or selfish (UE). User Equilibrium is reached when the conditions are stable and "no traveler can improve his travel time by unilaterally changing routes" (more details could be found in [83]).

For dynamic applications, solutions are proposed by several authors: [49, 51, 66, 81]. The Dynamic User Equilibrium (DUE), which is the dynamic version of the Wardrop's user equilibrium, is formulated in [81] or [80]. It is described as: "If, for each OD pair at each instant of time, the actual travel times experienced by travelers departing at the same time are equal and minimal, the dynamic traffic flow over the network is in a travel-time-based dynamic user equilibrium (DUE) state." This approach has been empirically proven to be the most consistent way of estimating the actual equilibrium in a traffic network. DUE is an iterative process to assign flows on a fixed maximal number of shorter paths for a different time period.

The algorithm for DUE (see in [47, 48] and [96]) is an iterative process to adjust OD flows for different time periods on a fixed maximal number of shortest paths. It proposes which are the most probable paths for a given OD pair and how many vehicles will use it during a time interval based on estimated costs. DUE can then be summarized by:
Let's fix R the number of iterations, and call $h_k^n(r)$ the flow assigned to path k during interval n at the r^{th} iteration. Let g_i^n be the demand for time period n between OD pair $i, s_k^n(r)$ the experienced travel time of path k at interval n in the iteration r, and $u_i^n(r)$ the cost of the shortest path of OD pair i at interval n in the iteration r.

1. At iteration r, do:
   - If $r \leq R$:

$$h_k^n(r) = g_i^n, \forall k \in K_i, i \in I, n \in N$$

   - If $r > R$:

$$h_k^n(r) = \begin{cases} h'_k n(r-1)\frac{r-1}{r} + \frac{g_k^n}{r} \; if \; s_k^n(r-1) = u_i^n(r-1) \\ h_k^n(r-1)\frac{r-1}{r} \; otherwise \end{cases}$$
$$\forall k \in K_i, i \in I, n \in N$$

2. Stopping criterion
   - If

$$\frac{\sum_{i \in I} \sum_{k \in K_i} h_k^n(r)\,(s_k^n(r) - u_i^n(r))}{\sum_{i \in I} g_i^n u_i^n(r)} < \epsilon$$

   (As Rgap indicator defined in Equation 8, with ϵ criteria fixed, based on requirement)

   or if a maximum number of iterations is reached,

   STOP

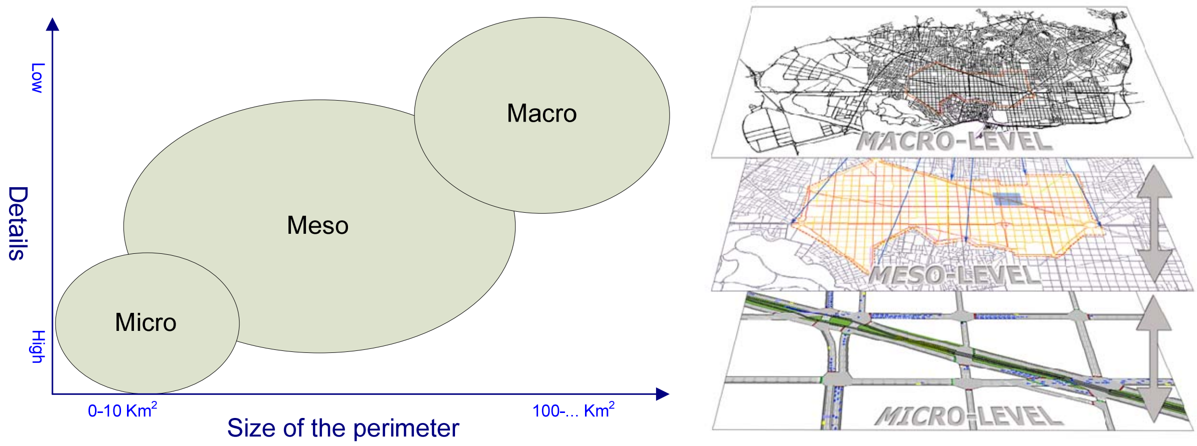
   - Else, go to 1.

Practically, Rgap around 10-15 % (ϵ = 0.10-0.15) is considerate as satisfactory (as the difference in the travel time perception by drivers).

- **Traffic simulators**

Traffic assignment is performed heuristically by traffic simulators. They are models, which are simplified representations of a part of the actual world, which concentrates on certain elements considered important for its analysis from a particular point of view. Hence, they are simulation tools that emulate the flow of vehicles around a road network. Three main families of simulators can be distinguished based on the level of detail and capabilities. Network representation is very different from one model to the next. Various possibilities exist depending on the application (planning or exploitation), the size of the perimeter, and the data available for the calibration. Global domains and the level of detail of each model are presented in Figure 2-4.

Figure 2-4 Simulation tools, level of detail



- **Macroscopic**

Macrosimulators or urban demand planning software use a traffic flow model based on simple algorithms. With a global and aggregate vision of the network, they could solve problems linked with long-term transport planning purposes, usually statically. This tool helps planners to analyze, control and represent the huge quantity of data linked with large transport systems. Network representation and traffic assignment use low detail information (no signal setting for instance) and in this way, utilize a low number of calibration parameters. The approach used is constituted by an iterative process for static User Equilibrium (presented previously) based on Volume Delay functions (see chapter 8.2.1) and is looking for a travel time global minimum (see Wardrop [99] and [46]).

Main macroscopic products are EMME/2 [56, 57], VISUM [PTV], AIMSUN Planner [95], METACOR [44], TRIPS, etc.

- **Microscopic**

Microsimulation, as the name suggests, looks at the microscopic aspects of traffic (physical proprieties of each vehicle such as position, actual speed, distance between cars, acceleration, deceleration, pollution emission, etc.). They use an individual and disaggregate representation of the traffic and provide dynamic (time dependent) and detailed outputs. Dynamic variations in the supply and demand (accident, variable message signs, parking, etc.) are possible. Traffic assignment is detailed as well; the behavioral modeling is based on car following, lane changing and route choice of an individual vehicle (safety distance between vehicle, acceleration and deceleration, turns in the network, waiting time, OD paths, etc.). Microscopic models take into account different fix and variable constraints such as priorities, stops, yields, adaptive and detailed signal setting and phasing schemes, parking availabilities, etc. To represent the different characteristics of the vehicle, links and junctions, high number of parameter is employed. Several of the model's parameters are stochastic and in this way, traffic variations could be obtained using replications. From all these features, microscopic models are adapted to detailed short-term operational studies on small networks but limited for large networks. Due to this level of detail (and then the number of parameters), calibration is time consuming and need experiences.

Main microsimulators are: AIMSUN [11, 93], VISSIM [PTV], MITSIM [103], CORSIM [1], DRACULA [63], TRANSIMS [75], CUBE [71], etc.

- **Mesoscopic**

So-called mesoscopic models fill the gap between the aggregate level approach of macroscopic models and the individual interaction of the microscopic ones. They are detailed dynamic models with simplified traffic rules. Usually, mesosimulators use aggregate traffic flows (and thus low number of parameters) but disaggregate vehicle representation to provide high level of detail for the traffic entities. In this way, assignment and network level of detail is close to the microscopic approach (detailed and dynamic) but traffic rules are simplified to improve the computation efficiency.

Various different forms of mesoscopic models have been developed. Some are grouping vehicle with common characteristics into packets or platoons to route them together. Speed of vehicle into links is estimated based on speed-density relationship. Others are using cells, which control car behavior to travel into the network; vehicle can decide to enter or leave cells when needed. Others are employing queue-server, which represent link by queuing part and running part (see Figure 8-17) to simplify the modeling. Some are using cellular automata; links are discretised into cells that can be empty or occupied by vehicles and behavior rules determine for each time step the number of cells that are traversed by vehicle. This non-exhaustive list presents some examples of mesoscopic approach.

Thus, mesoscopic level is the largest one in term of variability and diversity of approaches; nevertheless, common characteristics could be identified. Indeed, large network simulations are possible due to the low number of parameters and make dynamic planning analyses possible. Detailed dynamic traffic phenomena are fully captured and some parameters could be stochastic. Moreover, different route choice approaches are applicable as Dynamic User Equilibrium (based on simulation-based network loading) or Stochastic Route Choice (presented previously).

Most well-known mesoscopic simulators are: DYNASMART [65, 67], DYNAMIT [14], DYNAMEQ, MEZZO, METROPOLIS [42], AIMSUN Meso [95] or VISTA [107].

Table 2-2 summarizes the main characteristics of these three types of simulator models:

Table 2-2 Simulation tools characteristics

	Microsimulator	Mesosimulator	Macrosimulator
Application	Short- Med term	Short- Med term	Med-Long term
Network size	Small to Med	Small to Large	Med to Large
Geometry	Detailed	Detailed	Simplified
Car following	Detailed	Simplified	-
Lane changing	Detailed	Simplified	-
Vehicle representation	Individual	Individual or platoon	Flows
Static and Dynamic	Yes	Yes	Usually Static
Route choice	SRC-DUE	SRC-DUE	UE-Wardrop
Junctions	Detailed	Detailed	Simplified
# of calibration parameters	Large	Med	Small

However, a perfect traffic model does not exist. Choice is mainly dependant on the utilization horizon, network detail, size of the study/simulation area, route choice process, etc.

From those statements, mesoscopic simulators seem to be the most adapted tool for a traffic assignment in the goal of OD estimation. A mesoscopic simulator focuses on essential behavior without unnecessary details. The aim is to achieve a high level of analyses with great computational efficiency. Even though, a mesoscopic simulator offers almost the same level of detail as microsimulators, particularly in an urban context (dynamic demand, queuing, traffic lights, signalized intersections, etc.) but, due to simplified traffic rules, the number of parameters decreases and hence, reduces the complexity of calibration. Moreover, the model allows a Dynamic User Equilibrium for an accurate optimization of the user's travel time into the network. Different mesoscopic simulators have been developed (DYNASMART, DYNAMIT, AIMSUN Meso, etc.) and experiences show that they are well adapted for large urban network studies ([88]).

2.1.4 Flows adjustment process

The adjustment process consists of an adaptation of OD flows to actual and observed traffic data. Based on assignment and traffic counts, the least square formulation proposes a solution to this problem. Mathematically, this problem is called "under-*determinate*" because, in most of the cases, there are more unknown variables (OD pair's flows) than information (traffic counts data) or equations to estimate those. Keeping this in mind, an OD estimation is solved as an optimization

problem which proposes an infinite of number of solutions. The methodology adopted here must find the optimal one depending on the modeling constraints (initial OD matrix for instance). Several authors have considered this point in the literature: [43, 70] for instance. Moreover, Bierlaire dealt with the Level of knowledge of the OD matrix based on the network characteristics and detection layout configuration [22].
In our case, the optimization problem is considered as convex and in this way an adjustment task based on the least square formulation proposes a unique solution. More details and the least square solutions are presented in chapter 3.5.

2.1.5 Measured traffic data

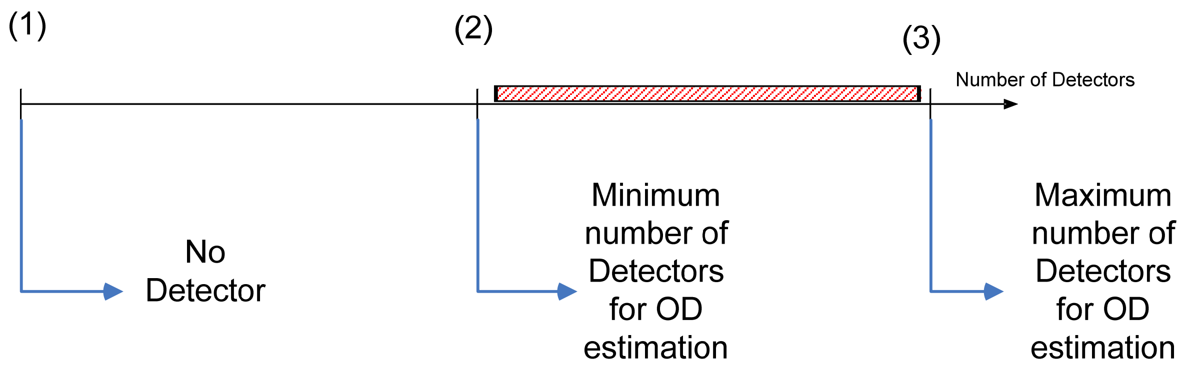
Traffic data, traffic counts in the case of OD matrix estimation, are only actual data observed in situ. Traffic counts are measurements made in the network, which evaluate the flow of vehicles in volume by unit time at a particular place. It is a combination of the trip matrix and the assignment pattern and it provides direct information about the sum of all OD pairs, which used the concerned link (as presented by equation1).

They constitute the matching point of the estimation. Nevertheless, these data provide no information concerning the origin and destination of network's users. In this way, the OD estimation process, based on assignment and adjustment process tasks, modifies an initial OD matrix to reproduce these traffic counts. This information is measured in several locations of the network and in an accurate way. Obviously, this information must be the most consistent possible with the initial reference OD matrix used for the first assignment and with the type of approach applied (static or dynamic OD estimation). The huge number of possibilities to place detectors (each link is a potential location) leads to the detection layout problematic. Indeed, *Do all these detection layout configurations provide consistent inputs for efficient OD estimation?*

The detector layout issue must answer two mains questions: where and how many detectors are needed to obtain a detailed enough picture of the traffic situation? To answer to these questions, several points must be focused.

As we will see later in this report (chapter 3.3.1), the OD adjustment process is using detector information (interception of the OD pair flows) to evaluate OD flow modifications. In case of a non-interception of particular OD flows, an adjustment process cannot adapt them based on measurements. Therefore, particular attention must be paid to the detection layout quality to intercept the majority of OD pair flows or at least the most important ones. Figure 2-5 illustrates the different configurations concerning the number of detectors (and the position) and the flow interception:

Figure 2-5 Detection layout quality

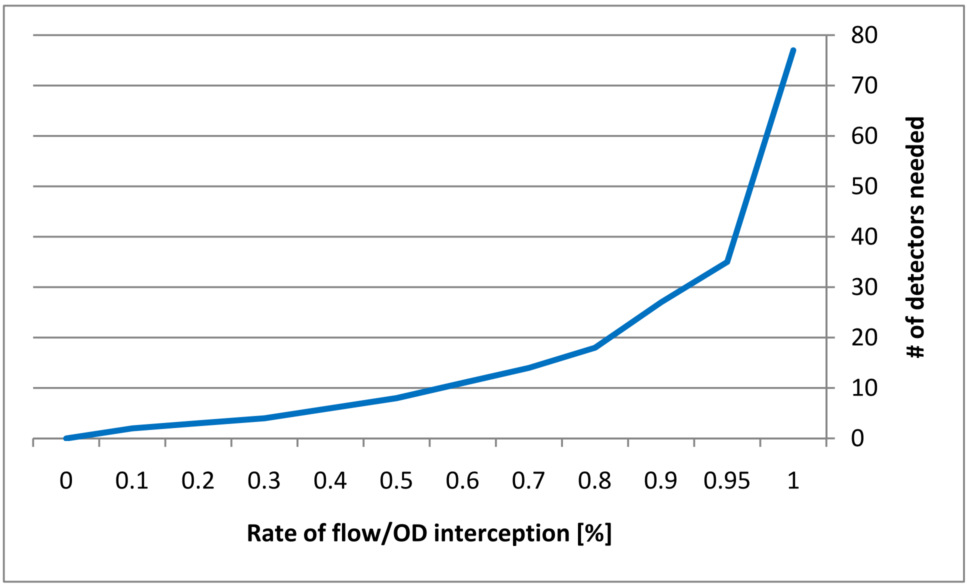


In Figure 2-5, three boundaries could be highlighted:

- Boundary (1): There is no detector in the concerned network.
- Between boundaries (1) and (2), there are few detectors into the network, but not all the OD pairs are intercepted for optimal OD estimation.
- (2): all OD pairs are intercepted. It is the minimum configuration to adjust each cell of the OD matrix.
- From boundaries (2) to (3), all OD pairs are intercepted and there are more and more detectors in the network. Redundant information exists.
- (3): all links of the network are equipped with a detector. It is the maximum detection layout solution.

For instance, using the Lausanne centre network (see chapter 4.1.3), Figure 2-6 presents the number of detectors needed depending on the percentage of flow/OD pairs intercepted. Results have been obtained using the algorithm developed by Gilliéron in [52].

Figure 2-6 Relation between number of detectors and flow/OD interception



We can see the exponential growth of the number of detectors needed to capture the OD flows. This figure highlights the importance of the choice of the level of interception needed for the network. Indeed, for a small increase in the interception rate, and then the OD estimation quality, many more detectors are needed. A compromise between cost (of measurement using detectors) and the level of quality needed for the final OD matrix must be found based on the requirement of the study.
In our case, from this curve, a rate of 95% of flow and OD interception has been chosen; 35 traffic counts are needed (presented in Figure 4-15).

It has been shown (different tests during this research and also [52]) that the quality of the matrix estimation is not necessarily improved by adding new detectors below the non necessarily i.e. boundary (2).

Several studies have been carried out to tackle this issue: [52] based on a heuristic combination of Tabu Search and diversification techniques, [22] using "The Total Demand Scale" approach for measuring the quality of estimated OD tables based on detection layout and a-priori OD table or [64] which uses Kalman Filtering method to explore time-dependent maximal information gains from sensors. Nevertheless, it has been seldom associated to OD estimation and even more rarely in the urban context.

Other issues concerning traffic data measurements are consistency of the data and observability of the estimation problem. These concerns have been developed in [78] and [3] and will not be detailed in this report.

2.1.6 Other sources of traffic data

Several other sources of data could be added to increase the quality (by decreasing the under-determination) of the demand estimation. Travel activity surveys (detailed but costly, time consuming and with low frequency), land use, employment rate, stream flow surveys, floating car data (FCD), travel time studies, cordon information, historical OD information, real time traffic data (for various days, seasons, etc.) as well as planners' knowledge and experience add value to the demand estimation process.

In this work, only network model, assignment process, traffic counts and an initial OD matrix will be considered because they are the minimum data needed to complete an OD estimation and in a majority of the cases, they are the only available data for the concerned perimeter area (including other type of measurement is a interesting area for further research, see chapter 6.3).

Obviously, consistency between all these inputs is required. Date of measurements or observations, perimeter area, time horizon, number of time period, and zone definition (centroïds) must correspond to provide useful information to the OD estimation process.

2.2 Demand estimation weaknesses and deficiencies

Detailed State of the Art has been done and is presented in Chapter 8.2 in annex. It deals with un-congested and congested traffic conditions, different formulation used for OD estimation and static and dynamic cases. A particular attention has been put on dynamic urban conditions. All approaches presented in the State of the Art propose a solution to the OD estimation problem. Nevertheless, limitations or disadvantages can be identified for an efficient approach useful for practitioners.

2.2.1 Static/Dynamic approach

Most commonly used methods by practitioners are dealing with the OD flows estimation problem using static approaches. They are estimating a unique OD matrix for the complete period study. Disadvantages or weaknesses 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 estimate time dependent traffic variation adapted for dynamic flow modifications (essential for short-term microscopic studies).
Usually, as presented in chapter 8.2.2, to use a statically determined OD matrix in a dynamic simulation (microsimulation with time sliced demand), it is common to adapt the demand based on traffic counts. The shape of traffic count 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 omits structure modifications of the matrix (commuter traffic or non-uniform modification 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 time sliced but it does not take into account previous time periods in the calculation of the current one; there is no link between different time periods. The propagation of flow is not considerate. In this way, dynamic characteristics of the demand, particularly in an urban context, could not be modeled in an efficient manner.

2.2.2 Assignment process

In the literature, we can find very little consideration about complex route choice possibilities in the lower level problem (evaluation of the assignment matrix). It could be done by observation, analytically or by simulation, but depending on the method, the quality of the assignment could be very different. To catch the complex evolution of traffic through time, heuristic approaches using traffic simulators are more adapted and cheaper (in time and cost) than other approaches. From this point and as DTA is not reaching model equilibrium, Dynamic User Equilibrium (DUE) looks to be the most adapted approach to take into account the user's travel time evolution into the network.

2.2.3 Network applications

A majority of traffic problems is observed in urban areas and presents more challenging and interest for traffic engineers due to the large effects of traffic perturbations (delays, pollution, costs, etc.). As we can see, in Table 8-3, there are very few tools adapted for medium to large complex urban networks. For rare cases, which are dealing with urban typography, usually, they are small networks with low route choice and signalized capabilities. Complex networks are characterized by many alternative paths between OD pairs and with a high density of traffic lights. This lack could be problematic for most traffic studies in city areas with congested and dense networks and with signalized junctions. An innovative approach must allow efficient and representative dynamic traffic assessment in various types of networks and not be limited to specific or simple cases.

Papers from Balakrishna [7], Chang & Tao [33] and Bierlaire [23] are the most relevant papers for urban applications. The first one uses a small and theoretical network and analytic approaches for the assignment matrix. The paper concluded that “much remains to be done to have a reliable dynamic OD system for efficient use in practice”. The second paper takes into account only freeways and main arterials. Bierlaire and Crittin applied KF in the Irvine network. This network is quite large in area and offers route choice capabilities (even if limited) however, in terms of link density (number of road per unit area) and OD matrix size, it is not large. Moreover, the paper provides no information concerning traffic lights. In addition, the process to obtain an assignment matrix (using DynaMIT) is not detailed. This research focuses more on computation time efficiency than OD estimation performances.

2.2.4 Detection Layout issue

None of the papers presented in Table 8-3 consider detector layouts problematic. The amount and the position of these detectors are never discussed and we can find no information concerning the rate of interception of flows or OD pair by detectors (assumed that 100% is intercepted, but this hypothesis is seldom reachable in practical applications). Nevertheless, this issue is critical for OD estimation formulation. Indeed, as presented in chapter 2.1.5, quality of the estimation is directly linked with the number of OD pairs intercepted by detection layout. In this way, it is essential to apply methodology (for instance [52]) to tackle this issue in the global OD estimation process and then advise practitioners to place detection layout in an efficient way.

2.2.5 Other issues

- **Utilization of external resources to solve the bi-level problem**

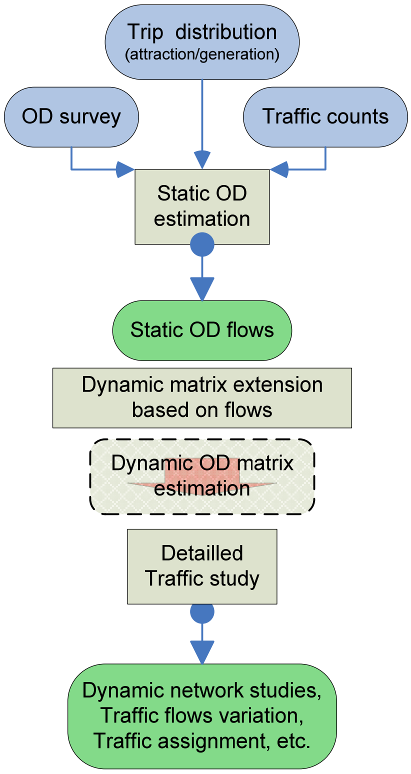
Particularly for dynamic approaches, most of them need the utilization of external software to be computed (added to the simulation software, if one is used). The adjustment and the assignment problems (lower and upper level) or the fixed-point problems are not solved directly in the simulator. To deal with these problems, the users must use a specific and complex mathematical tool: it could be Matlab® or Mathematica®, etc. for instance. This weakness could be a serious handicap for traffic engineers who have to deal with OD estimation. Indeed, a particular knowledge is needed and license prices could be expensive. This consideration is particularly important for the development of a tool for practitioners (compare to academic and theoretical researches).

2.3 Conclusions

Chapter 2 presents and highlights the different parts of the OD estimation process. Due to costly and time-consuming dynamic traffic data campaigns, the initial OD matrix obtained from static OD estimations using macroscopic assignment is often used as input of microscopic analyses.

Keeping this in mind, to improve the process presented in Figure 2-2, the dynamic OD estimation process is added in the global framework, as presented in Figure 2-7 to update and/or improve the previous initial OD demand. From the initial time-sliced OD matrices (generated from static OD flows for instance), it evaluates dynamic OD flows based on detailed traffic characteristics for matching microscopic needs.

Figure 2-7 Proposed traffic study approach



From that point, State of the Art of OD matrix estimation is presented and weaknesses of the current methodologies are highlighted:

- Static approaches
- Low assignment level of detail
- Non urban network applications
- No consideration of the detection Layout issue

Based on the deficiencies identified, the proposed methodology is focusing on several improvements of current solutions.
First, the proposed approach uses a mesoscopic simulator for demand assignment particularly adapted for large and complex urban networks. Quality of the equilibrium and level of detail of the network are important features for this step to provide an assignment representative of the actual one in whatever the traffic situation.
Second, assignment, as well as OD matrix adjustment must be done in a dynamic way. The methodology is going to tackle the major problems of the time dependant formulation i.e. travel time in the network, OD flow propagation, etc.
Third, particular attention will be put on the detection issue and accessibility of the process (complexity of the utilization). These features are indispensable to guaranty an acceptable method by traffic engineers.

3 Methodology proposed for dynamic OD estimation in urban networks

This chapter presents in detail, systematically, the proposed methodology. All steps of the process have been chosen based on the issues pointed in the previous chapter and to simplify its utilization. Table 3-1 presents lacks identified in the State of the Art and proposes the chosen practical solutions.

Table 3-1 Solutions of the proposed methodology

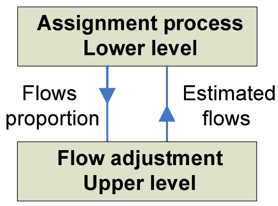
Lacks	Solutions
Static approaches	Full dynamic approach (time sliced)
Traffic assignment	Mesoscopic simulation based on DUE
Network application	Dense complex urban network
Detection layout issue	Applying existing solutions
External resources	Plug-in based automatic implementation

3.1 Bi-level formulation

Bi-level formulation (presented in section 8.2.2) has been chosen in our methodology to allow heuristic approach. Traffic simulator (mesoscopic model) is used to achieve a Dynamic User Equilibrium and provides a representative and detailed assignment matrix for OD adjustment.

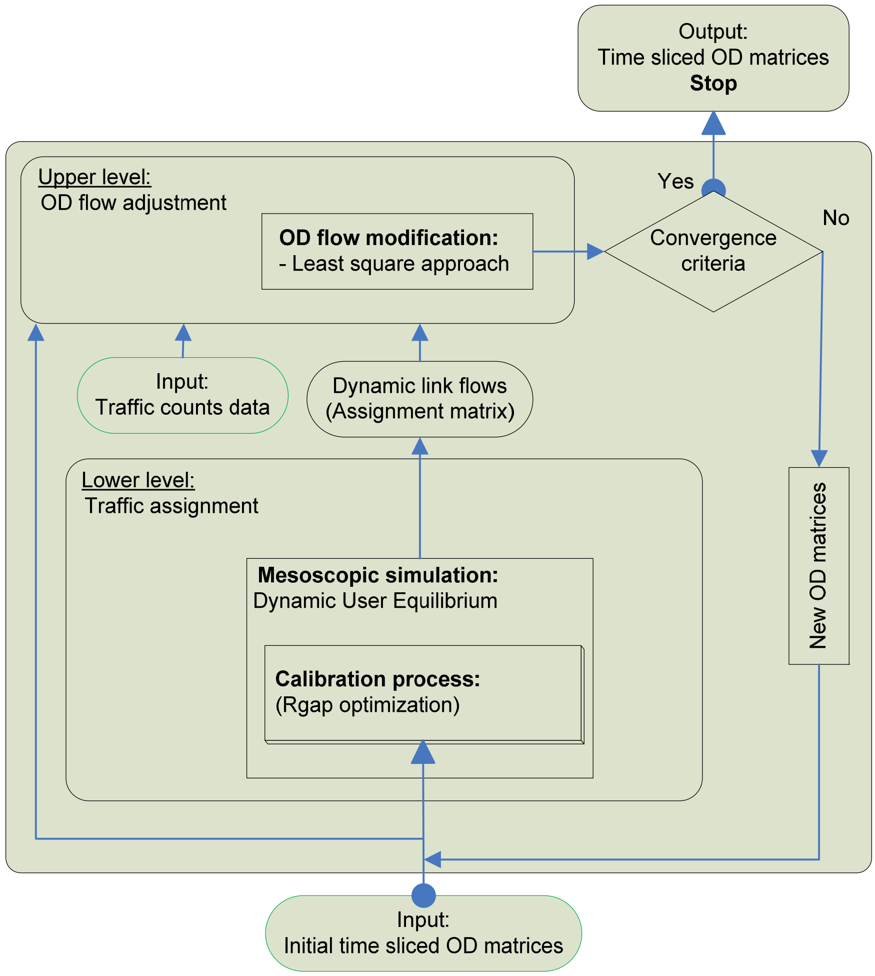
Lower – Upper level:
Bi-level formulation is dealing with OD estimation by interactions between Lower level and Upper level using iterations. Figure 3-1 presents a schematic illustration of the interaction between the assignment of the demand (Lower level) and the adjustment of the OD matrix (Upper level).

Figure 3-1 Traffic assignment / Flow adjustment



Based on this formulation, an innovative methodology is proposed to achieve dynamic OD estimation. Figure 3-2 shows the details of the bi-level mechanism in the proposed approach.

Figure 3-2 Detailed bi-level methodology proposed

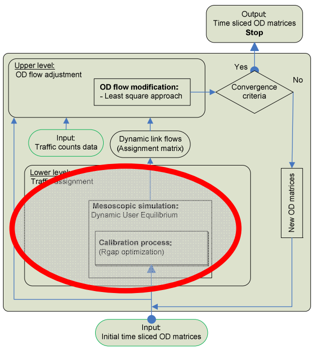


3.2 Lower Level

To improve the demand modeling, this study focuses on the distribution quality of the traffic in the network. This distribution has a strong influence on the utilization of the different roads depending on origins and destinations trips. The utilization of a simulation tool can allow an accurate and realistic modeling of the assignment. In the upper level problem, this route choice will be an input for OD matrix adjustment algorithms.

The aim of the lower level is to assign the demand to the network. To know how it is detected by traffic counts, paths between origin and destination for each vehicle must be determined. Using a simulator in the lower level allows performing detailed assignment in urban network taking into account dynamic evolution of the traffic, intersection controls, etc. with more flexibility and accuracy than analytical methods. Moreover, this method allows extraction of all the needed information useful for the process. Travel times, turn proportions, shortest paths, flows, etc. could be known for each location, vehicle and time interval.

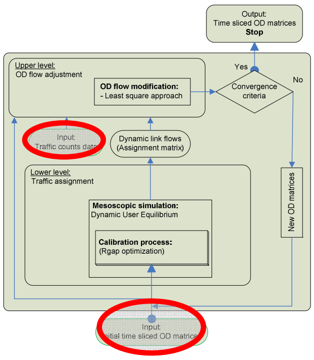
Figure 3-3 Presentation Lower Level



- **Process inputs**

As presented in chapter 2.1, inputs needed for OD estimation are initial OD matrices, traffic counts and of course a modeled network.

Figure 3-4 Presentation Process Inputs



Initial time dependent OD matrix is an important input of the system. In our case, initial OD matrix used as input is obtained from previous OD estimation using gradient approach ([87]) and extended to a time sliced OD matrix using observed flows in main arterials (see chapter 8.2.3).

Moreover, time dependent traffic counts (time sliced) at several places on the network (for optimal OD interception, see chapter 2.1.5) are indispensable for the matrix adjustment. This set of data are the points which reflect the real traffic conditions in the network and represents the matching points of the process, as presented in chapter 2.1.

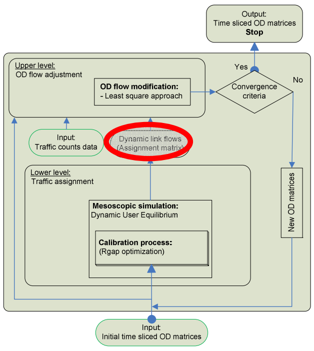
One step is the modeling of the road network. This task is dependent on the simulator use for the assignment. In our case, the network must be coded for mesoscopic study (links, junctions, traffic lights, etc.). Details useful for the modeling will improve the quality of the dynamic assignment in the network. More to the network modeling, the simulator need different parameters to provide consistent outputs. These parameters are related to the driver behavior or route choice model. At this step, these parameters must be fixed at a-priori values, usually common values associated to the type of network or obtain from a set OD data (historical or evaluated in another/previous study in the same or part of the network, with similar conditions). The calibration process (see 8.6.2) will estimate optimal parameters values.

Information and details concerning the choice and the utilization of a mesoscopic simulator to perform Dynamic User Equilibrium (network loading and traffic assignment) and the calibration task of the simulator are presented in chapter 8.6 in annex.

- **Outputs of the Lower level problem and conclusions**

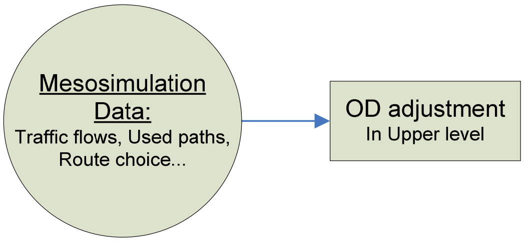
The simulation step results are clearly the utilization of the modeled road network by traffic demand. The path choice of each OD pair (assignment matrix) will be the input of the next step, the Upper level problem (see Figure 3-6).

Figure 3-5 Presentation Output Lower Level



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 (DUE) indispensable for the dynamic traffic assignment. Moreover, complex and large urban characteristics are fully considered.

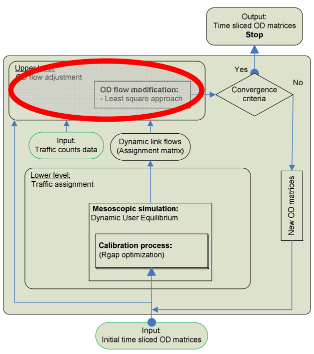
Figure 3-6 Data utilization by Upper Level



3.3 Upper level

The aim of the Upper level is to adjust each cell of the demand OD matrices based on initial reference matrices and traffic counts values.

Figure 3-7 Presentation Upper Level



The proposed methodology must find the best way to solve the Upper level problem. OD adjustment algorithm is going to minimize the gap between simulated data and actual data by modification of the OD flows used in the Lower level problem. OD adjustment could use various existing methods (least square approaches for instance), of course adapted to the constraints of the proposed approach.

In this research, several algorithms have been implemented and are presented in chapter 3.5. A first approach was carried out using Kalman Filtering (KF), but it has been abandoned for practical and computation reasons. This approach does not allow large network OD estimation (more explanations could be found in chapter 5.2). Finally, LSQR algorithm was chosen to perform an efficient OD adjustment in the proposed methodology.

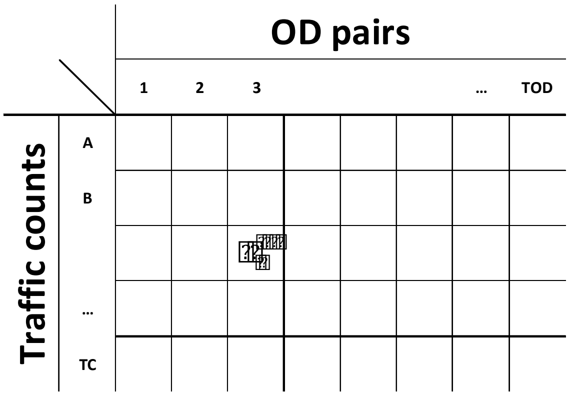
3.3.1 Assignment matrix

An assignment matrix is needed to provide information about the utilization of the network by users to adjustment OD flow process (see more details in [3]). It is computed by the Lower level, from the DUE assignment estimated by the Mesoscopic simulation. Indeed, from the assignment, each path is defined and therefore origin, destination and time period of the entrance into the network are known for each vehicle passing through detectors locations. Flows intercepted by these detectors are defined as the sum of the proportion of the different OD pairs passing thought detectors, as presented in Equation 1.

The assignment matrix is a matrix constituted by the totality of the a_i^{dn} for the different entrance and detected time interval (as presented in Figure 3-8).

Figure 3-8 Assignment matrix

For each Entrance time and detection time period:

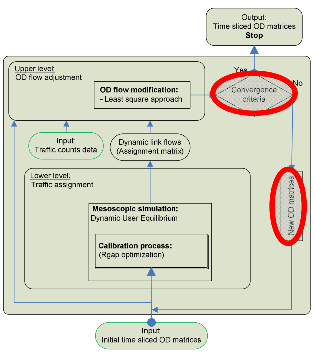


3.4 Stopping criteria

During our research, these stopping criteria's are secondary, because we need to analyze the behavior of the method even after the stabilization of outputs. A large number of iterations have been analyzed to see the evolution of indicators (see chapter 5).

Nevertheless, for a practical utilization of the approach, it is important to stop automatically the algorithm presented in Figure 2-3 and Figure 3-2. Stabilization of the results is an important characteristic which shows that the proposed solution reached an optimal solution. Moreover, to perform an efficient estimation for engineers, algorithm must do the minimum number of iterations which optimize the time consumption and the quality of the results.

Figure 3-9 Presentation Convergence Criteria



After satisfactory matching (between real and simulated traffic counts) using MSE indicators for instance, an evaluation of the convergence of the estimated OD matrix during iterations must be done compared to the results of the previous iteration. The following criteria have been implemented to stop iteration:

- **Criteria:**

Input parameters:
γ : fixed limit based on requirement
MM : number of value included in the average mobile

Sum of the maximum relative errors:
(ref. Manuel INRO Release 9, Chap 6 Algorithms, 6-3, [57])

Equation 2 Relative errors

$$max\left(\frac{T_i^{n,r+1} - T_i^{n,r}}{T_i^{n,r+1}}\right) \leq \gamma$$

With: T: OD flows, r: iteration, i: OD pair, n: time interval

Stabilization of the average mobile on flow differences is also considered:

Equation 3 Average mobile

$$\left(\frac{\sum_0^{MM} T_i^{n,r+1}}{MM} - \frac{\sum_0^{MM} T_i^{n,r}}{MM}\right) \leq \gamma$$

Minimum MSE on traffic count and matrix flows (summation of squared errors):

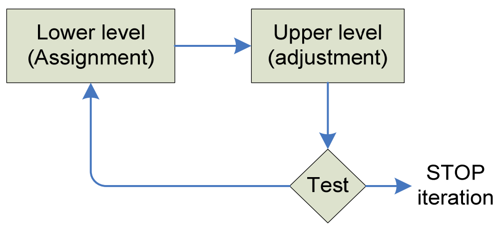
Equation 4 Mean Squared Error criteria

$$\frac{\sum_{\#E}\left(E_c^{sim} - E_c^{ref}\right)^2}{\#E} \leq \gamma$$

With: $\#E$, the number of value (traffic counts or OD flows), c index of value evaluated, the E_c^{sim} data from the simulation and E_c^{ref} reference data (initial or real data)

As presented in Figure 3-10, if convergence is not observed, the process goes back to the Lower level problem with the new estimated matrix to do iteration (Lower and Upper levels).

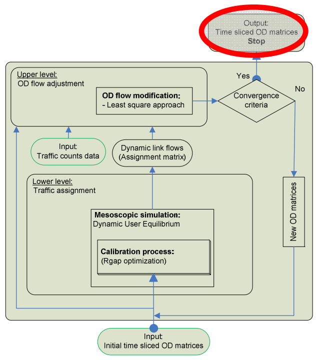
Figure 3-10 Iteration process



Others criteria could be also implemented based on the need on the study: MSE slope, GEH values, etc.

- **Outputs of the OD estimation process**

Figure 3-11 Presentation Output of the OD estimation process



If convergence criteria are satisfied, the result or output of the Upper level problem is an adjusted time sliced OD matrix. The OD matrix estimation process is over.

3.5 OD adjustment methods

OD adjustment problem could be solved using least square processes, entropy maximizing or maximum likelihood methods, for instance. Least square approaches present an interesting compromise between the inputs utilization and the solving complexity. The use of least square approach to solve the dynamic OD estimation linear problem has been originally proposed by Cascetta ([28]). In the approach proposed by Bierlaire and Crittin ([23]), they build-on their modeling framework by exploiting Ashok and Ben-Akiva ([4]) proposal of using deviation as state variables. In our case, a-priori (or initial) OD matrices are considerate as historical data and the estimation is working off-line, without prediction of the further states.

Several approaches have been tested in this work. After implementations and test, practical assets of each of these methods are presented (see global implementation in chapter 8.5 in annex). Detail description of the formulation of the model, and characteristics of the different approach chosen for OD adjustment (Kalman Filtering and LSQR algorithm) are presented in chapter 8.7 in annex.

3.6 Conclusions

Chapter 3 presents in detail the proposed methodology to estimate OD matrix in urban context. It has been developed to overcome limitations of the current methods, which are approach in front of time varying traffic and the low quality of the assignment in urban context. Thus, the proposed approach is bi-level and use:

- Mesoscopic traffic simulator to guarantee an accurate dynamic assignment
- Least square solution for OD adjustment process.

Indeed, Mesoscopic traffic simulator estimates Dynamic User Equilibrium which is the closest to the actual one for detail network models. Kalman Filtering and LSQR algorithms are presented for OD adjustment process. The later presents more abilities to deal with large urban networks. The global methodology has been implemented as a plug-in of a commercial tool (using SDK) to simplify and reduce the utilization cost of this new method.

4 Application - Cases

After theoretical development of the proposed innovative methodology, the global process has been coded as a plug-in of the AIMSUN software [11] (see 8.5 and 8.8 in annex). In this way, dynamic OD estimation using mesosimulation and least square formulation (Kalman Filtering and LSQR) are fully integrated in the commercial package. Few parameters must be defined as input of the process: constraint on OD flows (for LSQR algorithm), maximum number of iteration, minimum difference between iteration (criteria to leave the bi-level loop, see 3.4), etc.

Different tests networks are used to evaluate different aspects of the proposed methodology. From basic ones to complex and dense urban network with traffic controls and congestion, the applicability and the efficiency of the process is evaluated.

Special methodology is proposed to evaluate the quality of the outputs of the proposed approach compare to the common approach. As the goal of the OD estimation is to provide demand for traffic analysis, this methodology is assigning the estimated demand to analyze the traffic model's behavior. Moreover, different scenarios are performed to illustrate the practical competences of the approach.

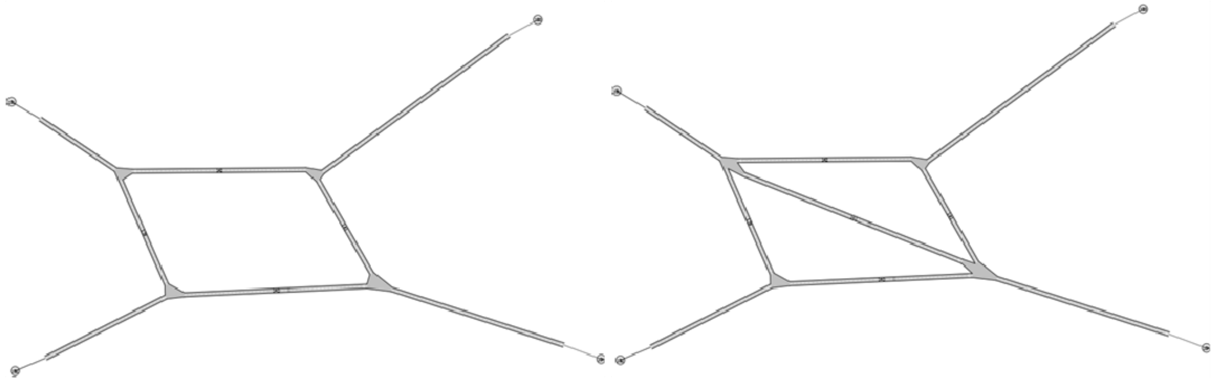
4.1 Test networks

4.1.1 Theoretical networks

To start, the reliability of the new methodology implemented is assessed. Very first networks have been built to run automatically the plug-in developed to execute the approach presented in the previous chapter. These networks are theoretical and basic but present usual route choice capabilities and all the needed characteristics to apply the method (time sliced demand, traffic counting values, etc.). The aim of this step is to check the proper functioning of the different steps of the methodology. This part mainly focused on verification of the implementation, good coherence and continuity between different stages of the process (data transmissions) and accuracy of the algorithms calculation.

Various different small networks have been used to improve the reliability of the code. Figure 4-1 illustrates the different basic shapes of network used for this step:

Figure 4-1 Theoretical networks



These networks have been designed to understand, capture and perform OD estimation in the best conditions. Simple demand is used with low number of origin and destination to minimize the size of the problem and the computation complexity. Nevertheless, this demand is fully dynamic. Route choice and delays characterize the assignment, and for these simple cases, all of the traffic is intercepted by the detection layout.

4.1.2 Dublin network

After the initial tests on the functioning of the process, OD estimation qualities and behavior are tested on more complex network. The different phases of the process are tested with a small urban network (Dublin city network, 5x5 to 7x7 OD matrices, see Figure 4-2). These first runs (several demand and supply scenario elaborated) will allow seeing influences of the different inputs of the bi-level approach chosen and the quality of the outputs. Indeed, the aim is to understand and evaluate the impact of each parameter of the algorithm (number of internal and external loops, variance-covariance values chosen, etc.). Moreover, this medium size network allows highlighting limitation of the Kalman Filtering implementation. Indeed, as presented in Chapter 5.1, even with this size of network (50 OD pairs), problems become very large and negatives flows could be proposed due to low flows values.

Figure 4-2 Dublin network

This network is coded to offer all characteristics of urban networks: traffic lights, route choice possibilities and dynamic demand. Moreover, congestion characterized by queues and delays could be observed. Several detection layout configurations have been tested to see the effect of added interception information in the assignment matrix.

"Dublin Min" with 15 traffic counts (TC) has the minimum number of detector to intercept 100% of the OD pair (boundary (2) in chapter 2.1.5). "Dublin H" (21 TC) and "Dublin H+" (25 TC) have more that the necessary number of detectors (between boundaries (2) and (3)) to assess the impact of these added detectors on the OD estimation process.

4.1.3 <u>Lausanne center network</u>

- **Description**

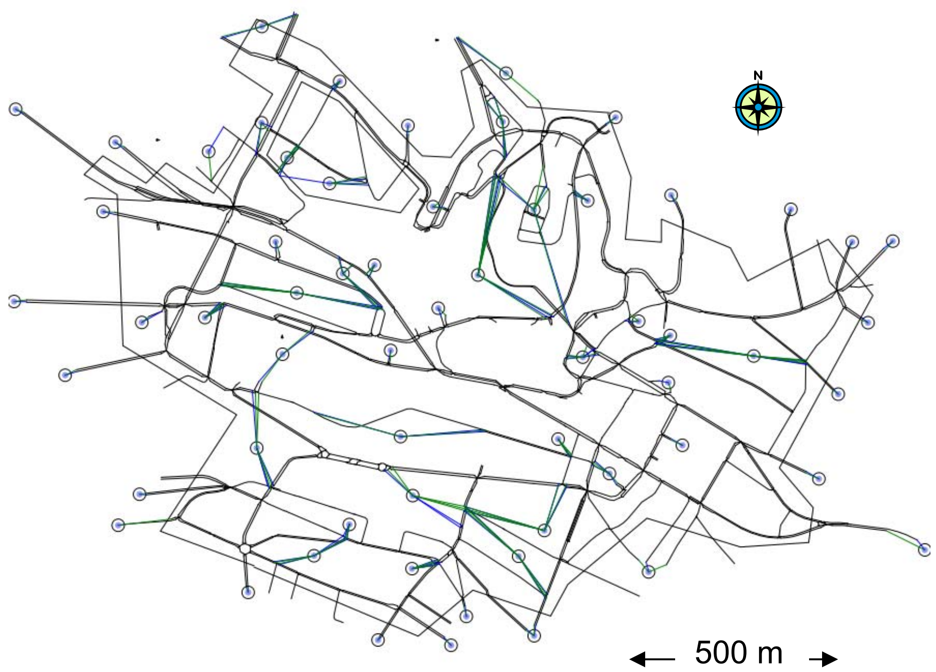
After the verification of the well process of the implementation, larger network must be used to assess full urban characteristics. Dynamic traffic demand, route choices, traffic signals and high-density road are particularities needed to evaluate the time dependant capabilities and urban features of the proposed methodology. The assignment part of the approach will be analyzed in the lower level (Rgap value convergence, calibration parameters and traffic characteristics). In the upper level, estimation of OD flow cells based on least square solutions proposed will be followed through periods and iterations.

Lausanne network has been chosen for several reasons. First, it is a typical dense and complex urban network, observed in many European cities. More, the network size is adapted for interesting route choice capabilities. Finally, this network is well known by the author. This feature helps to understand the global behavior of the process and is useful to identify no usual situations (see [17]).

- **Lausanne center network**

The city centre of Lausanne city (Switzerland) is a 2.5x2.5 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). Figure 4-3 presents the network considered with centroïds shown in blues dots and links shown in black.

Figure 4-3 ***Lausanne center Network***



This network is modeled using 60 zones or centroïds as origins and destinations. Therefore, OD matrix size is 60x60 (=3600 cells). It is constituted by 50 Km length section and 225 intersections (49 with traffic controls) as presented in Table 4-1.

Table 4-1 Lausanne centre Network

	City centre
# of sections	608
Total section length	50 Km
Total lane length	62 Km
# of intersection	225
Traffic lights	49
OD matrix size	60 x 60
# of OD pair/period	3'600
Average # trips/period	3'205
% of null OD pair flow	55
Rush hour traffic (veh/h)	≈ 13'000
Simulation time	16h45 - 18h15
Average density (veh/Km)	14.8
# of periods	6 x 15 min

- **Calibration parameters**

This network has been coded and calibrated during the SIMLO project [17]. Therefore, all parameters are known for vehicles, roads and route choice algorithms.

- **Traffic demand available**

Initial OD matrices have been obtained using static approach (common static approach, see Chapter 8.2.3). The one-hour Evening rush hour matrix is a transversal matrix of the larger Lausanne agglomeration network (more details in [17]).

Figure 4-4 informs about the structure of the matrices used. As the number of OD pair is large and the fact that it is an urban network, majority of them have no flow. The proportion of empty cell is 55 % (1943/3600). We can see, in Figure 4-4 that 90% of the cells have flows smaller than 2 veh/15 min and 75% of the total flow is provided by the 10% of cells, only.

Figure 4-4 Structure of the matrix SIMLO

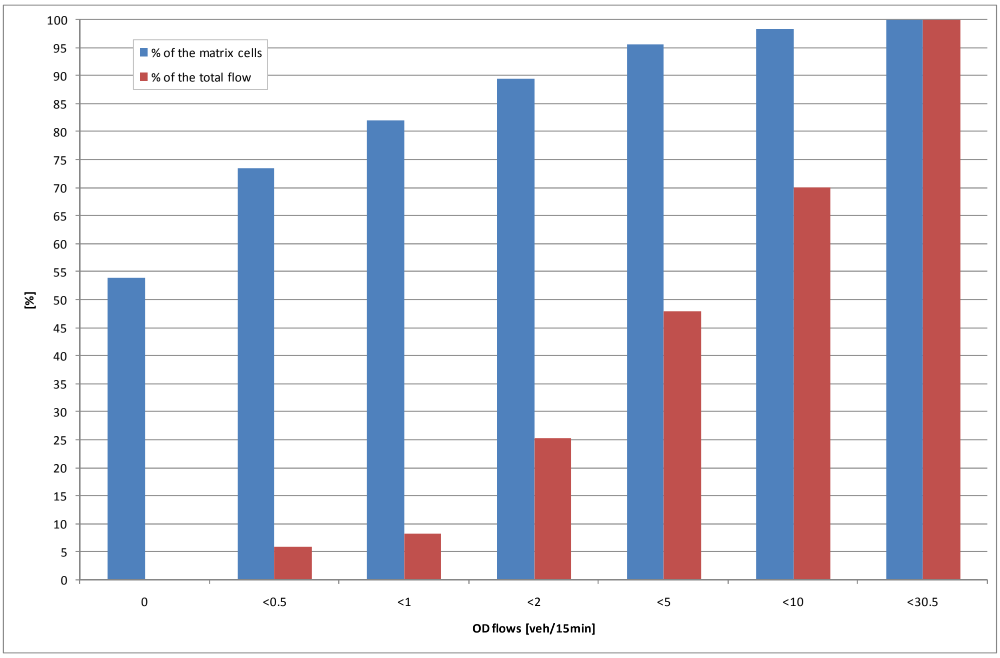
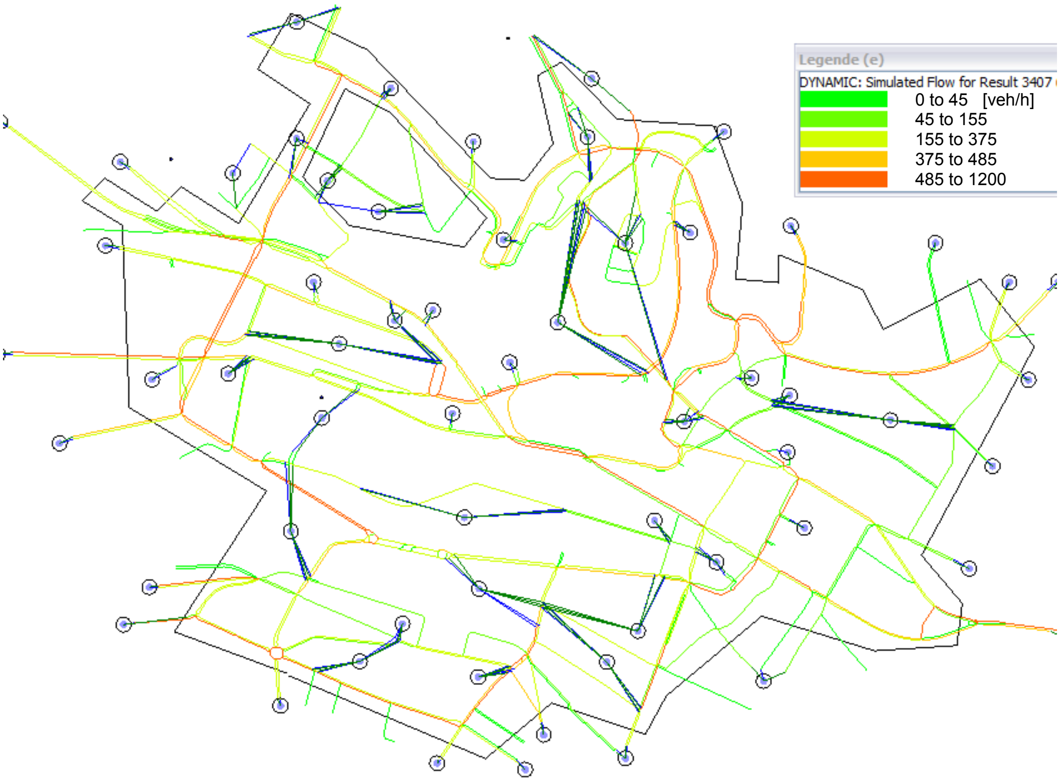


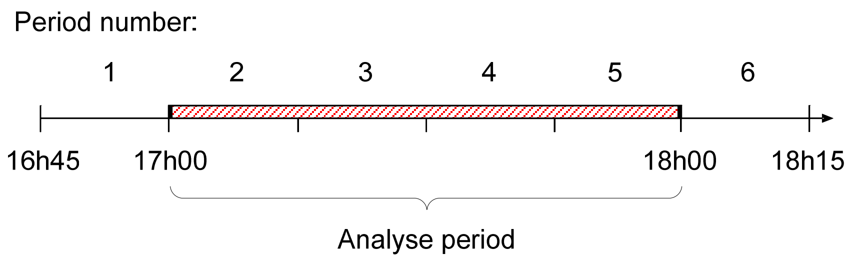
Figure 4-5 presents main flows into the Lausanne network (obtained using microscopic SRC assignment of the demand). It informs about main arterials used of the network. Links are colored based on flows observed (from green to red, as presented in the Legend in veh/h).

Figure 4-5 Main flows in the Lausanne network



Rush hour of this network is between 17h to 18h. For our study, we are interested in one-hour evaluation; nevertheless, in dynamic context, we have to take care of the loading and the un-loading of the network. Thus, we used 6 periods of 15 min, between 16h45 to 18h15 for load and empty the network before and after the time period studied, as presented in Figure 4-6 (based on first tests, analyze of the assignment matrix shows that one time period before and after the time study is enough for the concerned network).

Figure 4-6 Time period study



Period 1 (P1) is used to start the period study (analyze period, from 17h to 18h) with network loaded. Period 6 (P6) is useful to take into account vehicle included in the Period 5 (P5) demand matrix and passing at traffic counts positions during the next period. In this way, Period 5 demand could be fully adapted based on Period 6 traffic flows.

Therefore, time sliced OD matrices have been constituted based on the static one following the process presented in "Time slicing of traffic counts and demand" paragraph (on this page).

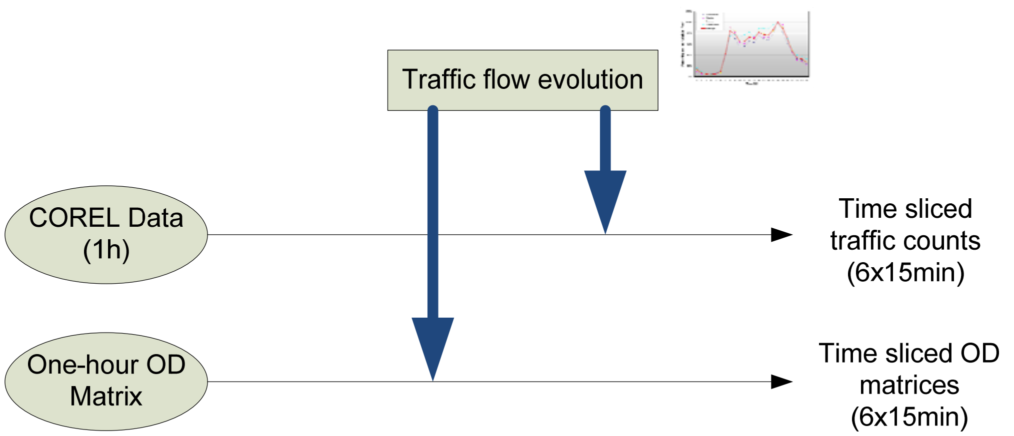
- o **Detection layout available**

Actual traffic counts available for this network are one-hour data for evening peak hour measured in 2000, and named COREL (presented in chapter 8.4 in annex). It consists in 51 detectors loop spread into the network with flow in vehicle par hour. These data have been adapted to time sliced traffic count using the same approach than the traffic demand (presented in the next paragraph).

- **Time slicing of traffic counts and demand**

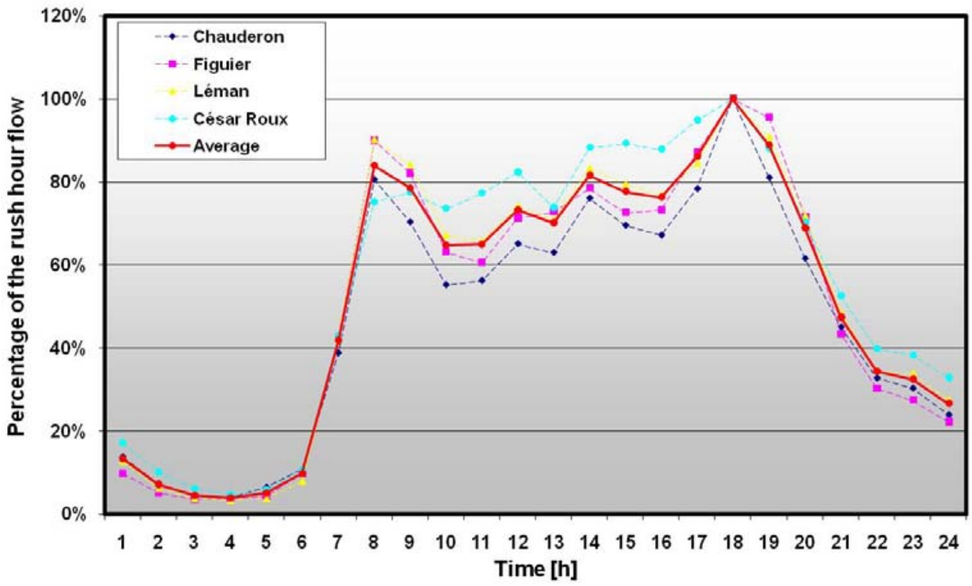
Only static data is available for this network. Therefore, traffic demand (one-hour OD matrix) and detector data (COREL flow values) must be split into 6 times 15 minutes period (according to the time period study, Figure 4-6) using dynamic flow curves of main arterials of the network. This methodology is presented in detail in [17] and summarized in Figure 4-7.

Figure 4-7 Dynamic extension of traffic counts and demand



Traffic evolution for few main arterial of the Lausanne center network is known using loops detectors (presented in Figure 4-8).

Figure 4-8 Traffic counts for main arterials



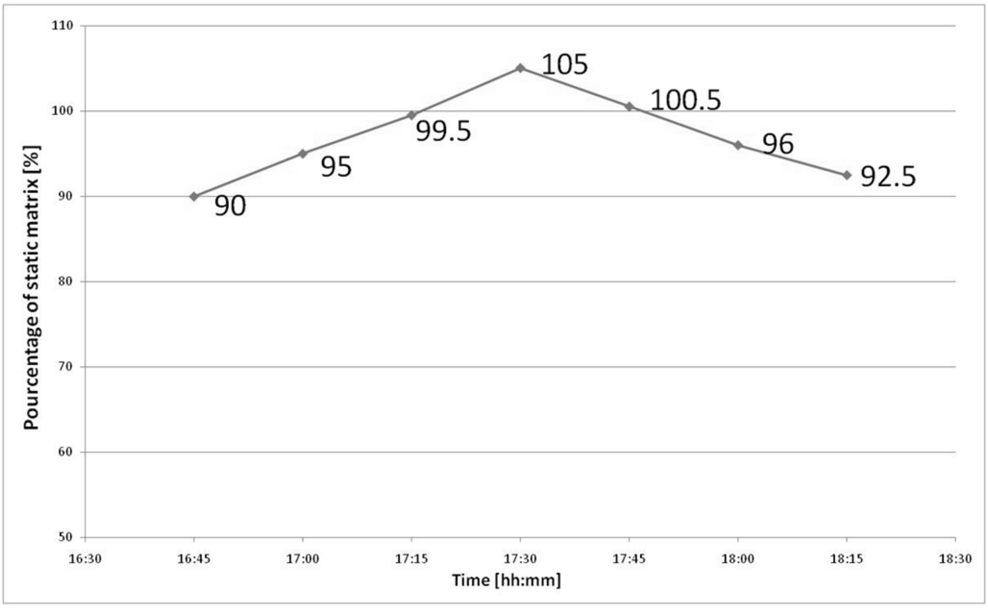
From these curves, proportion of the rush hour flows could be obtained for 15 min time interval by scaling (see Table 4-2).

Table 4-2 Fragmentation of the rush hour demand based on traffic counts

Time	%
16:15	82
16:30	86
16:45	90
17:00	95
17:15	99.5
17:30	105
17:45	100.5
18:00	96

According to the characteristics of the network, 100% of the matrix demand is observed between 17h to 18h. From this state, it is possible to create the dynamic evolution of the traffic between 16h45 and 18h15. Therefore, each time sliced is a percentage or scaling of the initial one-hour OD matrix and the succession of matrices make the demand time sliced, as presented in Figure 4-9.

Figure 4-9 Evolution of the demand

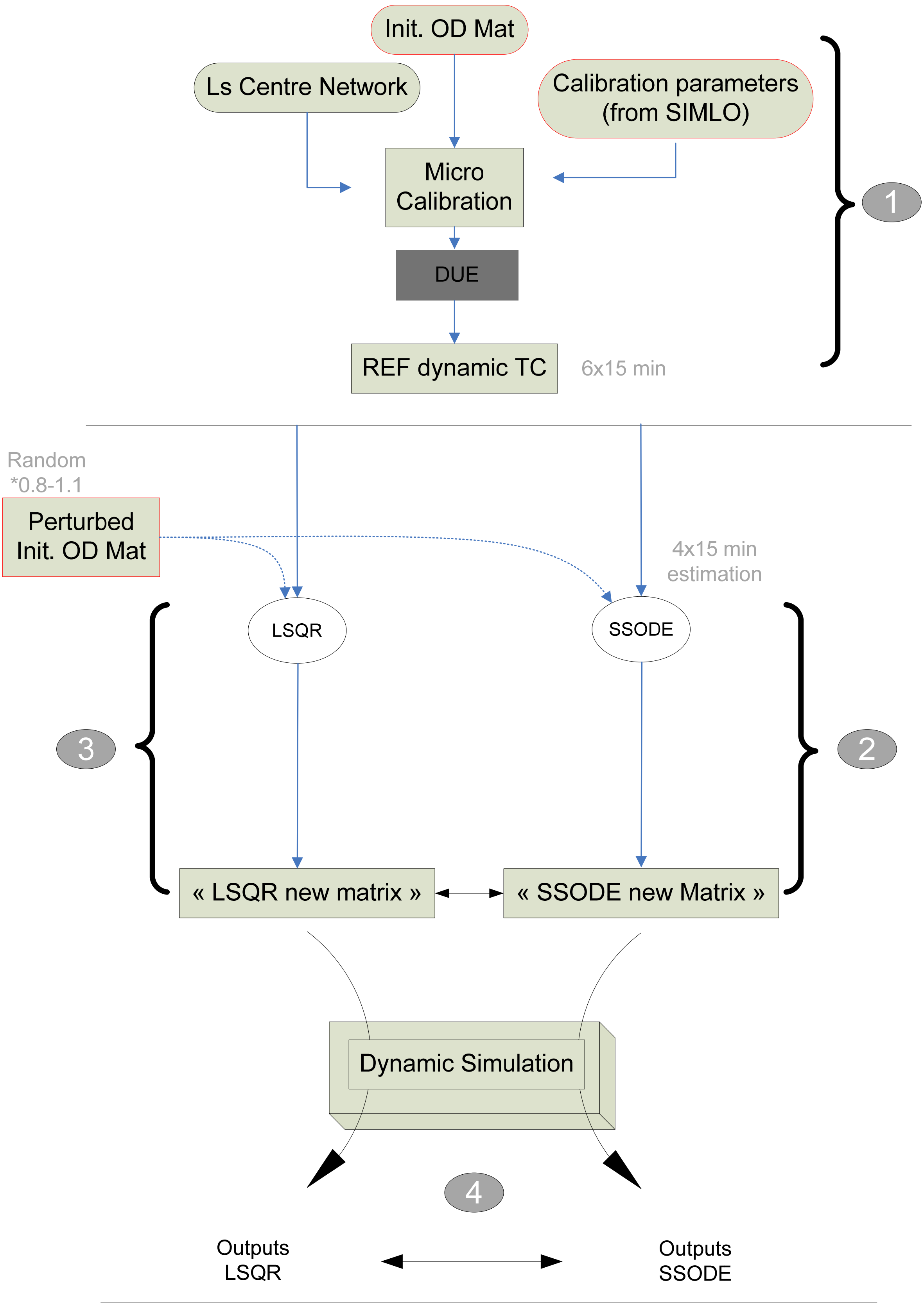


Results of this process are time sliced traffic demand (six scaled matrices, one for each period) and traffic counts (six flow values for each detector) which could be used for dynamic evaluation of the Lausanne network.

4.2 Applications of methodology

After presenting networks and data available, evaluation method must be developed to judge the quality of the new method and to illustrate the contributions of this research in the traffic simulation field.
After first verification of the KF and LSQR implementations using Dublin network, several scenarios have been developed to assess the methodology using Lausanne network (presented partially in Figure 4-10 for LSQR adjustment approach).

Figure 4-10 Evaluation methodology



- **Kalman Filtering adjustment implementation:**

Methodology implemented using Kalman Filtering algorithm for OD adjustment is evaluated to assess its performance and limitations.

- **Real case OD estimation[6]:**

Real case data input is studied to show the applicability of our approach (based on LSQR algorithm) in various situations (see chapter 4.2.2). More information and results are presented in the chapter 5.4.

- **REF case 1:**

Real case application shows the applicability of the proposed methodology, however, quality of the input data is not sufficient (data collected in different years) to evaluate fully assets of the proposed approach. It is important to go a step further using a more detailed and equipped network. It is the motivation for the utilization of a case as "reference" (REF) to have in-depth evaluation of the results (see 4.2.3).

Using traffic counts obtained from the REF case and a perturbed version of the demand (Pert. SIMLO OD), and in parallel, LSQR and the SSODE approaches perform OD estimation to compare differences in outputs.

- **SSODE 2:**

Sequential Static OD Estimation (SSODE) consists in static OD flows estimation for each time interval of the time period. This approach represents the most common practice to perform OD estimation (see chapter 4.2.4).

- **LSQR 3:**

LSQR task consists in performing OD estimation using the proposed approach presented in chapter 3. Outputs of the process are compared with the usual process for OD estimation (see 4.2.5).

- **Evaluation 4:**

The last box of the Figure 4-10 illustrates the evaluation of outputs (OD matrices) from both approaches, and compare to the REF case, using a dynamic simulator tool (see 4.2.6).

- **Practical application[7]:**

Various scenarios have been developed to assess capabilities of the methodology to deal with practical situations (see chapter 4.2.7).

[6] No represented in Figure 4-10.
[7] No represented in Figure 4-10.

Table 4-3 summarizes the terminology used in the report for inputs and outputs of the different case studies:

Table 4-3 Experiment terminology

	Real case	REF Case	SSODE Case	LSQR Case
Demand	SIMLO OD Matrix	SIMLO OD Matrix	Pert. SIMLO OD Matrix	Pert. SIMLO OD Matrix
Traffic counts	COREL 6x15	-	REF TC (6x15)	REF TC (6x15)
Calibration Parameters	SIMLO	SIMLO	EMME/2	REF
Outputs	"Real new Matrix"	REF TC (6x15)	"SSODE new Matrix"	"LSQR new Matrix"

It is important to note that different affectation solutions are used in the methodology presented: Traffic assignment using microscopic DUE for creation of the REF case, macroscopic UE in the SSODE, mesoscopic DUE in the LSQR and evaluation of the output using microscopic SRC. This choice is voluntary to be the most objective possible in front of the different methods evaluated and of the evaluation approach. Nevertheless, differences in assignment can be observed due to these various approaches (see chapter 5).

4.2.1 <u>Kalman Filtering implementation tests</u>

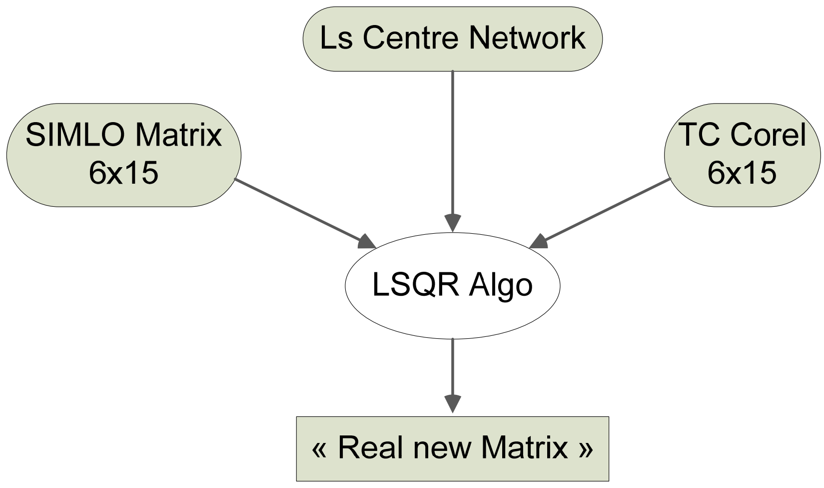
Dublin network has been used to perform tests on using the Kalman Filtering algorithm (see chapter 4.2.1). Results are presented in chapter 5.1. Based on these results, the author has decided to use LSQR approach to overcome limitations of this approach for the rest of the study.

4.2.2 <u>Real case OD estimation</u>

Methodology proposed (using LSQR algorithm) must be tested on real conditions. It means using available data of the Lausanne network time sliced SIMLO OD matrix (15 min periods) and COREL traffic count (6x15min). Indeed, in many cases, only partial and non-accurate data are available for a particular network.

From this test, we can show it is applicable on real world and it allows highlighting lacks and weaknesses of the input data.

Figure 4-11 OD estimation; Real case approach



Different parts of the Figure 4-11 are presented now:

- **Data used**

Network used is Lausanne Centre (as presented in previous chapter) coded in the SIMLO project [17]. Traffic demand used is evening rush hour OD matrix from the same project, extended to 6 periods of 15 minutes as presented in "Time slicing of traffic counts and demand" paragraph. Traffic counts used for OD estimation are also extension of the COREL data for 51 detector positions. Results and remarks concerning the "Real new Matrix" obtained are presented in chapter 5.4.

4.2.3 <u>Reference (REF) case creation</u>

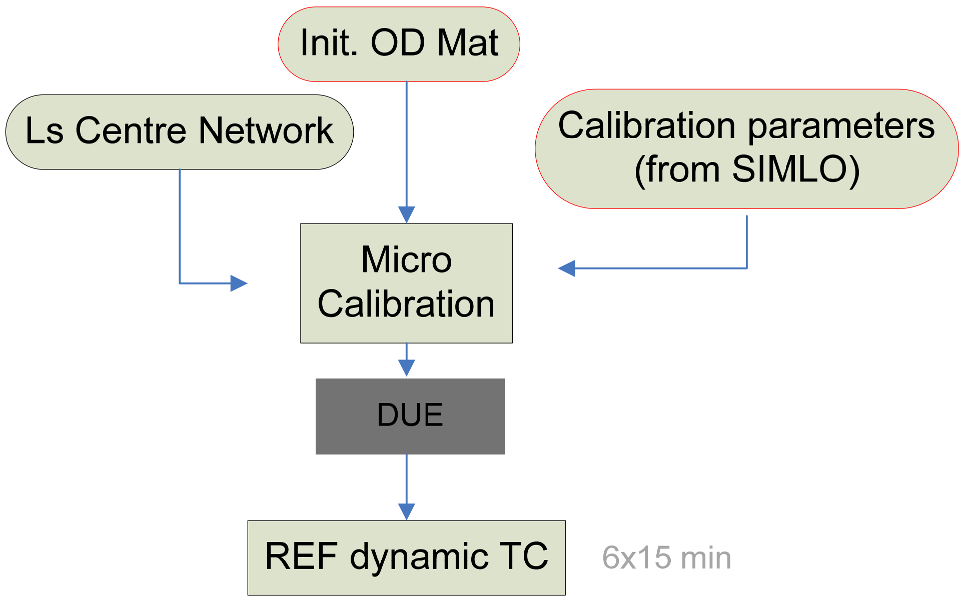
Results from real case have shown the applicability of the proposed methodology (see chapter 5.4). Nevertheless, inputs data quality is not detailed enough to allow full and in-depth analyses of the process outputs. In this way, a "reference" (REF) case is elaborated to generate all needed information for complete evaluation of the OD matrices estimated.

This approach is similar to method developed and explained in [104] to generate extra traffic information. Microscopic DUE assignment is performed to guaranty the best equilibrium and extract as much as traffic data needed. In this way, consistent time sliced traffic counts in various places could be used as inputs for the evaluation of the OD estimation process on the Lausanne Centre network. Moreover, various traffic data (as speed, density, travel time, etc.) can be extracted from this REF case to compare assignment using SIMLO OD matrix and estimated one using new approach.

For the REF case creation, it is important to keep in mind the consistence and the representativeness of the approach. Data available for this network are OD matrix (time sliced SIMLO OD matrices) and traffic counts (COREL). Unfortunately, both data were collected in different years and thus do not match well. Therefore, one or the other must be evaluated to achieve a consistent simulation of the reference case. One option consists in performing a complete OD estimation to obtain OD flows corresponding to measured traffic counts (using LSQR, SSODE or Furness [50] approaches, for instance). Another option to tackle the problem is to adapt the second input, traffic counts. That is using OD matrix and calibration parameters (from the SIMLO project) to generate corresponding traffic counts.

Therefore, to avoid using one or the other OD estimation method which will be also used later in the evaluations (LSQR or SSODE approaches) and taking into account the low quality detection layout of COREL data (due to un-adapted detection location choice and therefore problems of OD interception), the author decided to use SIMLO OD matrix and known calibration parameters to generate the reference case. In this way, approach is consistent (between matrix and new traffic counts obtained) and representative (using "known" data, OD flows and parameters obtained from previous study).

Figure 4-12 REF case creation



Different parts of Figure 4-12 are presented below:

- **Data used:**

Network used is Lausanne Centre. Traffic demand used is evening rush hour OD matrix from the SIMLO project, extended to 6 periods of 15 minutes. Calibration parameters used for that REF case are exported from the calibration of the network done during the SIMLO project.

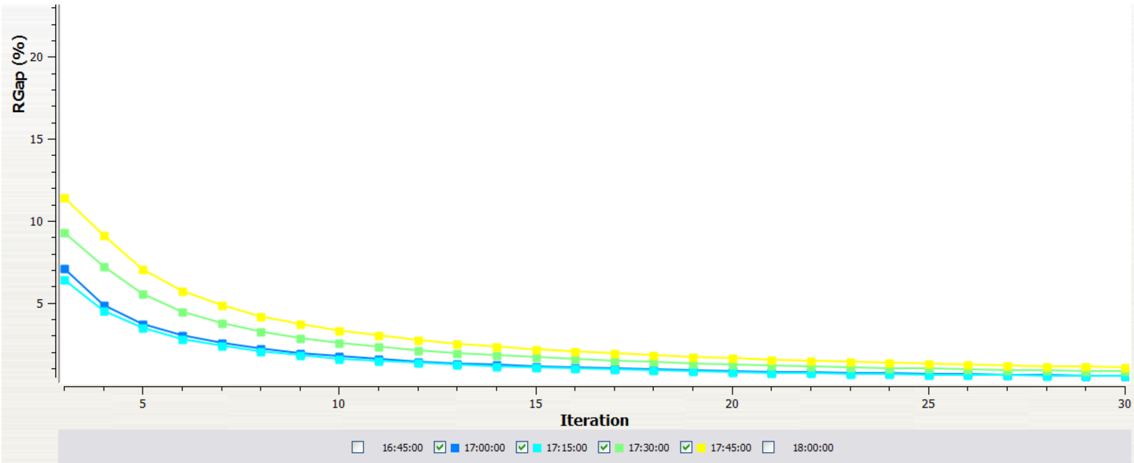
From these input (network, demand and calibration parameters) a microscopic simulation (DUE based) has been performed to generate traffic characteristic as reference for the network.

- **Reference case traffic situation**

The aim of the REF case is to create a realistic and consistent database of traffic information. In our case, dynamic traffic counts in various places are inputs indispensable for OD estimation, but other types of information are useful to compare the behavior of the estimated OD matrices with the reference ones.

Evaluation of the equilibrium obtain in the reference case using Rgap indicator (see Equation 8) informs about the quality and the representativeness of the dynamic utilization of the network by vehicles.

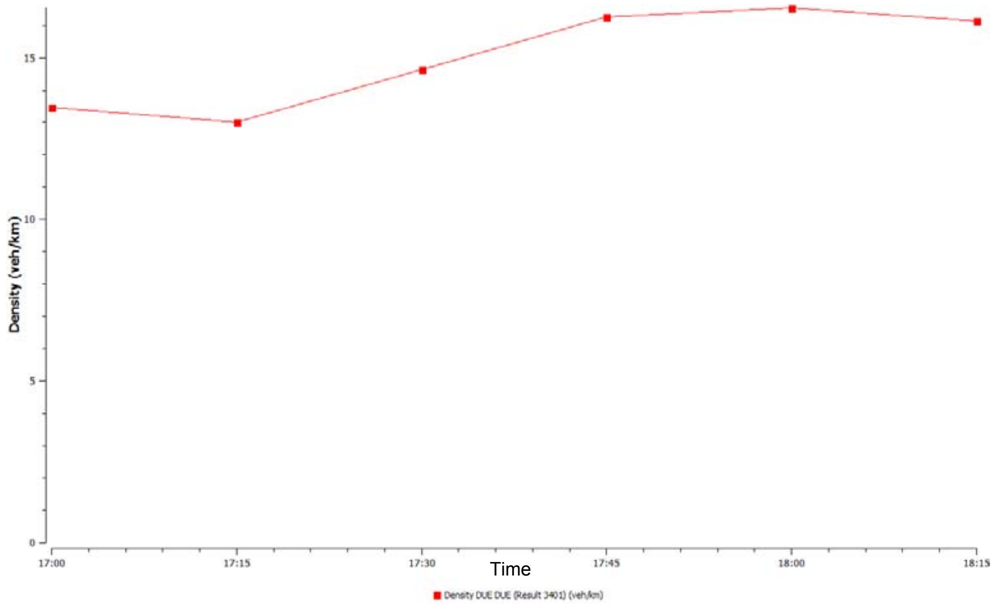
Figure 4-13   Rgap evolution of the REF simulation



Rgap evolution obtained from the simulation is quite satisfactory (below 5 for all the time period). Therefore, based on the traffic demand and calibration parameters, we can conclude that a dynamic user equilibrium which minimize users travel time through periods has been obtained.

Concerning traffic situation, we can see in Figure 4-14, the evolution of the density, the flows and the delay observed during the simulation.

Figure 4-14 Flux, Density and Delay evolution for REF case



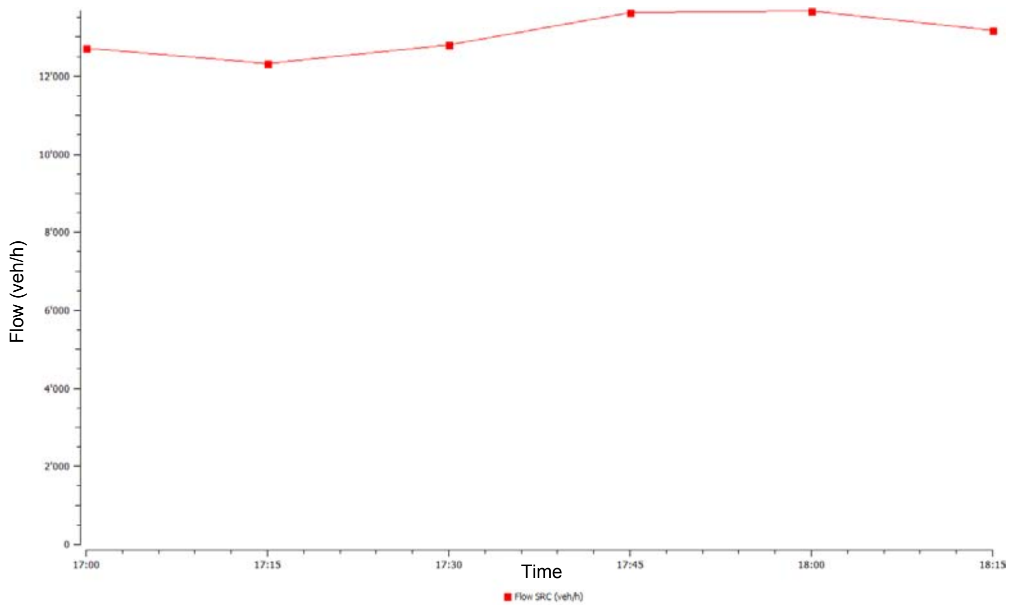
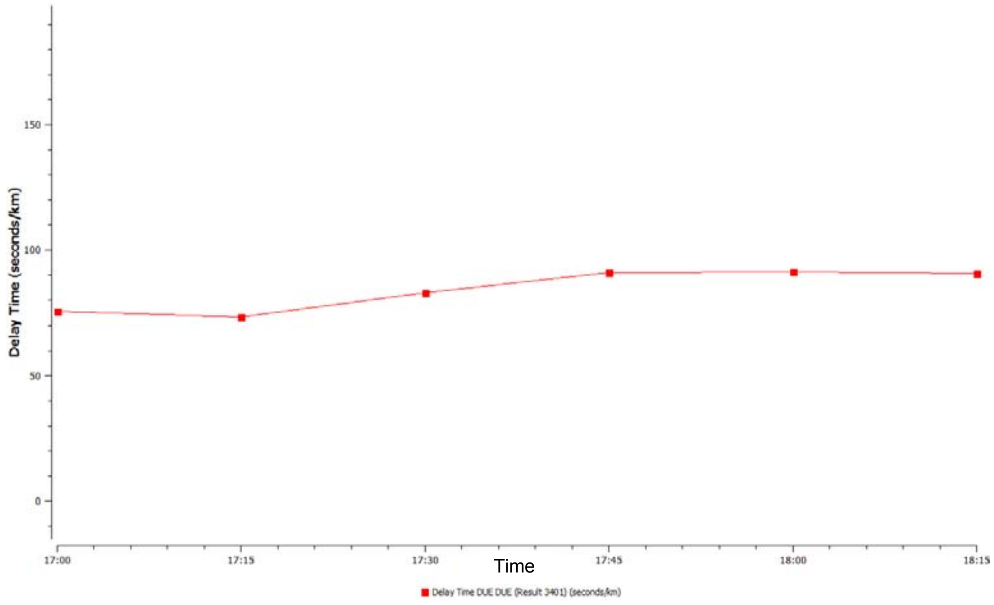


Figure 4-14 Flux, Density and Delay evolution for REF case



This information guaranties the normal process of the simulation, without excessive congestion or collapse of part of the network. Unload of the network is normally observed after 18h (following the demand volumes).

Table 4-4 Main characteristics of REF simulation

Simulation duration	5'400	s
Mean flow	13'057	veh/h
Average density	15	veh/Km
Mean speed	26.1	Km/h
Mean travel time	156.8	s/Km
Mean delay time	84.5	s/Km
Mean Stop time	72.2	s/Km
Number of Stop per veh	2.8	#/Km
Km travelled	31'886	Km
Travel time experimented	4'947'237	s

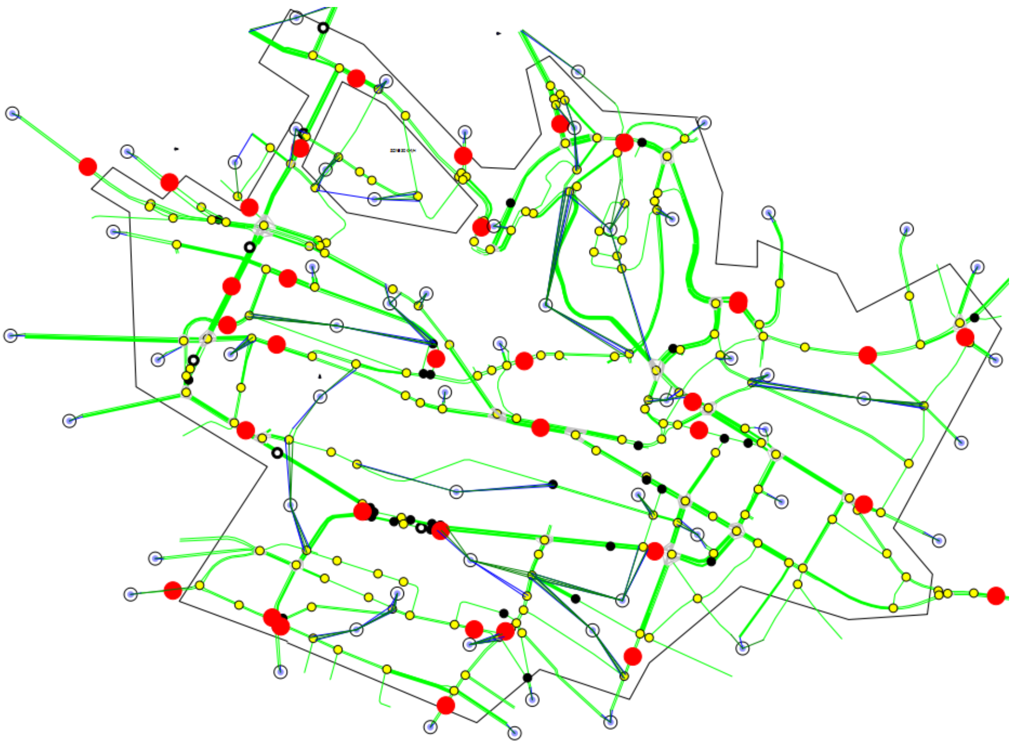
Table 4-4 presents main indicators of the DUE simulation. From this table, we can conclude that the network is reasonably congested. Vehicles cross the network on an average of 5 minutes and the average speed, number of stops and density is coherent with usual urban traffic conditions.

- **Detection layout of the REF case**

Using the simulated reference case, traffic counts data could be obtained for each links. For OD estimation, detection layout configuration must be defined to intercept maximum of OD pairs flows (see chapter 2.1.5). From the structure of the demand used as input (presented in Figure 4-4), it is crucial to choice in an optimal way the position and the number of the traffic counts. Author proposes to use the algorithm developed by Gilliéron ([52]) to obtain the optimal position of the traffic counts. It has been decided to intercept 95% of the OD pairs (non-null OD pair flows) and 95% of the flows in our case.

Based on these parameters, the algorithm proposes 35 detectors into the Lausanne network (see positions in Figure 4-15). Therefore, for these 35 links, 6x15 min traffic counts values are extracted for OD estimation and called "REF TC".

Figure 4-15 Optimal detector configuration for Lausanne network



- **Perturbed traffic demand**

To simulate low quality or perturbed input demand used as initial OD matrix for the OD estimation process and therefore utilize a in-perfect initial point as in real case application (updating of older one or inexact matrix), the SIMLO OD matrix has been perturbed by multiplication of each cell of the SIMLO matrix by a random number between 0.8 and 1.1. This set of six matrices is called Perturbed matrix- "08-11".

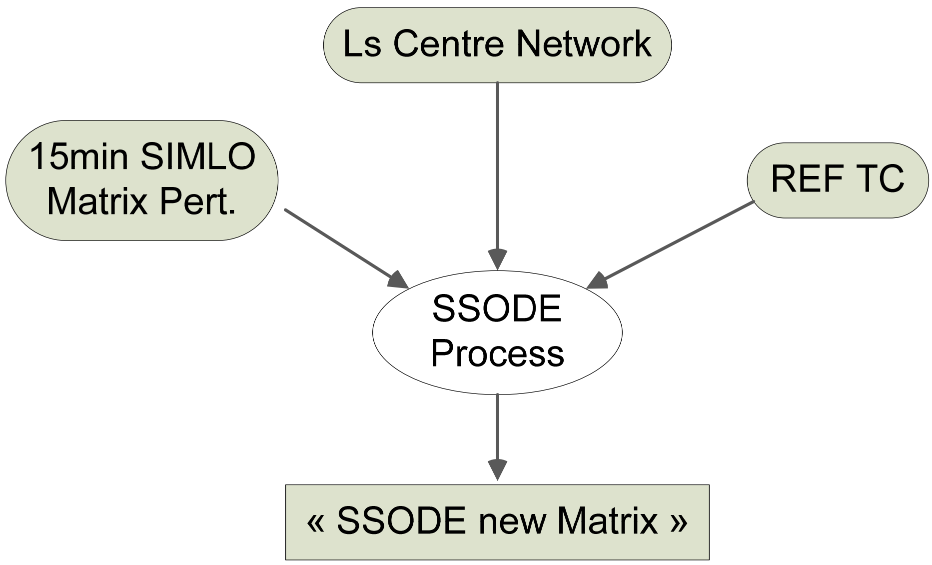
4.2.4 SSODE case application

To compare results of the proposed approach, Static Sequential OD Estimation (SSODE) using the EMME/2 software (see [57]) is performed. In this way, outputs of this approach could be considered as the comparison point (point which must be improved) to judge the quality of the outputs of the new proposed OD estimation approach. Therefore, a network has been developed based on the same GIS data and presents the same characteristics as SIMLO network: number and position of links, links length, number and position of intersections, movements at intersections, number of lanes, number and links with centroïdes, etc.

Of course, due to the static approach of the SSODE process, four different OD estimations have been executed, one for each period considered in the time study (periods 2 to 5). In this case, periods 1 and 6 (presented in Figure 4-6) are not taken into account. Indeed, the static character of this approach does not allow propagation of the traffic through time intervals. As presented in Figure 8-12, each period is independent and there is no influence of the traffic of one period to another.

To avoid bias in the application of the SSODE method using the EMME/2 software, an expert user (Mr. J.-P. Levraz, EPFL-TRANSP-OR) of this package did this part in the usual way. Outputs of these estimations are provided to the author to perform an objective evaluation of the corresponding matrices.

Figure 4-16 OD estimation; SSODE approach



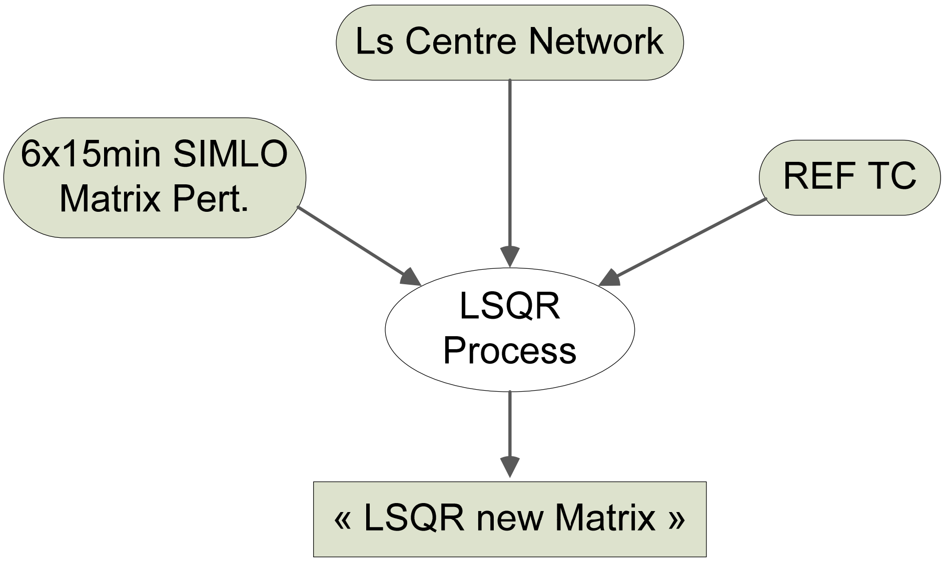
- **Data used**

REF traffic counts and perturbed OD matrix is used, as presented in the Figure 4-16.

4.2.5 LSQR case application

In parallel of the SSODE approach, the proposed methodology (called LSQR, due to the utilization of the LSQR algorithm for OD adjustment) is tested using same inputs. In this case, the method used is dynamic. Therefore, six periods are considered to take into account the propagation of the traffic as presented in Figure 4-6.

Figure 4-17 OD estimation; LSQR approach

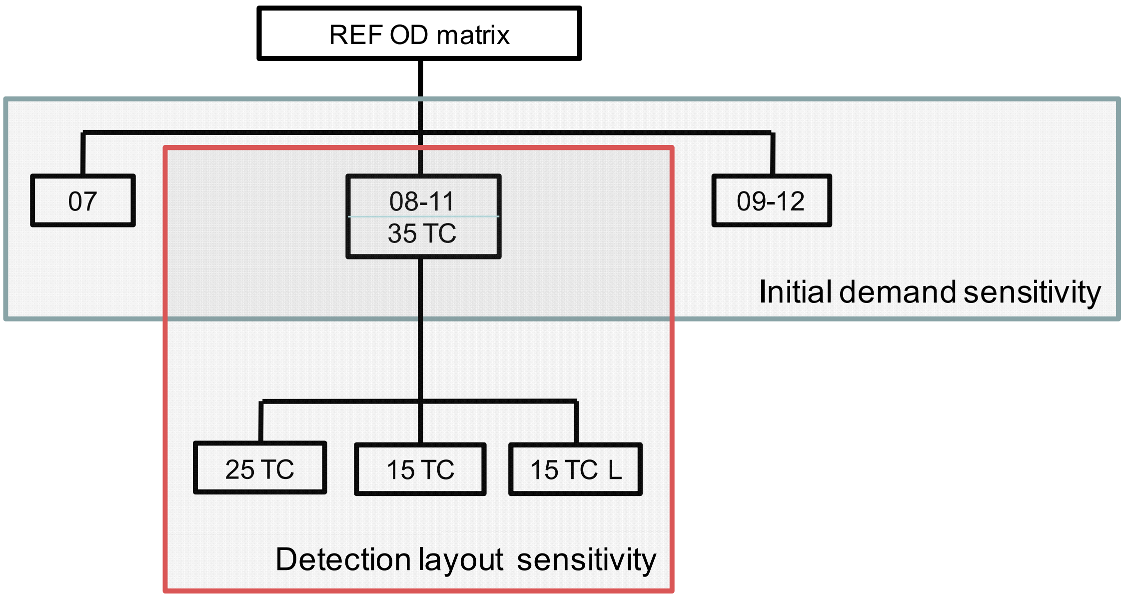


- **Data used**

Data used as input are similar to ones used in the SSOED case. Perturbed matrix and REF TC are used but defined from period 1 to 6 in this case.

Moreover, to evaluate influences of inputs of the process, a sensitivity analyses have been developed, as presented in Figure 4-18. Initial perturbation of the OD matrix and the number and the quality of detector layout has been modified. Results and more details are presented in chapter 5.5.2.

Figure 4-18 Sensitivity evaluation



4.2.6 Outputs evaluation

Evaluation part of the Figure 4-10 presented by the box "Dynamic simulation" is a crucial step to assess the quality of the demand estimated. Indeed, the first goal of OD estimation is to produce demand which could be used as input for detailed dynamic traffic studies. In this way, even if this demand is not perfectly matching the real one, the goal is to obtain relevant outputs after utilization of this demand by traffic models.

REF traffic conditions from dynamic models are compared with traffic conditions obtained with SSODE and LSQR demand. Simulations performed at this step are microscopic and based on Stochastic Route Choice assignment (the most common approach for detailed dynamic studies). Ten replications are performed to compare average behavior of the traffic simulation. Results are presented in chapter 5.5.4.

4.2.7 Practical applications

- **Scenario 1:**

Effect of a time varying attraction augmentation in a particular area is evaluated. OD matrices estimated and traffic modifications into the network are detailed to highlight benefit of the methodology.

- **Scenario 2:**

Local incident induce closing of road for 10 minutes during the evening rush hour. From that statement, REF case demand and "LSQR New Matrix" are assigning using microscopic simulator and results are analyzed to assess reliability of the estimated demand to represent realistic traffic situations.

4.3 Conclusions

Chapter 4 focuses on test networks and methodology used to evaluate the proposed method results. Different sizes and complexities of network are used to understand, develop and verify the dynamic OD estimation process. Final network is a large and complex urban network which has the typical urban characteristics needed to perform challenging demand estimation (high number of centroïds, complex route choice possibilities, high level of traffic controls, etc.).
Due to low quality data available for this network, a particular framework has been developed to allow accurate and consistent evaluation and comparison between outputs of proposed approach and most used method. Sensitivity analysis is presented to evaluate effects of different inputs for the OD estimation process. An important aspect of this evaluation is the comparison of the quality of outputs of utilization of the estimated demands. Demand is estimated for utilization by models to generate traffic conditions useful to understand traffic patterns into networks. In this way, evaluation of this traffic conditions based on demands estimated using different approaches informs about the quality of these estimation processes. Finally, practical

realistic scenarios have been developed to assess the applicability and consistency of the proposed methodology.

5 Results, Discussions and Applications

After presentation of the innovative proposed methodology in Chapter 3 and the evaluation process developed in chapter 4, the results obtained based on the new approach are detailed in this chapter.

- **Results steps**

In a first step, the Dublin network is used to assess capabilities and highlight restrictions of Kalman Filtering algorithm for OD estimation.

Second step consists of verification of the implementation and the working of the proposed LSQR method (based on LSQR algorithm). Dublin network is used to spot the good behavior of the methodology in front of various input configurations.

Third step consists of presenting results of the methodology based on available data of the Lausanne network. Outputs are shown and limitations of this case study are highlighted: low input data quality induces difficulties to assess the methodology. For these conclusions, in-depth evaluation of the proposed method is performed on a "reference" case. Outputs of LSQR approach are compared with sequential static common approach used by practitioners (SSODE). Two sensitivity analyses focusing on initial traffic demand and detection layout configuration are also performed to assess the robustness of the proposed approach.

Step five evaluates the capabilities of the OD matrices obtained using both method (LSQR and SSODE) to reproduce traffic patterns in case of utilization of these demand in a traffic simulator.

Finally, practical applications are assess based on the proposed methodology to demonstrate its applicability to deal with realistic problems.

- **Preliminary remarks**

As can be seen in figures, Periods 1 and 6 are not considered and not presented in results of chapter 5. As presented in chapter 4.2.5, these periods contribute to the loading and unloading of the network in dynamic case for the period study (periods 2 to 5) and do not represent the traffic demand estimated.

In the next graphs of chapter five, distance between the reference matrix/traffic count and estimated ones are evaluated using: Mean Square Error (MSE) indicator (Equation 5) and Mean Error (ME) indicator (Equation 6).

Equation 5 MSE formulation

$$\mathrm{MSE} = \frac{\sum_{\#E}\left(E_c^{sim} - E_c^{ref}\right)^2}{\#E}$$

Equation 6 ME formulation

$$\mathrm{ME} = \frac{\sum_{\#\mathrm{E}}\left(E_c^{sim} - E_c^{ref}\right)}{\#\mathrm{E}}$$

With: $\#E$, the number of measurements, E_c^{sim} data from the simulation and E_c^{ref} reference data (initial or real data). MSE indicator informs about the square of the error which penalize large errors and ME informs more about the sign of the error.

5.1 OD estimation Plug-in presentation

Methodology proposed in chapter 3 has been implemented as a plug-in in the commercial traffic simulation software AIMSUN (TSS). Following pictures are presenting the integration and utilization of the process in the software. Figure 5-1 illustrates the main window of the AIMSUN software after load of a specific network (Lausanne network, in this case).

Figure 5-1 AIMSUN software main window

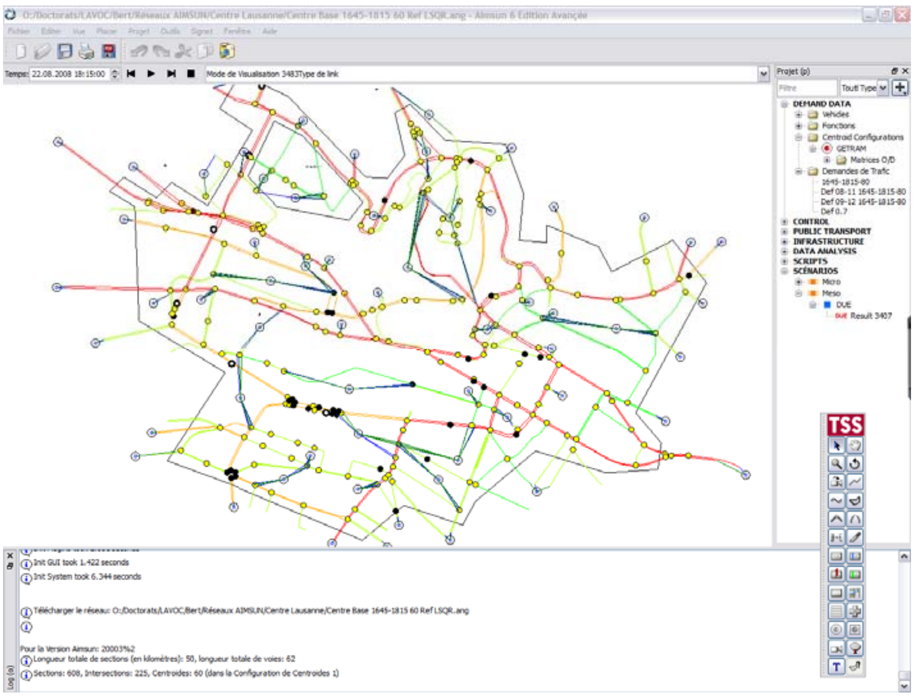
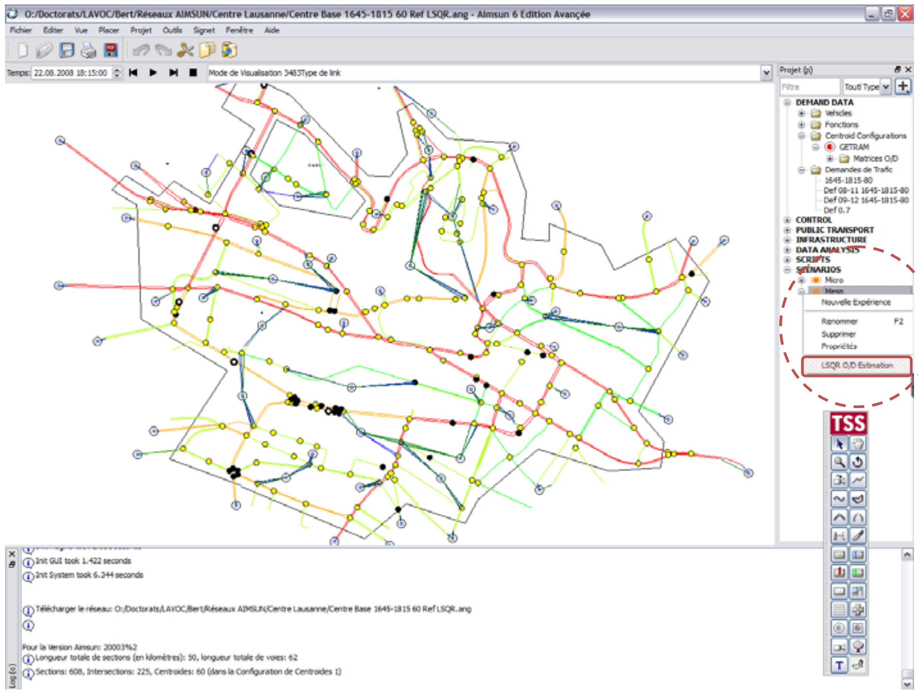


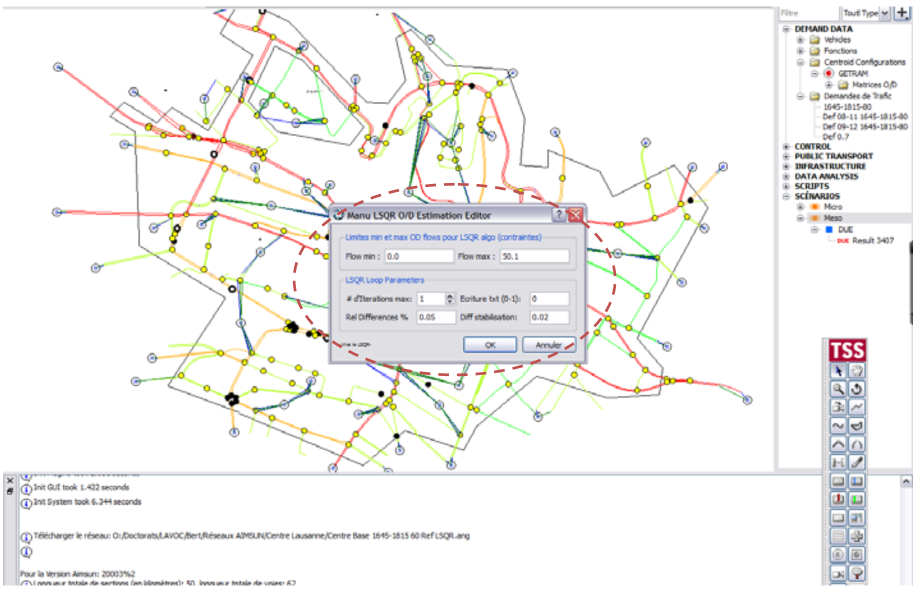
Figure 5-2 presents the new menu line included in the original scenario menu.

Figure 5-2 Plug-in menu (LSQR O/D Estimation)



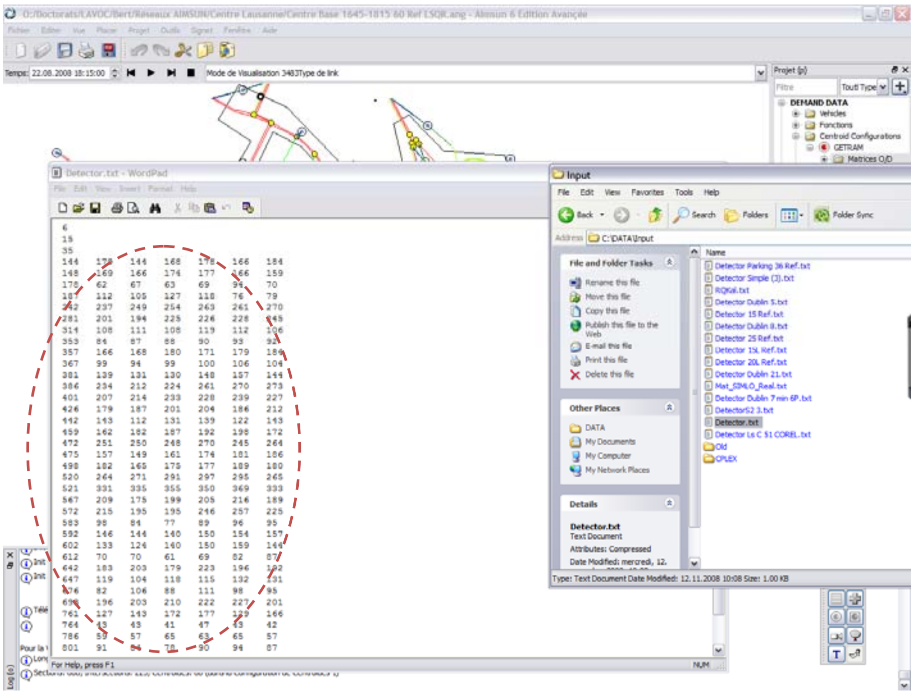
From that new function, the specific OD estimation box (see Figure 5-3) allows setting of the different parameters of the process. (OD flows constraints, number of iteration, detail of the information stored, and stopping criteria)

Figure 5-3 LSQR plug-in Box



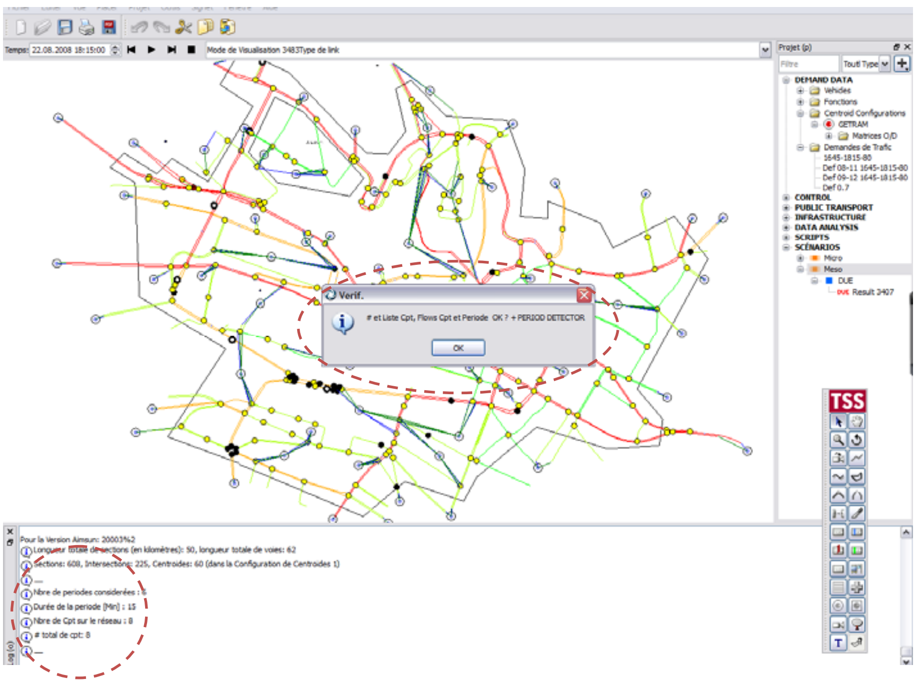
Inputs needed for OD estimation (actual traffic counts, etc.) are currently defined in an external text file (see Figure 5-4).

Figure 5-4 Inputs data file



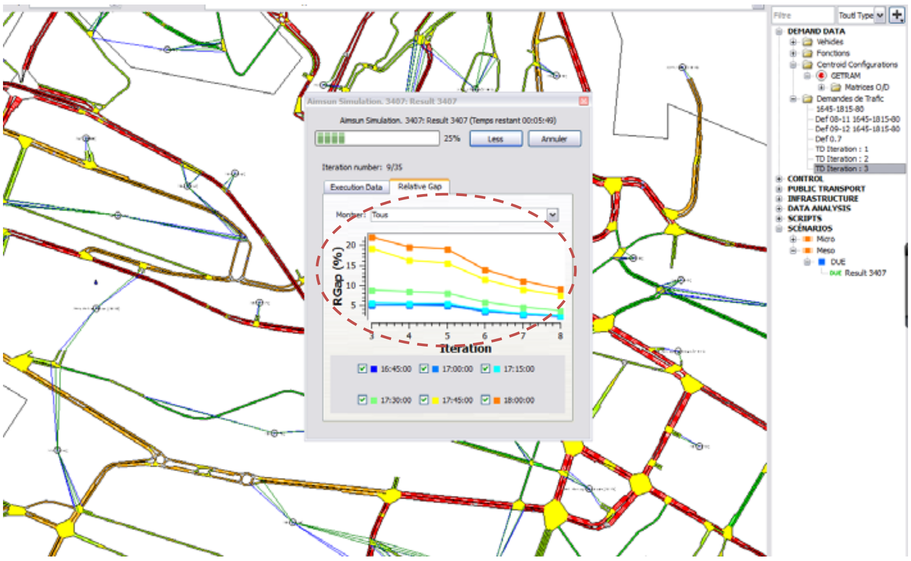
From these parameters and inputs, initialization toolbox allows checking the good parameterization of the process (Figure 5-5).

Figure 5-5 Plug-in initialization (based on Inputs)



After validation, OD estimation process starts. Succession of assignment and adjustment task are performed until reaching stopping criteria's defined[8] (simulation task for traffic assignment is presented in Figure 5-6, curves represent Rgap minimization)

Figure 5-6 Simulation process (Adjustment task)



Finally, after reaching stopping criteria (number of iteration, OD flows stabilization or other) process stops and presents computation outputs (see Figure 5-7: number of iteration executed, time, etc.).

Figure 5-7 End of the process

[8] As presented in chapter 3 in Figure 3-2.

Figure 5-8, Figure 5-9, Figure 5-10 and Figure 5-11 illustrate different outputs stored during the OD estimation process through iterations (detailed executing time, estimated OD flows for each period and iteration, LSQR algorithm internal details, OD flows and traffic count differences through iteration, etc.).

Figure 5-8 OD estimation process outputs (Execution time)

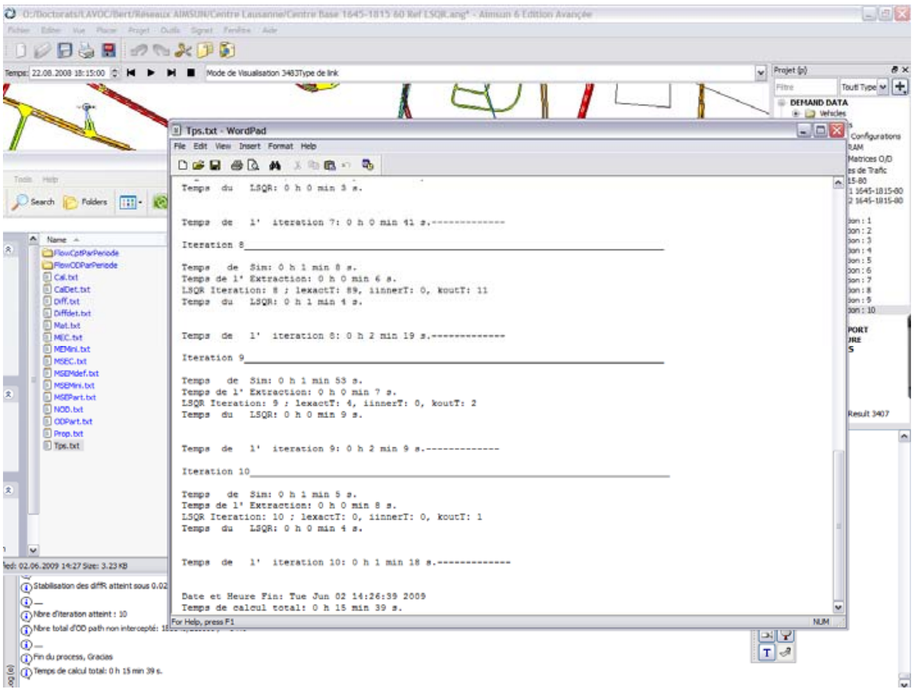


Figure 5-9 OD estimation process outputs (OD flows)

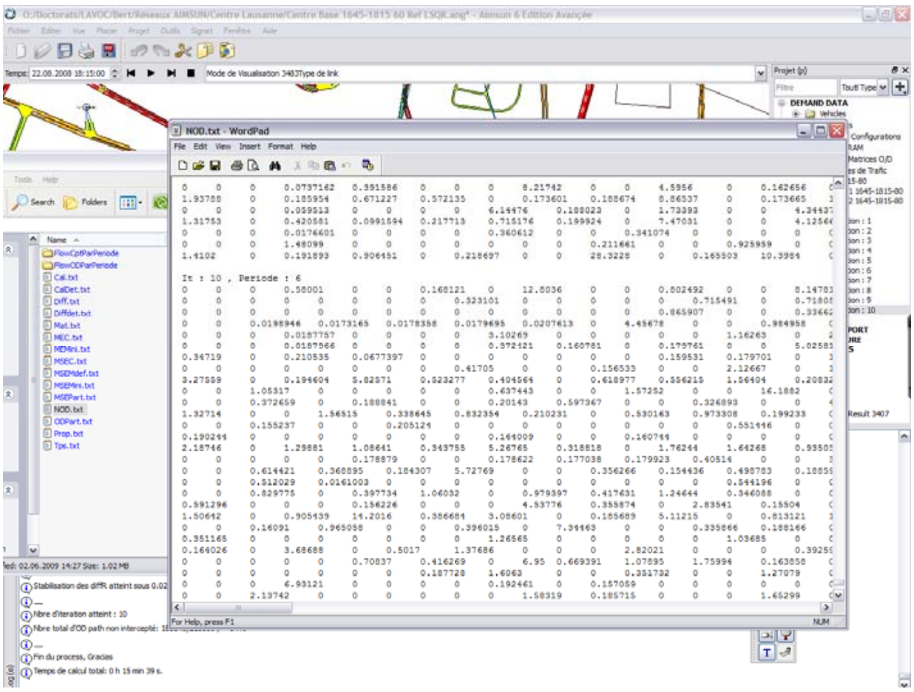


Figure 5-10 OD estimation process outputs (LSQR execution details)

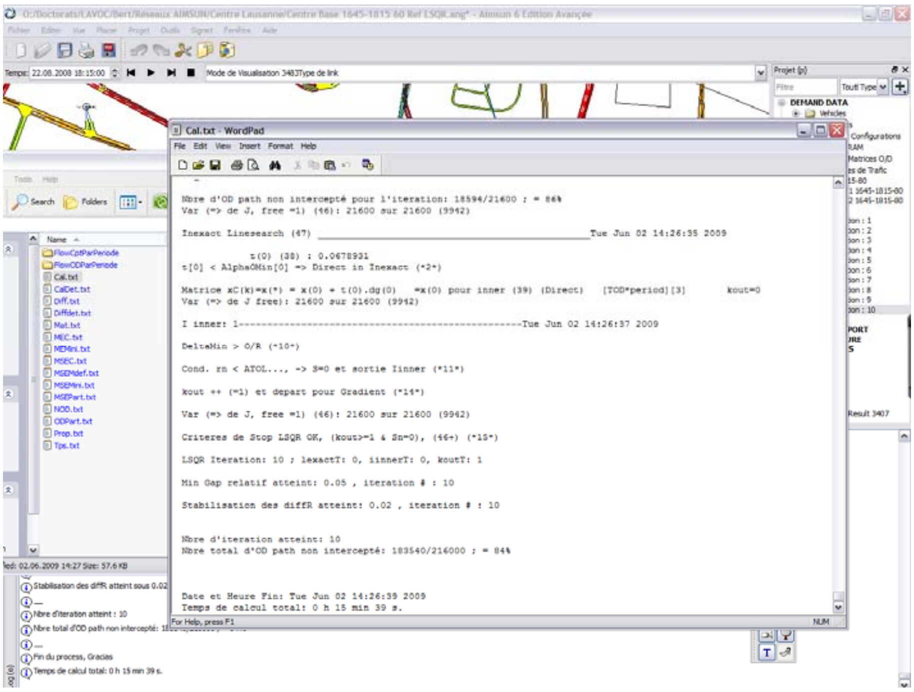
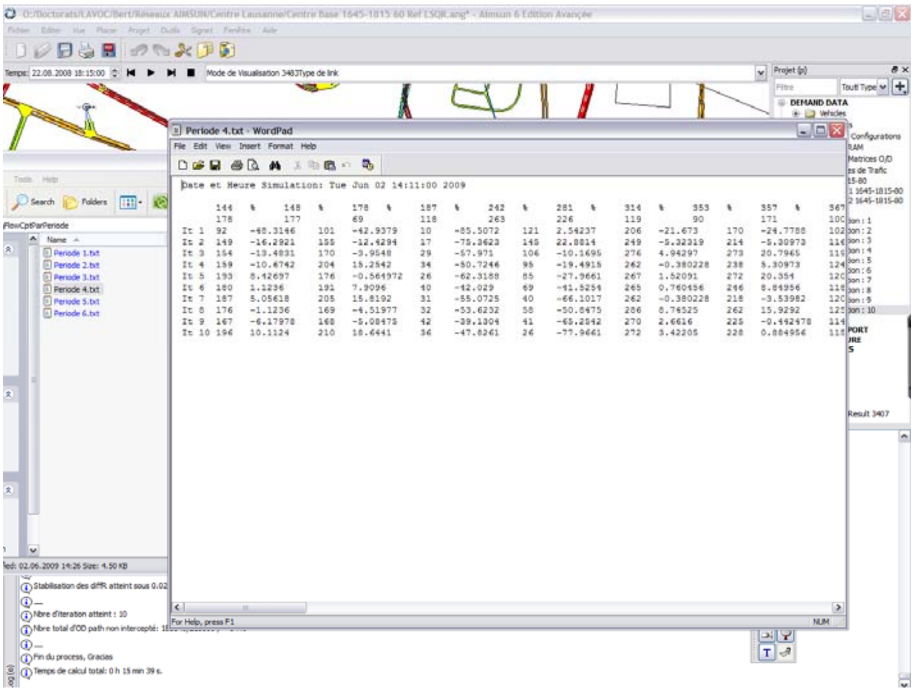


Figure 5-11 OD estimation process outputs (Evolution trough iterations)



5.2 Kalman Filtering results and limitations

Based on the implementation of the Kalman Filtering algorithm on the Dublin network (KF cannot be applied on Lausanne network due to limitation on the size of the problem, presented in the next paragraph), several tests have been done to evaluate robustness of the approach. Limitations of this algorithm for OD adjustment have been detected in first runs and are presented in next paragraphs.

- **Size of the problem (computed matrices)**

As presented in chapter 8.7.1, implementation of the filter has been done as proposed in [23]. The different steps performed and variables used (matrices and vectors) are presented in Equation 12. These matrices and vectors are stored for each time interval and iteration of the adjustment process.

Table 5-1 shows the size of each variable, its number of rows and columns. In the implementation, *TOD* is the number of Origin to Destination pairs in the network (usually equal to row multiplied by column or number of centroïd squared), *TC* is the number of count detectors and n is the number of periods or time intervals considered (six in our case).

Table 5-1 ***Matrices dimensions for Kalman Filtering implementation***

Variable	Rows	Columns
$X_n, \hat{X}_n$	nx*TOD*	1
F_{n-1}	*TOD*	nx*TOD*
$H_n, \widehat{H}_n$	nx*TOD*	nx*TOD*
C_n^d	*TC*	nx*TOD*
y_n	*TC*	1
R_n	n	n
Q_n	*TOD*	*TOD*

As defined in part 4 of Equation 12 and in Table 5-1, complexity of the problem increases rapidly with the number of OD pairs and time periods. Dimensions of largest matrices change with the square of the number of centroïds. If we consider a medium to large urban network, Lausanne Center presented in chapter 4.1.3 for instance, we can reach to very large matrices. The model of the center of the city of Lausanne has 60 centroïds (3600 OD pairs) and one and a half hour study period is constituted of six periods of 15 minutes. More than fifty traffic counts could be used to adjust the demand (as defined in the Real case in chapter 4.2.2). Then the size of main matrix is:

X_n = [21'600 ; 1]	is a matrix with:	21' 600	cells
H_n= [21'600 ; 21'600]		466' 560' 000	cells
C_n^d= [50 ; 21'600]		1'080' 000	cells

H_n matrix must be inversed in the process (as shown in Equation 12). Hence, the mathematical resolution of this inversion becomes very complex. For a larger network, Lausanne Center for instance, Kalman Filtering algorithm does not manage to find a solution.

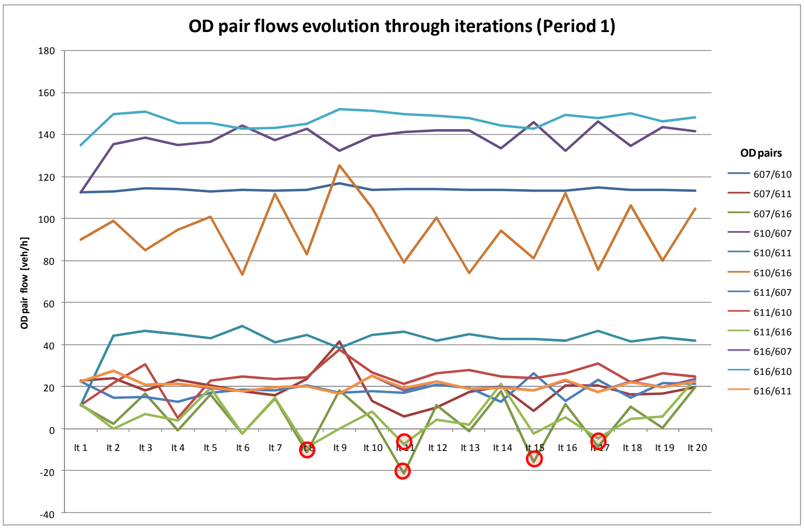
- **Constraints on outputs**

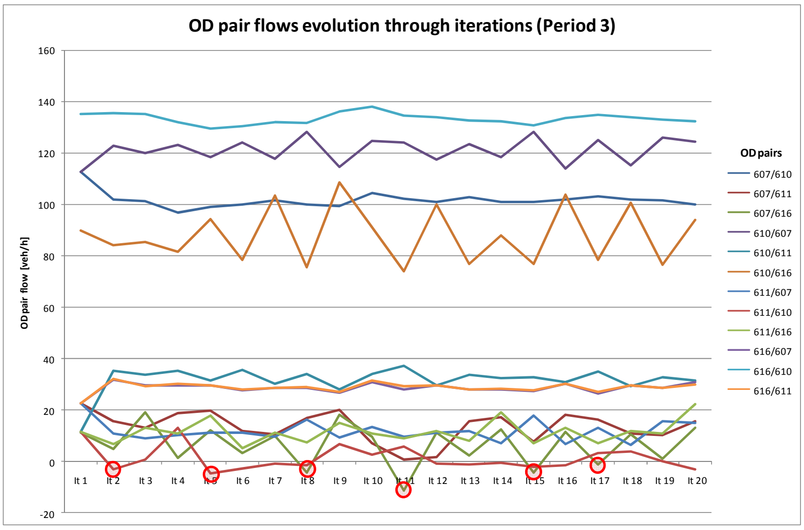
In an urban context, due to high number of centroïds, the traffic is spread out on various OD pairs (see more detail in chapter 1.1.4). Thus, majority of the cell of the matrix (OD pair flow) have a low number of vehicle flows (see Figure 4-4 for the Lausanne case). During the process, through iterations, results from the adjustment algorithm are oscillating around the target value for stabilization and in some cases; this variation could be quite large.

Figure 5-12 gives an example of the evolution of the results of KF (flows for OD pairs) through iterations for two different time periods of the dynamic OD matrix. As you can see for several iterations, KF is proposing negative values for different OD pairs (red dots). Indeed, mathematically, negative flows are a possible solution of the problem but it is not realistic for traffic demand.

This limitation is related to urban application cases. Indeed, in other kind of network, OD flows are usually larger, thus, there are fewer problems with negative values.

Figure 5-12 Negative flows using Kalman Filtering algorithm





It is important to note that the detection layout configuration can have consequences on this drawback of the KF approach. Indeed, if non-optimal detection layout will lead to low number of flows intercepted and therefore, large variation on these flows could be applied by the adjustment algorithm to fit traffic counts. In this way, for intercepted flows close to zero, negative values can be obtained through iterations variation.
In front of negative outputs, one solution consists to apply a projection of the flow vector on the constraint plan (defined by the flow limitation). This solution is simple and easy to implement but does not take into account the modification of the adjusted values in the optimization least square resolution. Indeed, this artificial adaptation, external of the KF algorithm, can lead to non-conservation of the consistency in term of volume of vehicles in the whole matrix. Other solution can be to use a Constraint Kalman Filtering (CKF, for instance [85]), but this approach does not address the problem of the size and complexity of the computed matrices raised earlier.

Kalman Filtering algorithm proposes interesting results for OD adjustment but presents several limitations in our case (urban applications). Indeed, as explained partially in [23], the size of the problem increase with the number of OD pair of the network. For medium to large networks, the mathematical resolution of the different steps of the algorithm becomes highly complex or even impossible (impossibility to find a feasible solution). Moreover, the computation efficiency decreases proportionally to the size of variables. In addition, Kalman filtering allows no possibilities of controlling the outputs.

For these reasons, it is important to evaluate an alternative to achieve OD adjustment in the upper level. LSQR presented in [25, 79] has been chosen for the OD estimation process for the smaller size of the variables inside the resolution and for its possibilities of constrained on OD flows output. More details about LSQR approach are presented in [21] and noted in chapter 8.7.2 (computation time advantages and ability to deal with sparse matrices). From this point, results presented in next case study have been obtained using LSQR algorithm for OD flow adjustment.

5.3 Implementation verification

Verification of the good behavior of the implemented process is a crucial step to guaranty accurate and right outputs. To perform this verification, all steps of the LSQR algorithm have been tested and compared systematically with Matlab® software results to check the accuracy of the calculation and implementation (same approach has been performed for Kalman Filtering algorithm but are not detailed in this report).

Based on LSQR algorithm, to assess the sensitivity of the OD estimation process on input matrix, several scenarios have been elaborated. From the reference time sliced demand (six different matrices, as presented in 4.1.2), the following three configurations have been tested:

- *0.7* scenario: All cells of the matrices multiplied by 0.7
- *1.1* scenario: All cells of the matrices multiplied by 1.1
- Up and Down *UaD* scenario: The time sliced matrices have been multiplied by 0.7 or 1.1 alternatively as presented in Table 5-2.

Table 5-2 Factors for *UaD* scenario matrices

Period	P1	P2	P3	P4	P5	P6
Scaling factor	1.1	0.7	1.1	0.7	1.1	0.7

5.3.1 Verification results

For this small Dublin network and as argued by Bierlaire (see reference in chapter 8.7.2), the LSQR algorithm adjusts OD flows to right value a few iterations only. Indeed, the number of LSQR internal loop is small (from two to five on average) and therefore, time to perform a bi-level iteration is around 5 second.

In the verification results, focus will be put on global working and on specific aspects of the process. Therefore, full set of results are presented for the *0.7* scenario and partial set for the scenario *UaD*. Scenario *1.1* is not present because is confirming results obtained from scenario *0.7*. Aggregate results for all scenarios are presented in Table 5-3.

Figure 5-13 Matrix and traffic count error results - *0.7*

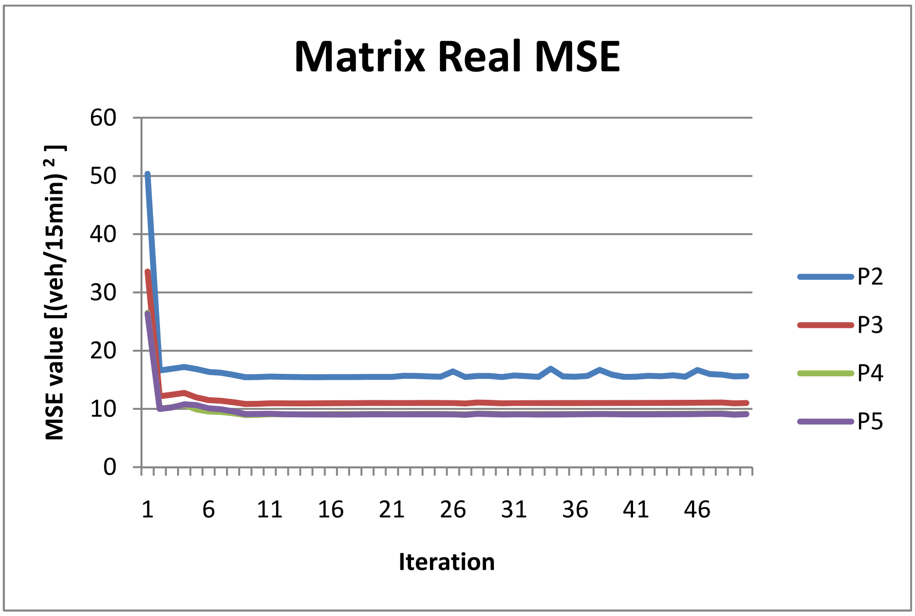
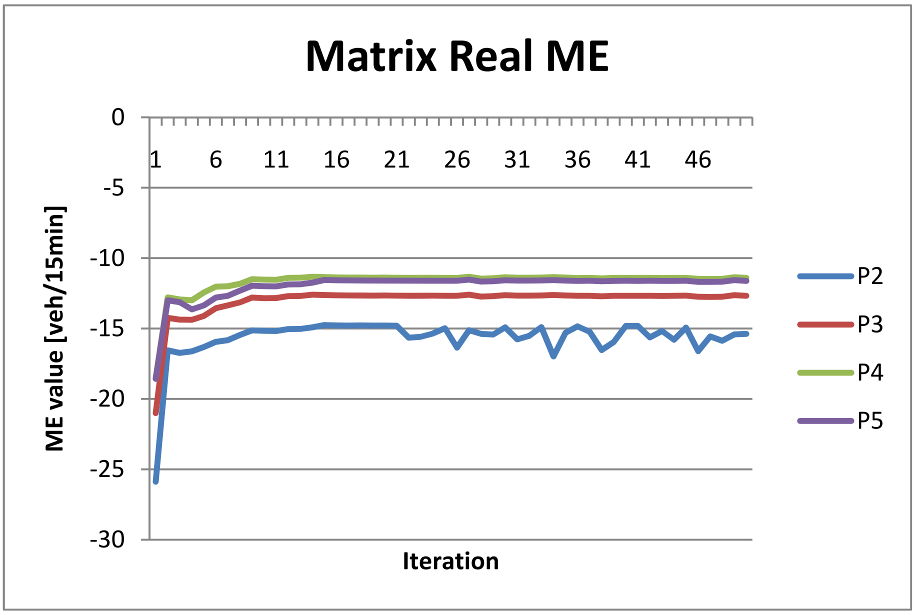


Figure 5-13   Matrix and traffic count error results - *0.7*



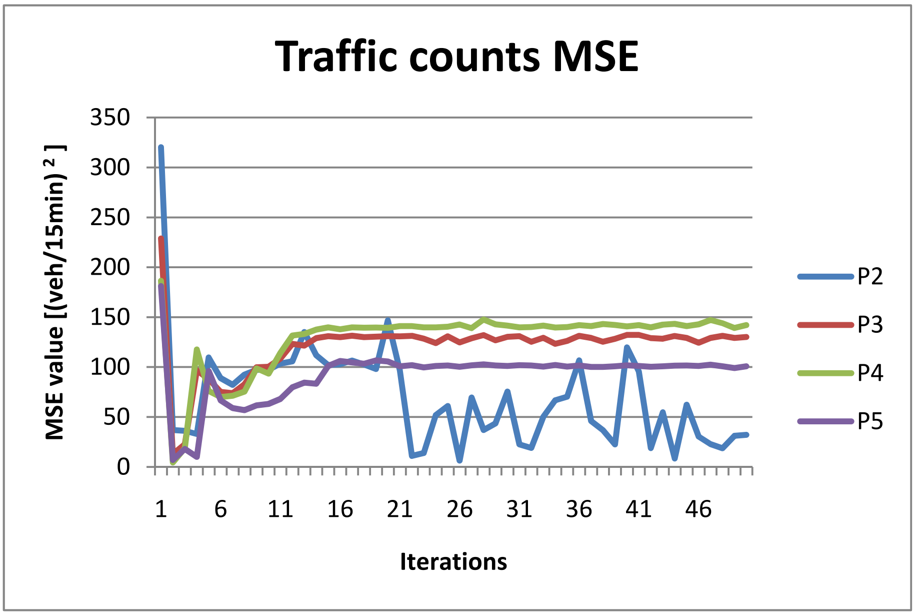
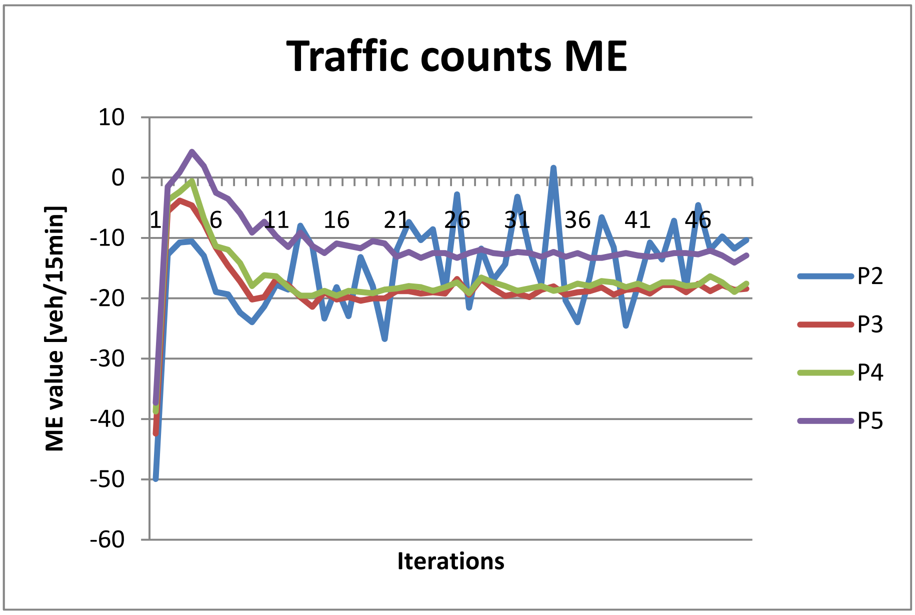


Figure 5-13 Matrix and traffic count error results - *0.7*



From graphs of Figure 5-13, we can observed the convergence of the OD trips and traffic count flows from the starting point to a stabilized values closer to zero.

After this aggregate information, individual OD trips and traffic counts flows, presented in Figure 5-14 give disaggregate detail of the estimation process.

Figure 5-14 OD trip and traffic count flow evolution - *0.7*

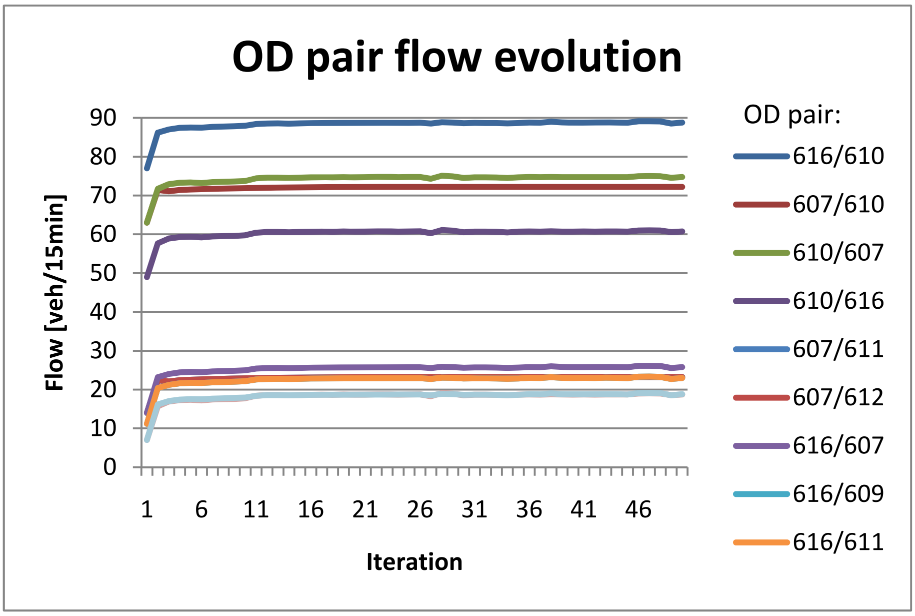


Figure 5-14 OD trip and traffic count flow evolution - *0.7*

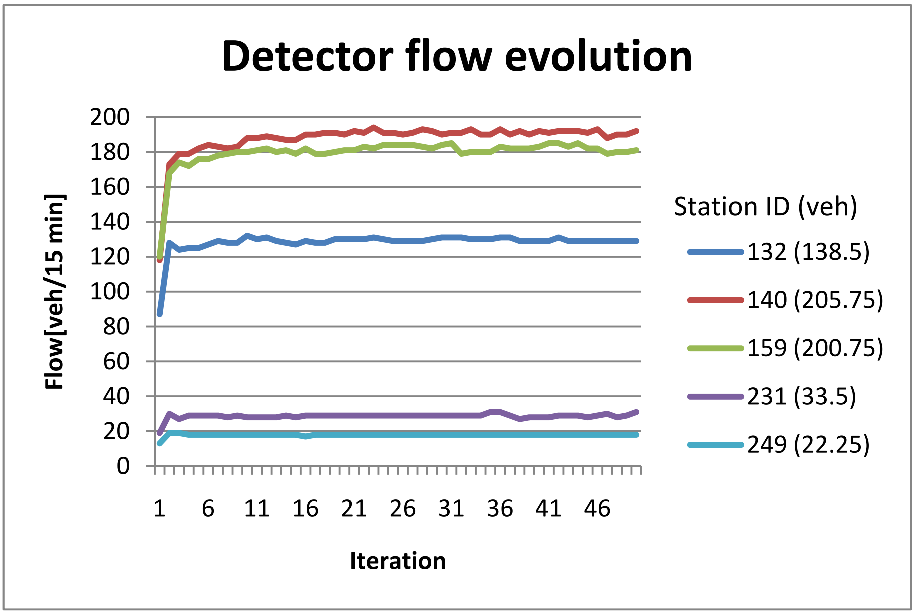
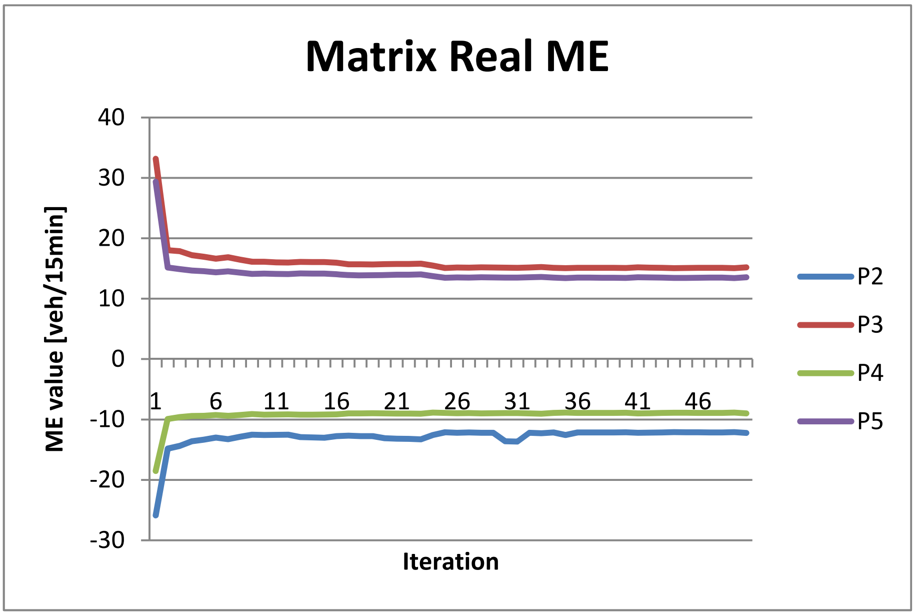


Figure 5-14 illustrate the adjustment of the OD flow (increase from *0.7 initial values) and also the good fitting of the detector values based on the assignment of the initial demand and the estimated demand through iterations. Moreover, we can observe good stabilization of the results after little iterations.

Figure 5-15 ***Matrix error results - *UaD****



For the particular *UaD* scenario (Figure 5-15), Mean Error illustrates the evolution of OD cells period per period. Therefore, Periods 2 and 4 (multiplied by 0.7, see Table 5-2) start from negative values to go up close to zero. In the opposite, Periods 3 and 5 start from positive value and converge down to the horizontal zero line.

Table 5-3 summaries the totality of results obtained for the three scenarios. It presents for each of them the MSE ($(veh/15min)^2$) and ME (veh/15min) final convergence for matrix and traffic count comparison.

Table 5-3 Summary results Dublin network - Verification

	0.7				*1.1*				*UaD*			
	OD pair		Traffic Count		OD pair		Traffic Count		OD pair		Traffic Count	
	MSE	ME	MSE	ME	MSE	ME	MSE	ME	MSE	ME	MSE	ME
P2	16	-15	45	-13	28	18	10	-8	12.5	-12	350	-55
P3	11	-13	130	-18	18	14	20	-12	20	15	190	-3
P4	9	-12	140	-17	14	12	28	-16	10	-9	192	-40
P5	9	-12	100	-13	13	12	22.5	-13	16	13	162	1

This table illustrate constant results (same order of magnitude) whatever the scenario used and confirm the stability of the approach.

Next graphs present X-Y OD flow plots (in veh/15min) for the different scenarios proposed:

Figure 5-16 X-Y OD flows plots - Verification

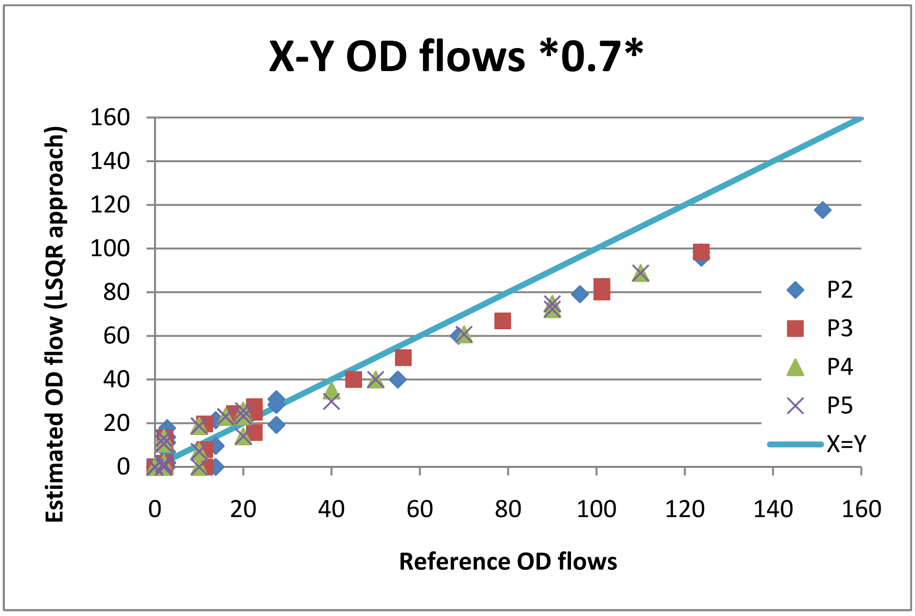
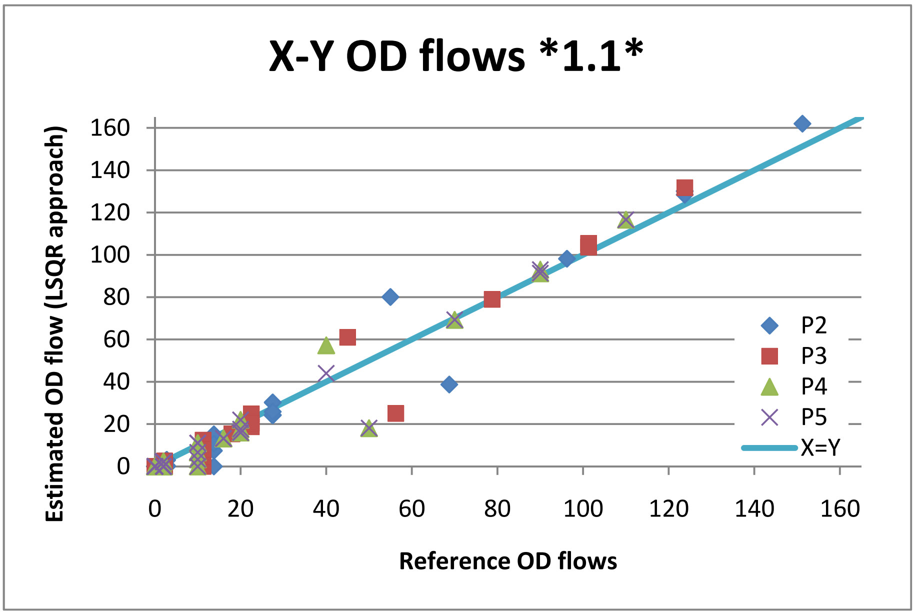
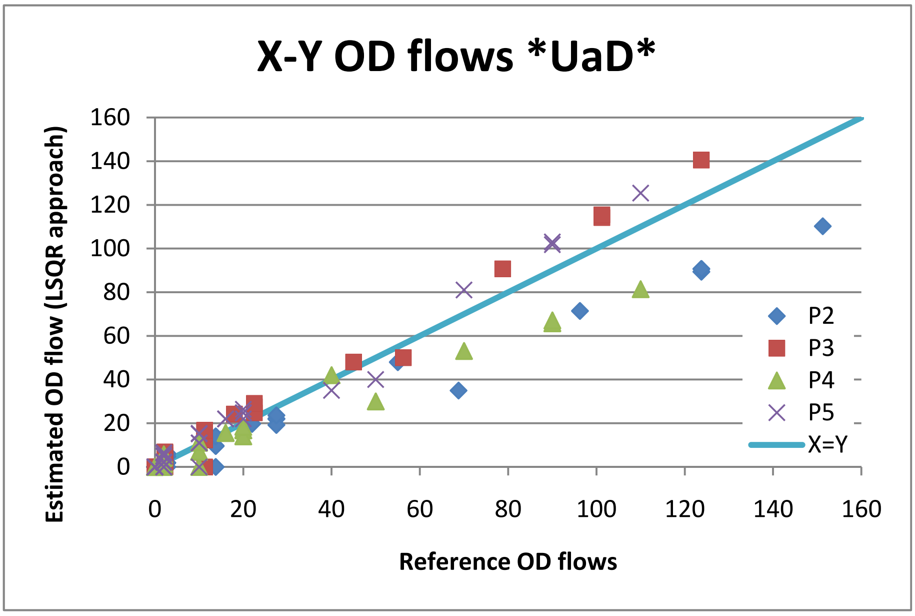


Figure 5-16 X-Y OD flows plots - Verification





X-Y plots graphs (Figure 5-16) confirm results presented in Figure 5-13, Figure 5-14 and Figure 5-15. Correspondence between estimated OD flows and reference ones are observed. We can note that OD flows are slightly underestimated in cases of initial OD matrix reduced (see scenario *0.7*) and the opposite for larger demand. In the last graph *UaD*, patterns of each period of OD matrix are observed. Indeed, P2 and P4 are underestimated and P3 and P5 are upper estimated.

As we can remark, for few dots, differences could be observed between reference OD flows and estimated OD flows using LSQR approach (see OD flows around 50-60 veh/15min in *1.1*, for instance). These variations are due to the initial matrices used and the assignment differences between real demand and one used during the OD estimation process. Nevertheless, we can observed a compensation of these flow around the X=Y axis which lead to a total number of trip similar but dispersed slightly differently.

As a conclusion, evaluation of outputs from the simple Dublin network highlights the correct dynamic behavior of the flow estimation process in front of several input configurations.

5.4 Real case study

As explained in chapter 4.2, methodology proposed must be applied on real condition of OD estimation to prove its capacity to deal with practical situations for urban network i.e. using only available data to perform the dynamic OD estimation task. Then, as presented in chapter 4.2.2, LSQR approach is used on Lausanne network based on SIMLO initial OD matrix and COREL traffic count data.

5.4.1 Real case results

The obtained results are presented in Figure 5-17 for MSE values and in Figure 5-18 for X-Y plot graphs (in veh/15min).

Figure 5-17 Error results - Real case

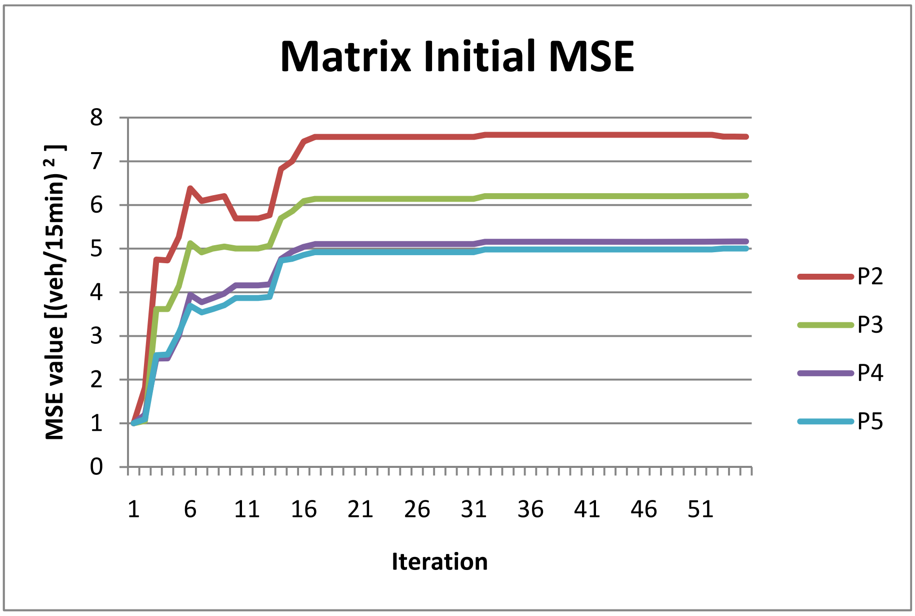
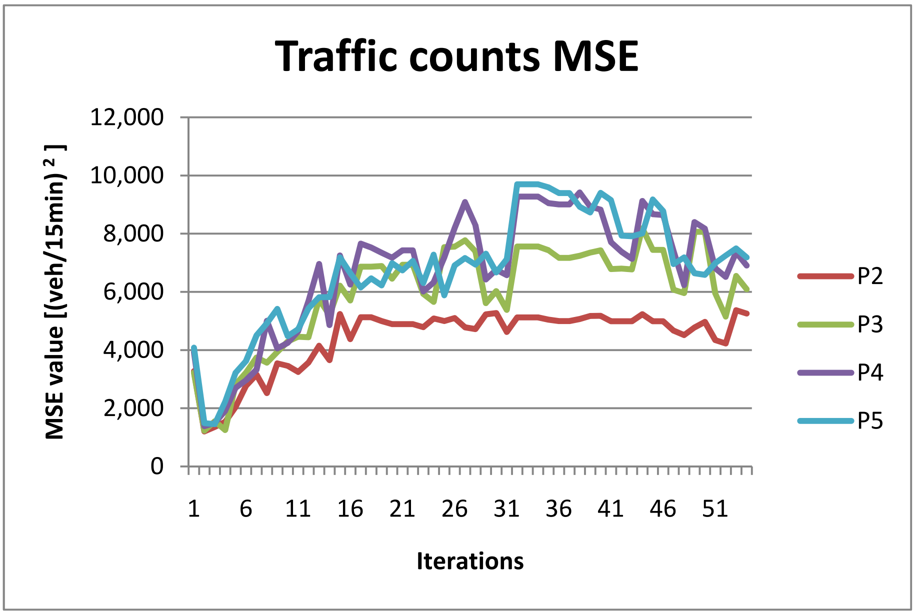
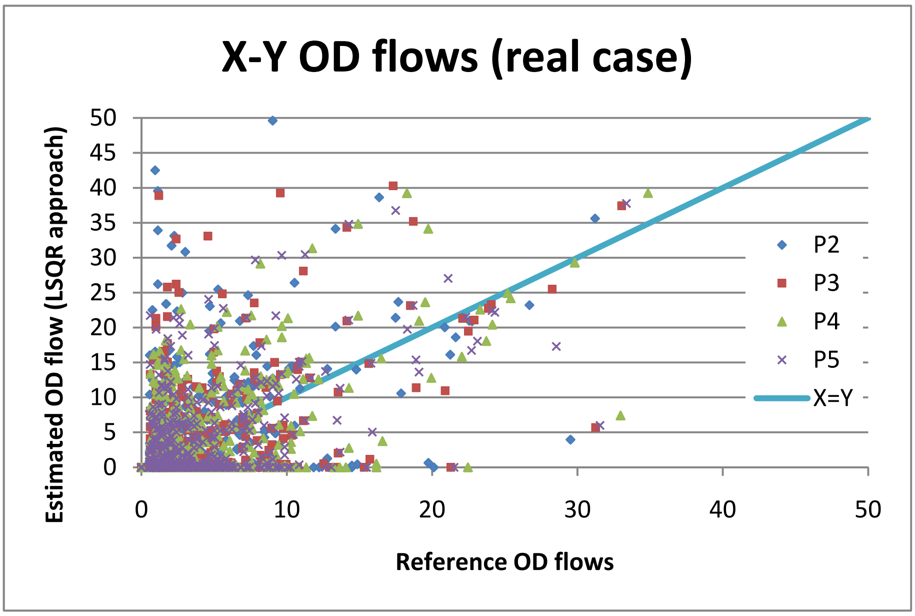


Figure 5-17 Error results - Real case



MSE evolution results for matrices and traffic counts present expected outputs. Indeed, stabilization of curves is observed (even if MSE values stay quite large).

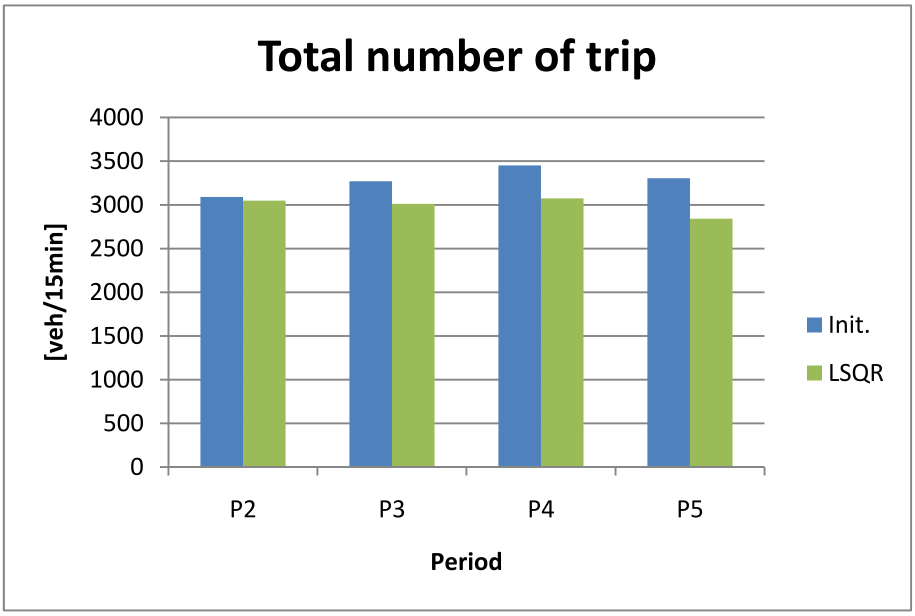
Figure 5-18 ***X-Y OD flows plot - Real case***

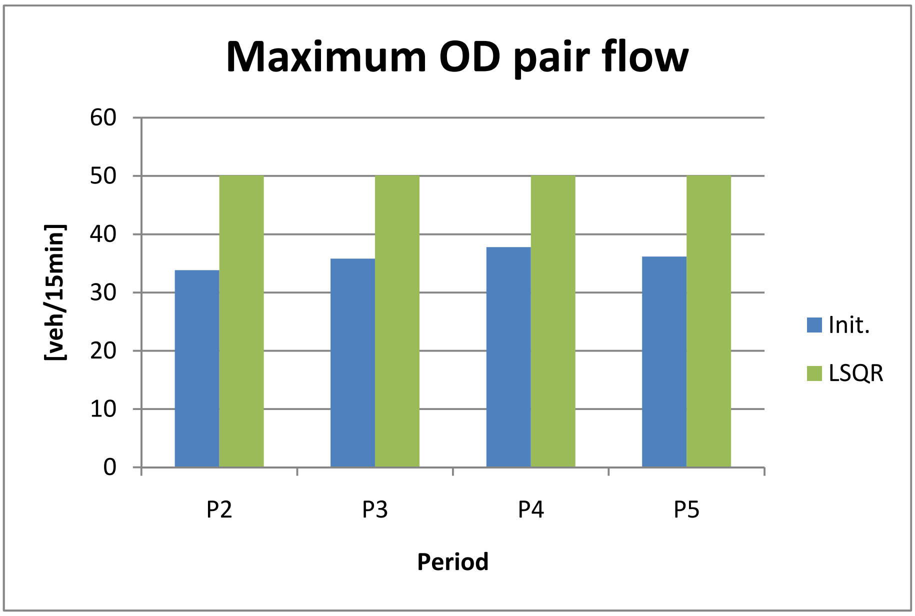


X-Y plot illustrates a low level of correspondence between estimated OD flows and reference ones. This result was expected knowing the poor consistency between initial demand and traffic counts used as input (different time origin of the inputs).

Next results are comparing OD matrices obtained period by period. "Total number of trip" represents the volume of the estimated OD matrix, "maximum OD pair flow" is the values of the cell with highest flow and "mean OD pair flow" is the average of all the cell of the matrix. In Figure 5-19, Init. and LSQR represent initial OD matrices data (SIMLO) and matrices obtained after OD estimation process ("Real new Matrix" [9]) respectively.

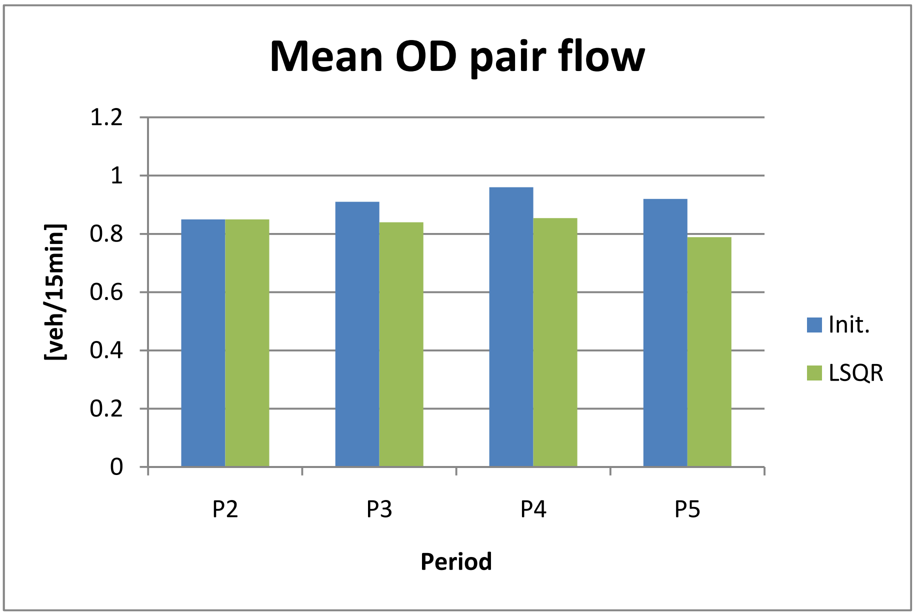
Figure 5-19 Matrix comparison - Real case





[9] As defined in Table 4-3

Figure 5-19 Matrix comparison - Real case



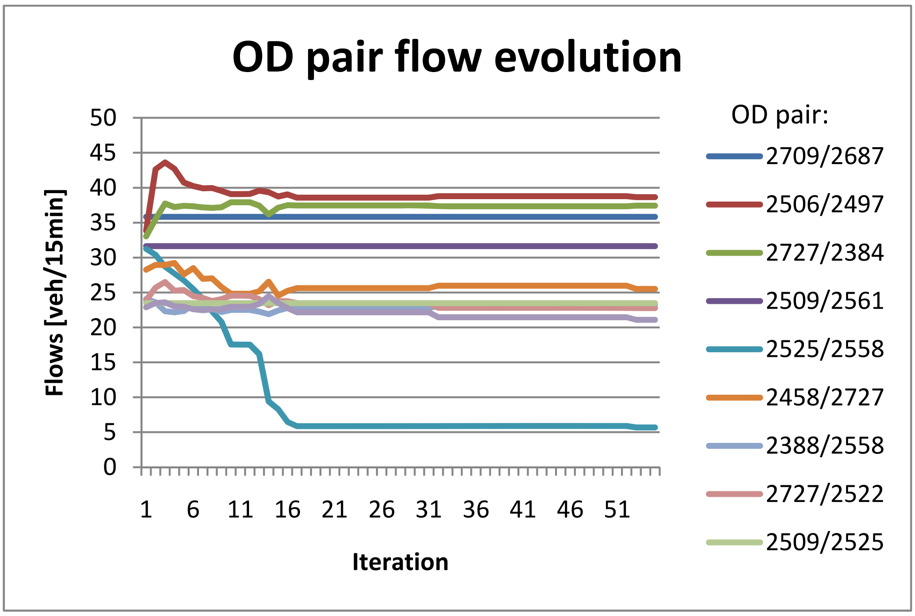
Aggregate indicators of the matrices are quite satisfactory, even if "maximum Cell value" for LSQR is limited by the constrain defined for the algorithm (Max flow = 50.1 veh/15min)

These results are justified by the low quality of OD flow interception. Due to non-optimal detection layout, only few OD flow are intercepted by detectors. This deficiency induces a very small number of OD pair which could be adjusted by the LSQR algorithm to fit traffic counts. 90% of OD flows are non-intercepted and therefore not modified as presented in chapter 3.3.1. Number of OD pair intercepted is low and quality of these OD flows is not adapted for OD estimation. 10% of the OD flows intercepted are not the largest flows or the most crucial ones (as illustrated in Figure 5-20). Therefore, LSQR tries to adjust 10% of the OD cell values and need large modifications of them to reduce the discrepancy with detector measurements.

This low number of intercepted OD flows added to the non consistency of the input data (matrix and traffic counts) lead to high number of LSQR internal loops because of the difficulty for the least square algorithm to find optimal solution. Hence, large computation time is needed to perform the bi-level process. Single bi-level iteration (traffic assignment and OD adjustment) takes more than 5 hours to execute.

Ten largest OD flows have been isolated to see their evolutions and are presented in Figure 5-20.

Figure 5-20 Largest OD flow evolution - Real Case



We can observe unrealistic behavior in OD flow evolution and several un-intercepted OD pairs (horizontal lines due to non-modification of the OD flow through iterations). This is mainly due to the un-adapted detection layout for the network. If we consider that this 10 largest OD pair are influencing the final output, it justifies previous poor results.

5.4.2 Limitations of the real case

Results presented in the previous chapter highlights the applicability of the method in real condition. OD matrices are modified to match traffic counts and stabilization of the MSE values of OD flows and traffic counts are observed after several iterations.
Nevertheless, limitation and difficulties could be identified. Indeed, OD interception, high MSE stabilized values on matrix and traffic counts, etc. are not relevant for OD estimation process. These results are mainly due to:

- Inputs quality

Known divergence between initial OD matrix used and detector values due to different years these data sets were collected makes OD estimation process difficult to achieve. Note that these two inputs are the only source of information for OD estimation and therefore quality and consistency of these data sets are paramount. In case of non-correspondence of these inputs, matching point could not fit with inputs. Moreover, static initial OD matrix obtained from a previous process has been obtained using a planning analyses approach (aggregate traffic data for long term purpose) added to the methodology ("time sliced OD matrices extension") used to obtained dynamic OD matrices as presented in chapter 4.1.3 lead to low quality and non adapted inputs for efficient OD flow estimation.

- **Detection Layout**
As already presented, difficulties observed in this real case application OD estimation process are also due to the detection layout used and defined by COREL data set. Indeed, low OD interception rate indicates that detection configuration is situated between boundaries (1) and (2) in Figure 2-5 (means that not all OD pairs are intercepted by detectors and in this case only few OD pairs are intercepted). This COREL detection layout is justified by economic, practical and others reasons but is not adapted for efficient OD estimation and thus not for maximum OD flow interception. Only few flows are intercepted and not the most important ones.

These weaknesses presented based on these data induce another difficulty for practical utilization of the OD estimation process, execution time. Indeed, such a long execution time is not acceptable for engineer to estimate OD flows.

5.5 REF case study

From limitations of the real case presented in chapter 5.4.2, a better-input quality is needed to assess the proposed approach. Then, "artificial" case has been developed to analyze fully the methodology (see method description in 4.2).
Thus, based on the REF case presented in Chapter 4.2.3, we can perform in-depth evaluation of the proposed approach using large and complex urban network and consistent inputs. OD estimation task will be performed in parallel using the proposed LSQR approach and the common approach, SSODE.

5.5.1 SSODE results

As presented in chapter 4.2.5, OD estimation is performed, in parallel using the sequential Static OD Estimation approach to compare results with the proposed method. The technique used is iterative and similar to the one presented in Figure 8-12. Hence, no propagation (vehicle transfer through time intervals) is possible into different periods considered. Four different demand estimations are performed and each of them provides one OD matrix (15 minutes duration each). This particular estimation process has been executed by an external expert user of the EMME/2 software.

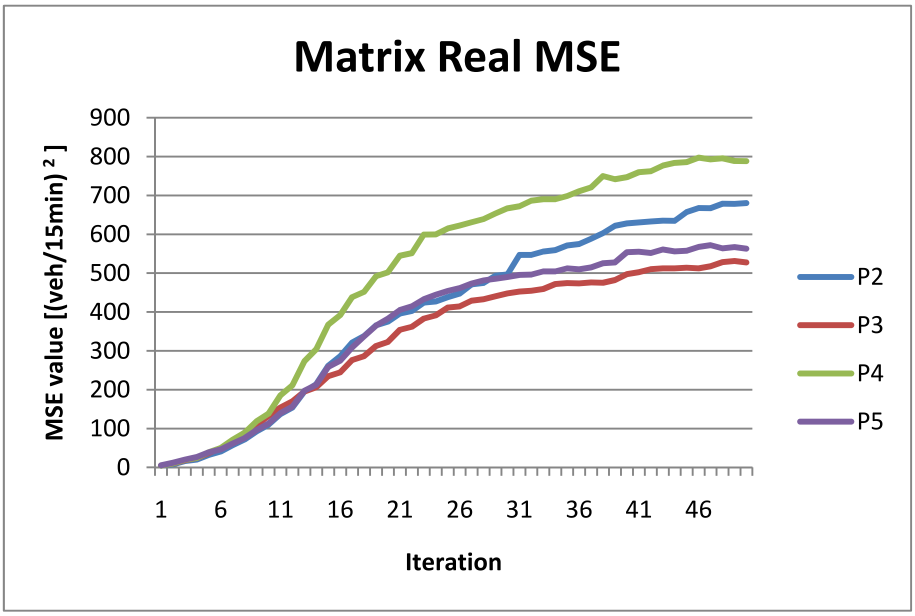
OD matrices estimated by the SSODE process present different characteristics dependent on the number of iteration executed. The process is starting with the initial OD flows and, with iterations, produces results closer to traffic counts. Therefore, OD matrix obtained with low number of iterations is closer to the initial demand whereas high number of iteration demand is closer to the traffic counts.

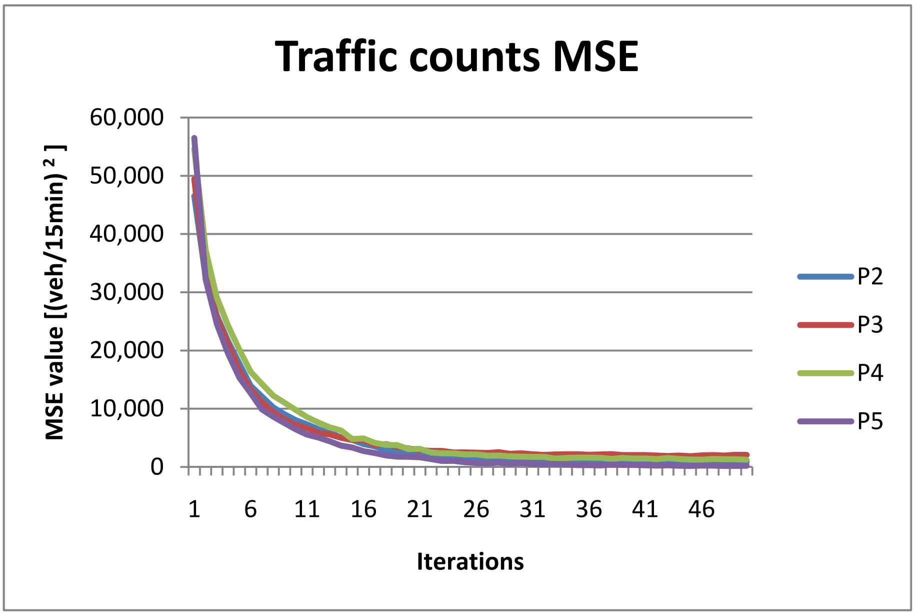
From that statement, the author decided to study two different set of matrices:

- "SSODE 10" from the 10th iteration ("closer" to the initial OD matrix)
- "SSODE 50" from the 50th iteration ("closer" to the traffic counts values)

SSODE estimation process needs around 10 minutes to perform 50 iterations. Therefore, full time period evaluation needs 40 minutes.

Figure 5-21 Matrix and traffic count error results - SSODE 10





Analyze of errors on matrix cells shows high MSE values after several iterations. It is due to few very large differences in OD flows as presented in Figure 5-22 and Figure 5-33. Different assignment processes (User Equilibrium based on macroscopic approach) leads to slightly different repartition of the traffic into the network and justify high values for MSE on detectors for very first iterations. Afterward, adjustment process reduces this gap.

Figure 5-22 X-Y OD flows plots - SSODE 10

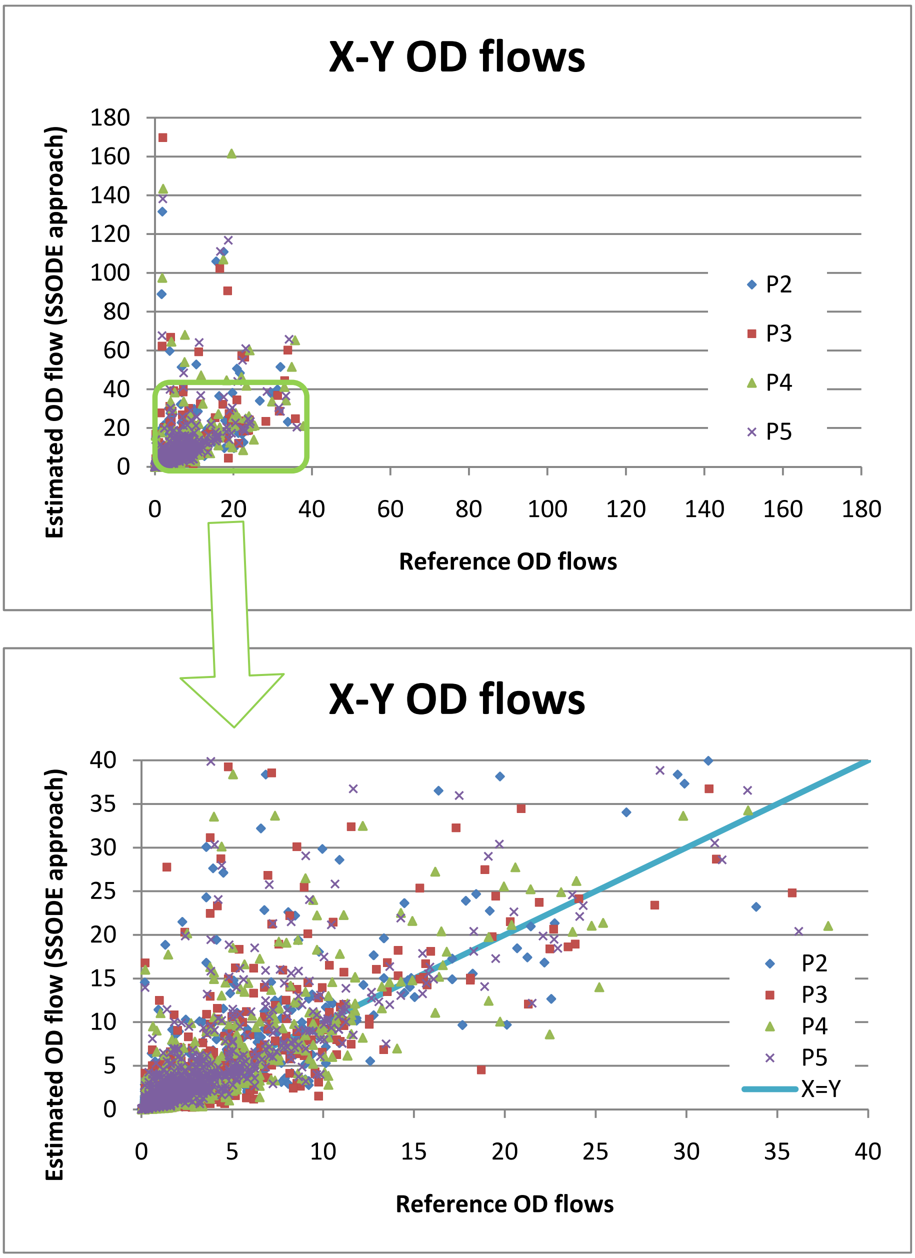


Figure 5-22 illustrates correspondence between reference and true OD matrix and the estimated one using SSODE approach after 10 iterations. We can observe large flow modifications and thus differences for OD pairs on the above graph. The lower graph (which is a zoom of the first one) presents dots close to the X=Y line but highlights numerous of OD pairs with estimated flow larger than the reference one.

Analyze of "SSODE 50" matrices have shown that the proposed demand is unrealistic. Compare to reference OD matrix, large modifications of the matrix to fit traffic counts have lead to large values for various OD pairs and shorter trip lengths. Therefore, OD cell values are far from the actual ones and inconsistent with the reference demand.

Impossibility to assign this demand using microscopic approach due to large increase of the trip's volume and high maximum flows (see more details in 5.5.4), has decided the author to abandon this demand and to use only SSODE 10 for the evaluation methodology (expect in the OD flow comparison in chapter 5.5.3).

5.5.2 LSQR results

After applying OD estimation using the common approach (SSODE), the methodology developed and proposed (LSQR) in chapter 3 is applied to judge its abilities.

- **LSQR outputs**

Various results presented in next lines have been done based on 50 iteration of the bi-level process. This number is justified to achieve the minimum iteration number for stabilization of results and to check if values stay constant after this stabilization.

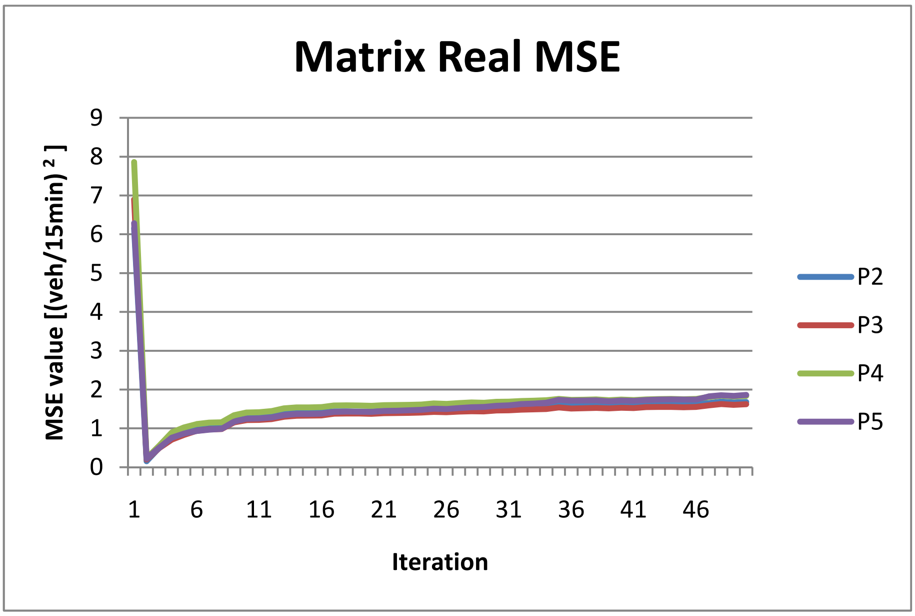
Variance-Covariance matrices used to take into account the precision of the model and the measurement are based on R and Q values of 20 and 1, respectively (see context in chapter 3.5 and more details and analysis in chapter 8.9 in annex). It represents a realistic compromise between traffic counts and state accuracy. In practice, these values must be evaluated (sometimes empirically) as accurately as possible before OD estimation process to set errors term correctly according to the confidence on model or traffic counts.

To analyze results objectively, mainly for ME values, it is important to know that average traffic count values is 170 veh/15 min and average OD flow is 0.9 veh/15min for the reference data.

Calibration of the different parameters of the mesoscopic model has been done using SIMLO study and REF case (defined in chapter 4.2.5) and adapted using methodology developed and presented in chapter 8.6.2. To perform assignment in the bi-level process, parameters of the mesoscopic DUE have been set to achieve a Rgap values smaller than height. In majority of the simulations, mesosimulator needs less than five MSA iterations to reach this value.

In general, only few internal loops are necessary to achieve LSQR stopping criteria and time to execute single bi-level iteration is around one minute (majority of the time used for mesoscopic simulation).

Figure 5-23 Matrix and traffic count error results - LSQR



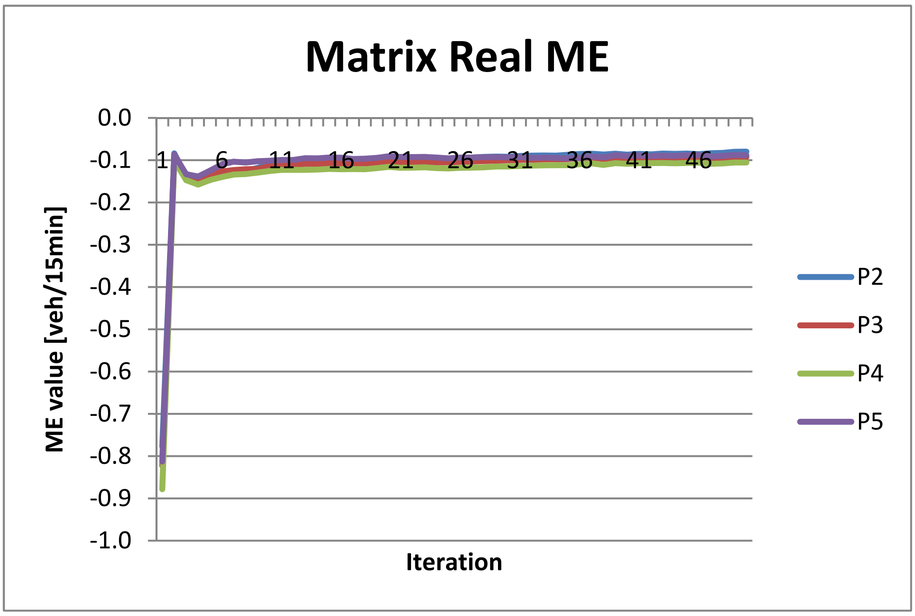
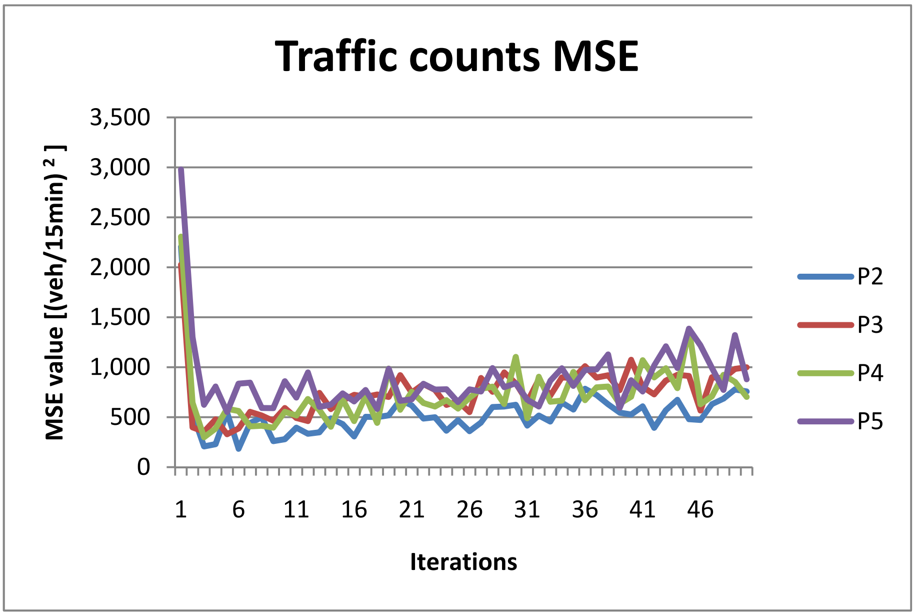
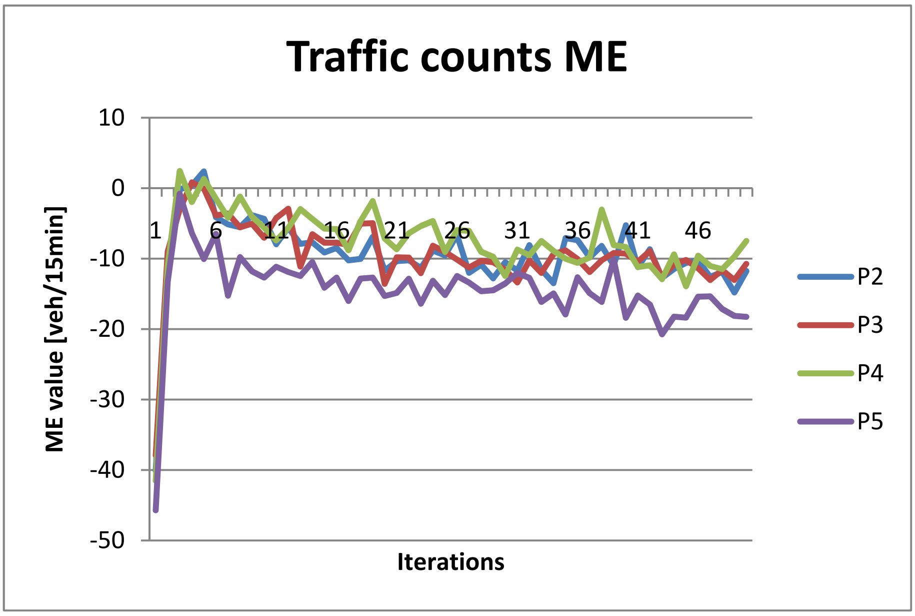


Figure 5-23   Matrix and traffic count error results - LSQR

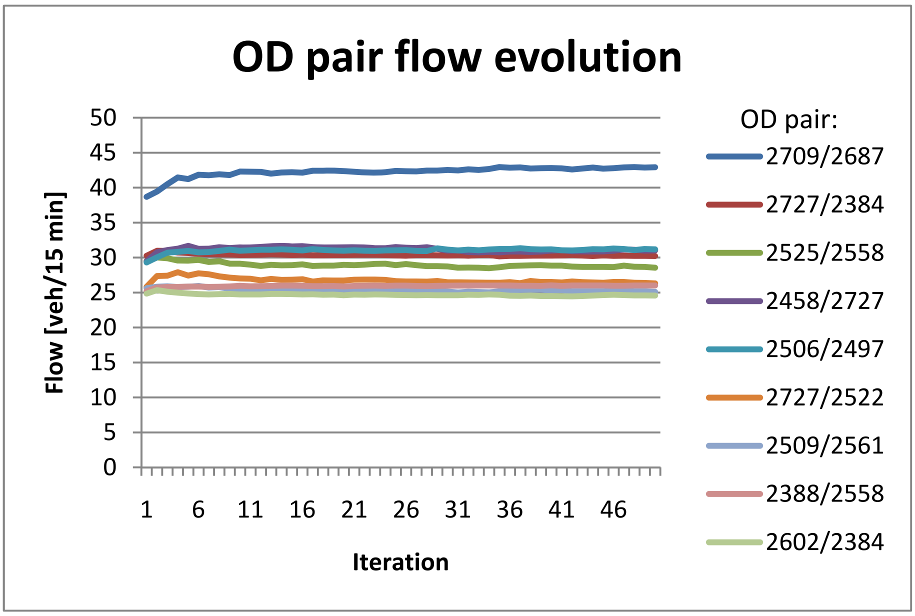




Results obtained, using proposed methodology based on mesoscopic assignment and LSQR algorithm for OD adjustment are satisfactory (see Figure 5-23). After only few iterations (less than 10), stabilization is observed close to the reference target demand. ME graphs presents an error of 10% (0.1/0.9) on OD flow compare to reference matrix and 6% on traffic counts (10/170). These good results are similar for all time intervals of the study period.

Ten largest OD pair flow are shown in Figure 5-24 to see the behavior of most influencing streams.

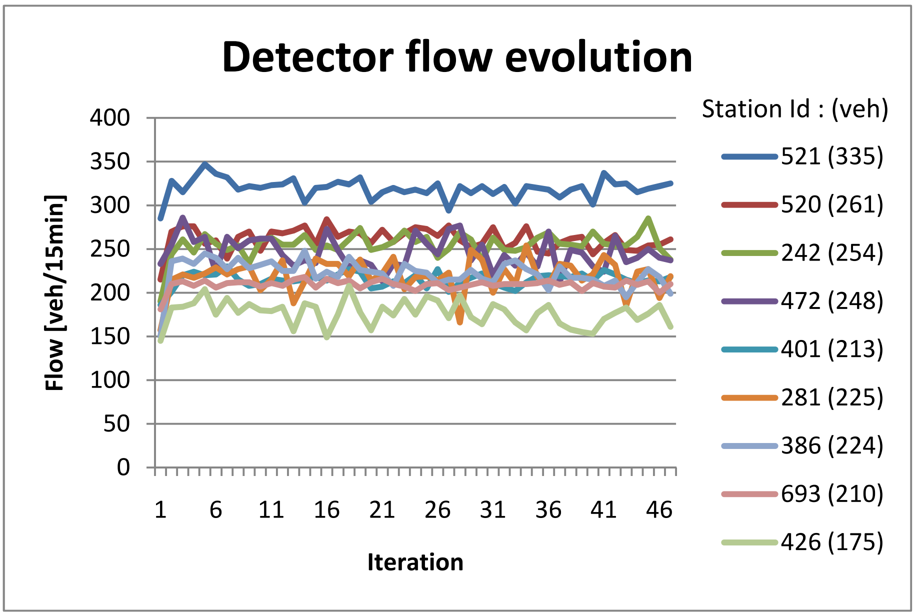
Figure 5-24 Largest OD flows evolution - LSQR



Small adaptations are observed on first iterations to fit detector values followed by stabilization of OD flows. We can note that due to an adapted detection layout, all of these OD pairs are intercepted by detectors.

Moreover, evolution of the different traffic counts of the REF case configuration (see Figure 5-25) informs about the stability and the efficiency of the global OD estimation methodology.

Figure 5-25 Traffic counts evolution - LSQR



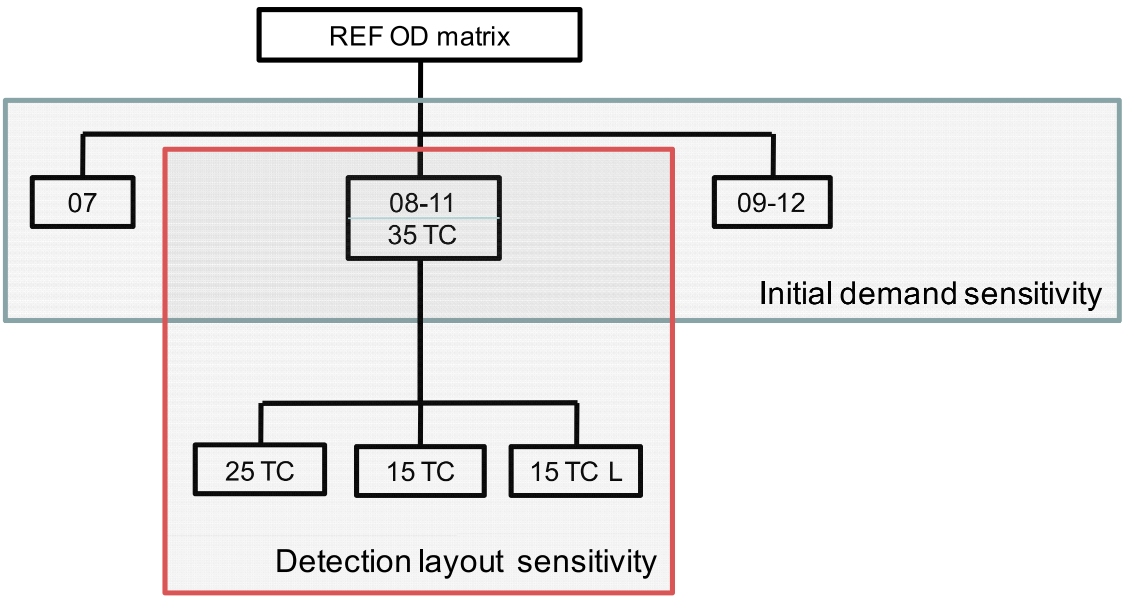
Traffic counts values are oscillating (due to assignment differences through iterations) in ± 15% around the target values.

Based on different OD estimation executed and results obtained, author advices to perform a minimum of at least five bi-level iterations before stopping the OD flows estimation process. Nevertheless, total number of iterations does not need to be high. Based on stabilization of the Average Mobile (Equation 3 in chapter 3.4) on MSE on matrix or traffic count for instance, number of iteration smaller than 20 is enough to reach stabilized conditions (Average Mobile modification smaller than three, for instance).

- **Sensitivity analyses**

As presented by Figure 5-26, a particular sensitivity analysis is proposed to observe the effect of input variation on the results:

Figure 5-26 Sensitivity analyses approach - LSQR



- o Initial OD matrices demand sensitivity

First perturbed matrix has been built by random multiplication of each cell by numbers between 0.8 and 1.1 (08-11 matrix, presented in chapter 4.2). Two additional perturbed initial demands are tested:

- Random modification of each cell by 0.9/1.2 (09-12)
- Scaling of each cell by 0.7 (07)

It is important to note that even if different initial demands are tested, they stay satisfactory input for OD estimation.

X-Y plots (in veh/15min) of the three different initial demands are presented in Figure 5-27.

Figure 5-27 Results summary X-Y OD flows plots, Initial matrices - LSQR

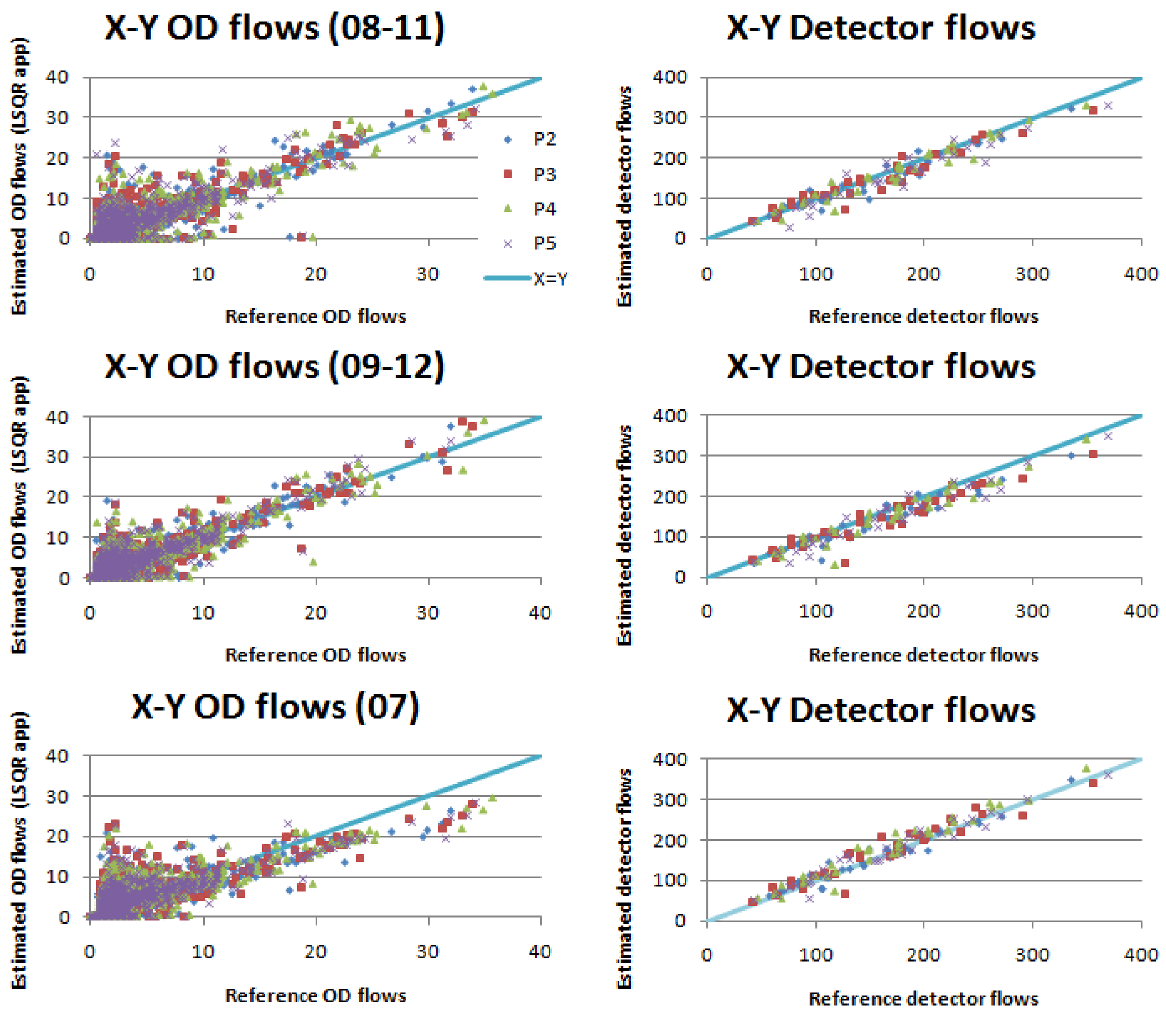


Figure 5-28 shows the coefficient of determination obtained from the clouds of dots presented in previous figure. They are global value for all OD flows for all time intervals.

Figure 5-28 ***Coefficient of determination for initial matrices - LSQR***

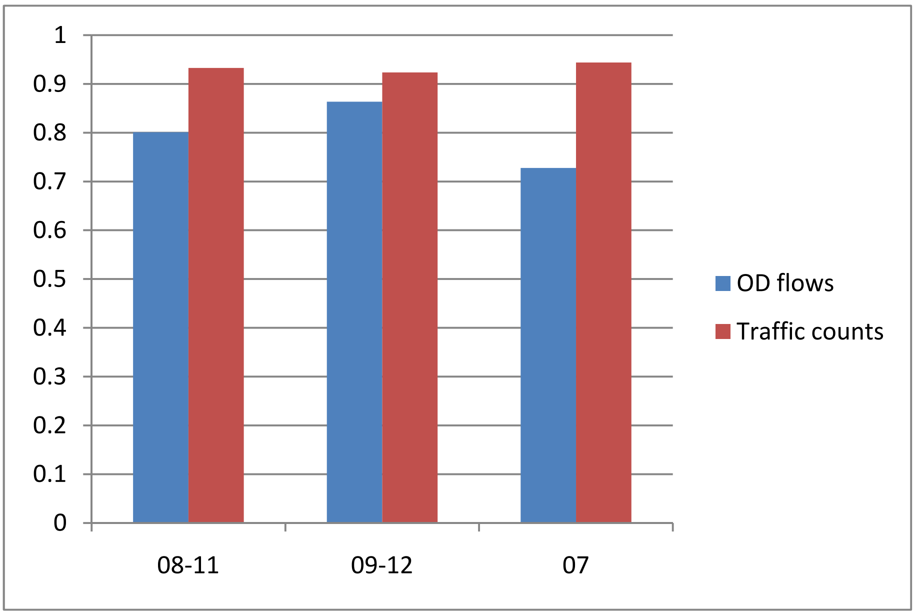


Figure 5-27 and Figure 5-28 illustrate the stability of the approach in front of initial demand. Indeed, global repartition of the different OD pair flows and coefficient of determination presents low differences whatever the input demand.

- Detection layout configuration sensitivity

Moreover, a sensitivity analyze is also carried out on the number and the "quality" of traffic counts used for flow adjustment. Indeed, the number of detectors and vehicle intercepted can be reduced to assess the approach. The goal is to compare results obtained using different detection layout configurations. Added to the 35 traffic detectors layout presented in Figure 4-15, three other configurations are evaluated considering:

- Traffic detectors with 25 highest flow (called 25 TC)
- Traffic detectors with 15 highest flow (called 15 TC)
- Traffic detectors with 15 lowest flow (called 15 TC Low)

Figure 5-29 illustrates the number and the percentage of the OD pairs intercepted by the different detection layout configurations. To analyze this graph, we must remember that 55% of the cell of the matrix is null, and thus not intercepted and modified.

Figure 5-29 OD intercepted based on detection layout - LSQR

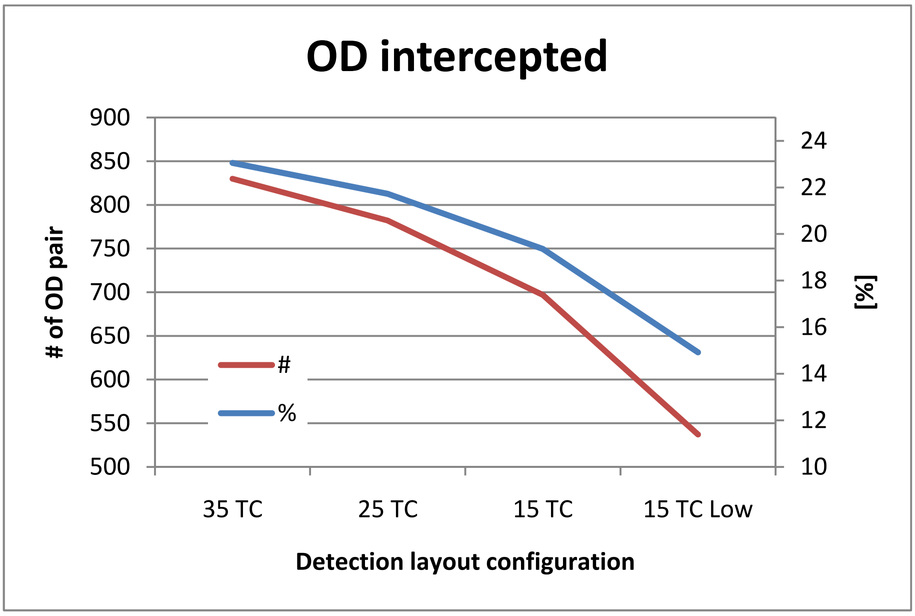


Figure 5-30 Results summary X-Y OD flows plots, Detection layout configuration - LSQR

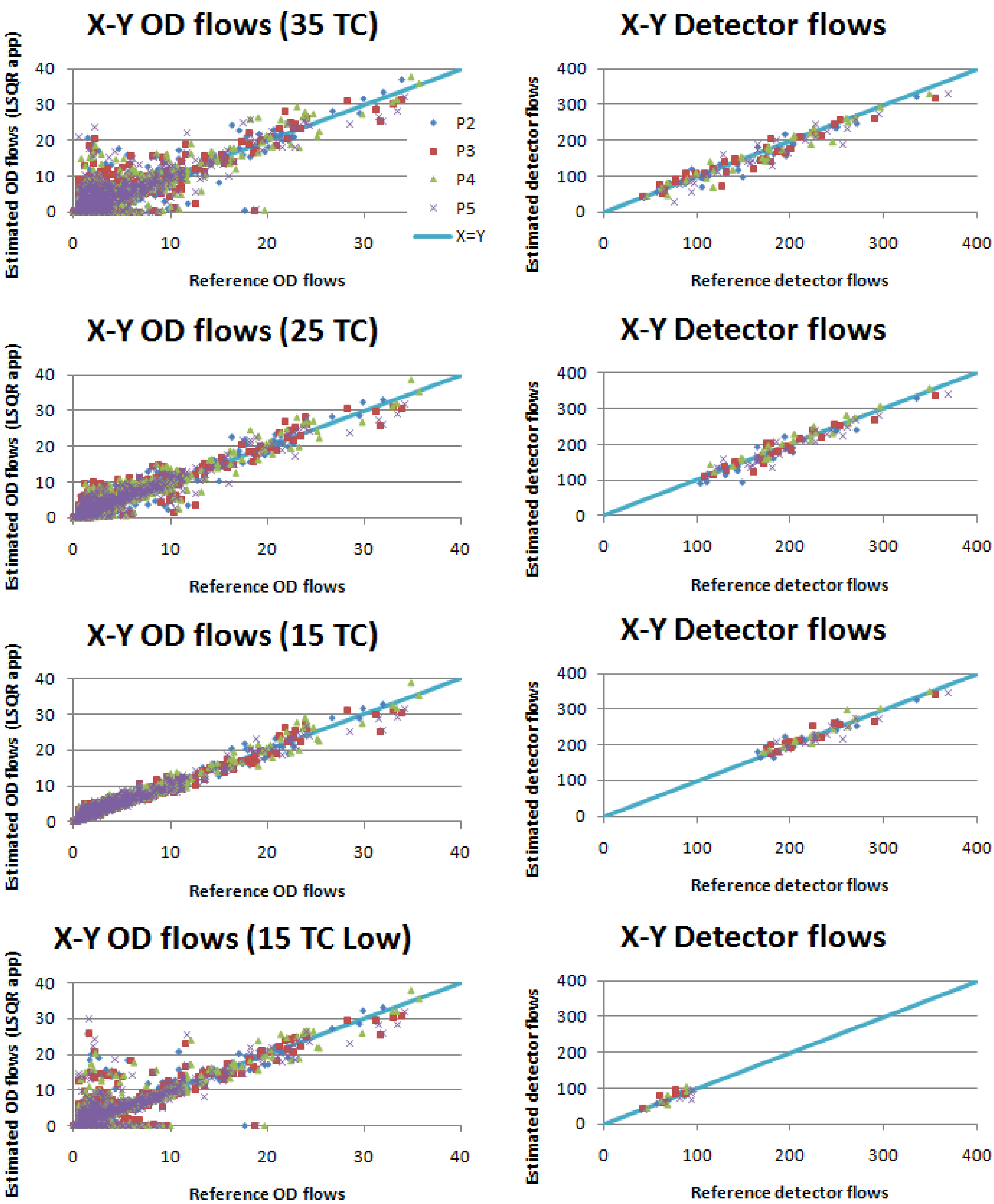


Figure 5-31 shows the coefficient of determination obtained from the clouds of dots presented in previous figure. They are global value for all OD flows for all time intervals.

Figure 5-31 Coefficient of correlation for detection layout configuration - LSQR

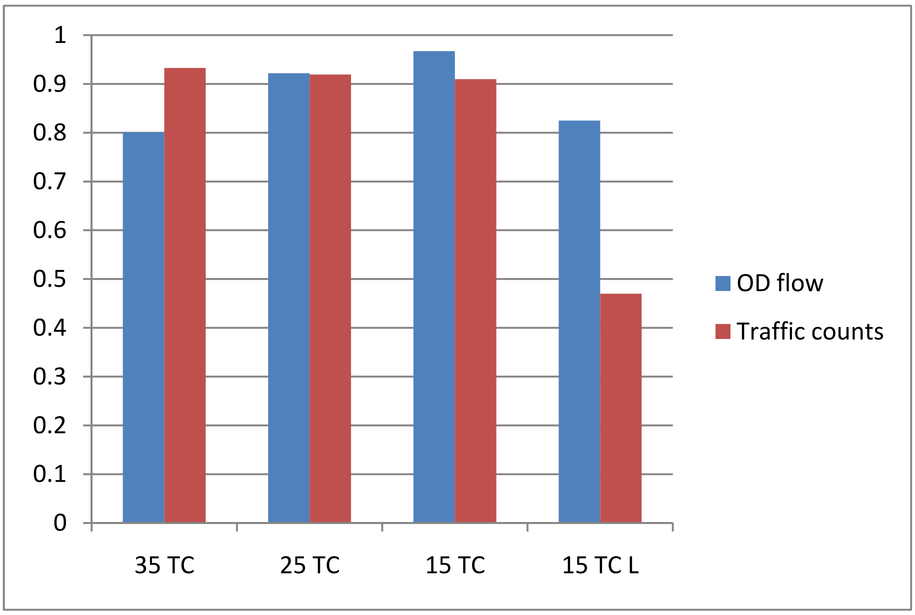


Figure 5-30 and Figure 5-31 show that the methodology manages to fit satisfactory the different traffic counts used by configurations. OD adjustment based on 15 highest detector flows induce a satisfactory fitting of the OD flows. Using greater number of traffic counts leads to observed "noise" on small OD pair flows. Nevertheless, these low values do not affect the network performance. Using the 15 lowest traffic counts (15 TC L) flows for adjustment lead to worst results due to the un-interception of the main and most influencing OD pair flows.

Table 5-4 presents the global results for the different detection layout configurations tested (with MSE and MSE P. in $(veh/15min)^2$ and ME in veh/15min). "MSE P." is a partial MSE calculated only on modified OD flows during the process to isolate the effect of the different detection layouts. That is, if an OD pair is not intercepted or not modified but different from the reference OD matrices (compare to the initial one), this constant error is not taken into account.

Table 5-4 Summary sensitivity analyzes - LSQR

	35 TC					25 TC				
	OD flows			Traffic counts		OD flows			Traffic counts	
	MSE	ME	MSE P.	MSE	ME	MSE	ME	MSE P.	MSE	ME
P2	1.65	-0.08	7	600	-11	0.52	-0.09	2.5	490	-9
P3	1.55	-0.09	6.5	860	-11.3	0.63	-0.13	2.9	460	-1.75
P4	1.8	-0.1	6.9	880	-10.5	0.64	-0.14	2.8	420	6.3
P5	1.8	-0.08	7	1020	-17	0.53	-0.09	2.4	600	-8.5

	15 TC					15 TC Low				
	OD flows			Traffic counts		OD flows			Traffic counts	
	MSE	ME	MSE P.	MSE	ME	MSE	ME	MSE P.	MSE	ME
P2	0.2	-0.09	1.04	320	0.11	1.3	-0.02	8	825	-11
P3	0.26	-0.1	1.21	330	2.6	1.3	-0.05	7.6	1140	-4
P4	0.3	-0.11	1.23	430	2.6	1.27	-0.04	6.9	1170	-6
P5	0.3	-0.1	1.17	530	-6.5	1.6	-0.035	9	600	-13

Table 5-4 confirms the results already presented in Figure 5-30. Different points can be observed from these outputs:

- MSE values of OD flows and traffic counts, MSE P. and ME of traffic counts decrease with the number of detectors (expect for 15 TC Low)
- ME values of OD flows is constant whatever the detection configuration
- 15 TC Low results are similar to the 35 TC

These results help to conclude that smaller number of traffic counts produce more accurate and fitting results. This observation is true for 25 TC and 15 TC but not for 15 TC Low. It show the limitation of the minimum quality required for the detection layout to perform OD estimation. ME value on OD flow shows the global fitting on the number of trips. Therefore, volume of matrices is similar whatever the detection configuration.

Based on results of this sensitivity analysis and real case application presented in chapter 5.4, this process has demonstrated its large sensitivity to quality of the detection layout configuration. Indeed, based on the same initial demand but on different traffic counts (COREL and REF ones), results obtained are largely different (see Figure 5-18 and Figure 5-27). Therefore, a particular attention must be put on this traffic counts input.

This sensitivity analysis allows making conclusions about the detection layout for OD estimation. For this study, detection layout which intercepts 95% of the flow and OD pair has been chosen (see details in chapter 2.1.5). From the results presented previously, we can conclude that 15 traffic counts are sufficient to obtain satisfactory results on OD estimation. Therefore, using this number of detectors, 80% of the traffic flow must be intercepted (see Figure 2-6). These results are important for practitioners. Indeed, for similar results, it represents a real saving in cost (installation and maintenance of fewer detectors) and in time (OD estimation process is much faster using less traffic counts data).

- **LSQR algorithm stability**

A "longer" (high number of iterations) bi-level process has been performed to assess stability of the algorithm within 200 iterations. MSE values evolution are presented in Figure 5-32.

Figure 5-32 Matrix and traffic count error evolution for 200 iterations - LSQR

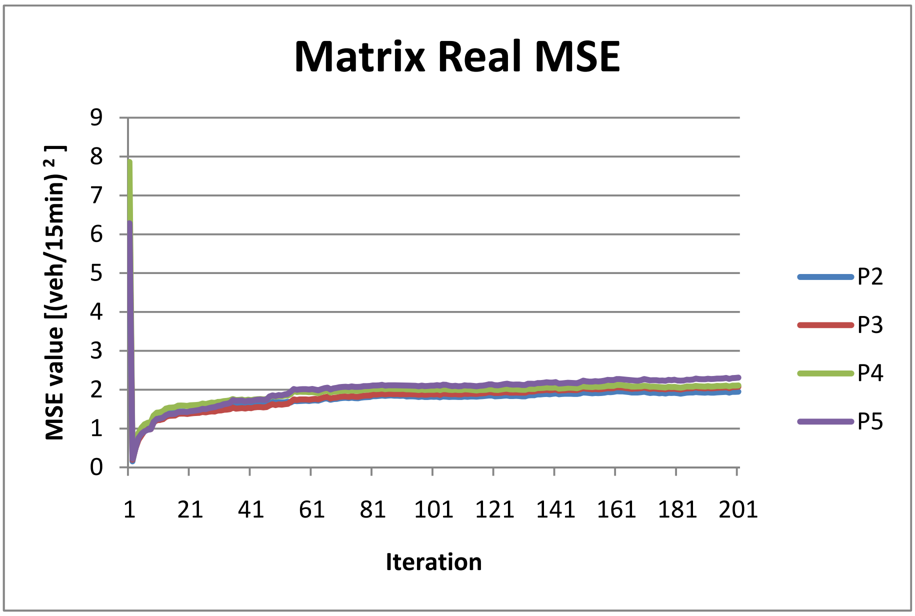


Figure 5-32 Matrix and traffic count error evolution for 200 iterations - LSQR

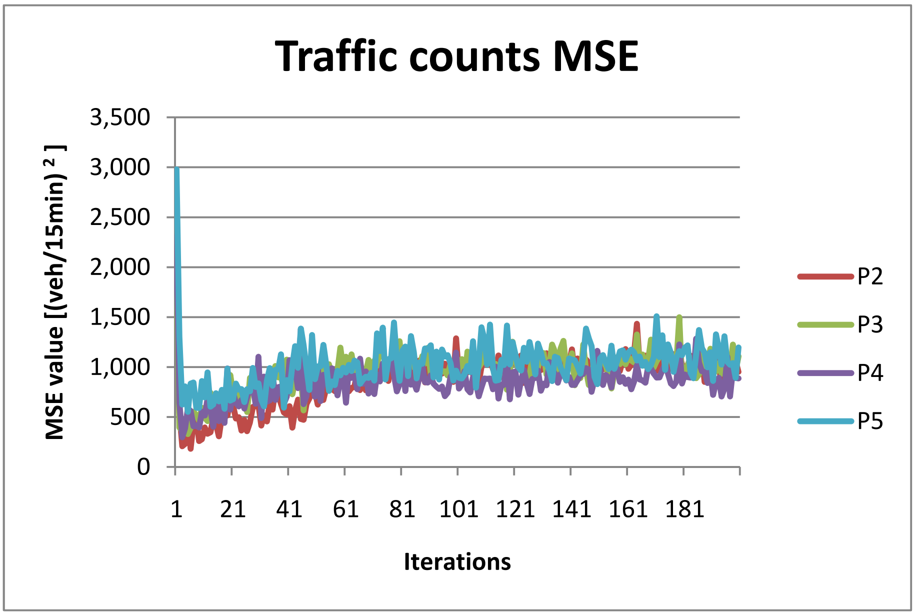


Figure 5-32 graphs confirm the stability of the methodology even after high number of iteration.

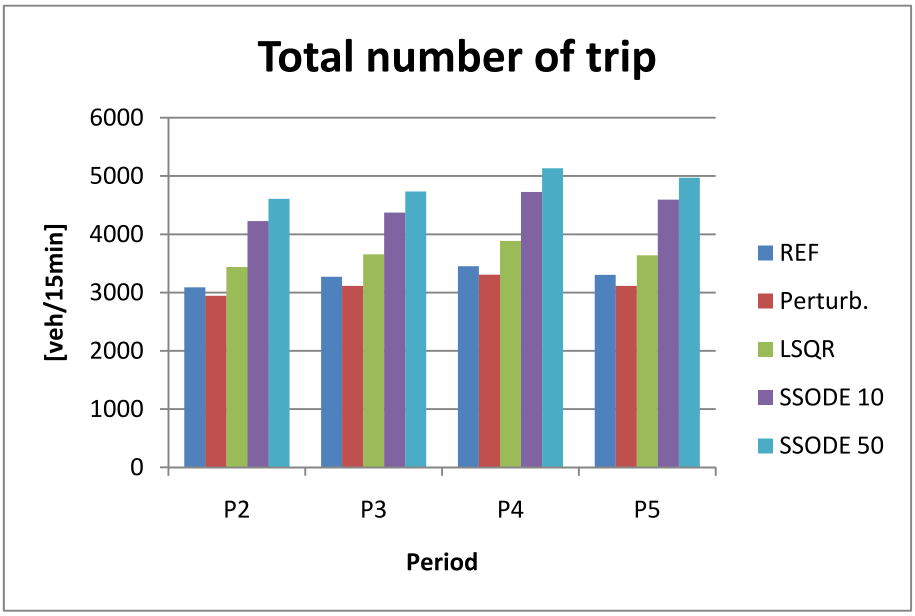
5.5.3 SSODE and LSQR outputs comparison

Previous analyses consist of examining the characteristics of the raw outputs from OD matrices obtained using the two different approaches (LSQR and SSODE): cells of OD matrices (as explained in chapter 4.2.6).

Next results are comparison of OD matrices obtained period by period. "Total number of trip" represents the volume of the estimated OD matrix, "maximum OD pair flow" is the values of the cell with highest flow and "mean OD pair flow" is the average of all the cell of the matrix. In Figure 5-33, REF is used for reference OD matrices data (SIMLO), Perturb. for the perturbed matrix used as input OD matrix of the process (08-11), LSQR for matrices obtained after OD estimation process using LSQR algorithm ("LSQR new Matrix" [10]) and SSODE 10 and 50 for matrices obtained after static sequential OD estimation process for 10 and 50 iterations ("SSODE new Matrix") respectively.

[10] As defined in Table 4-3

Figure 5-33 Matrices comparisons



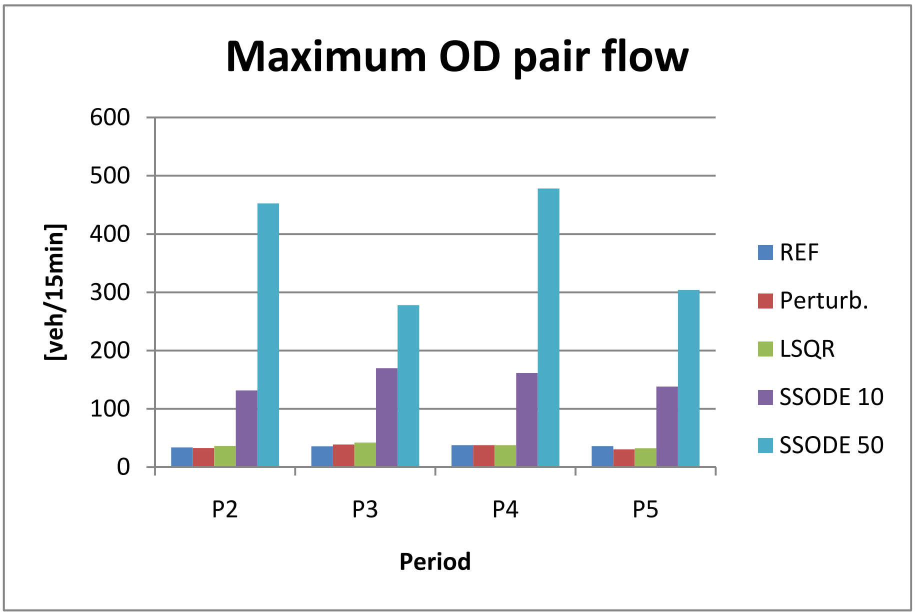
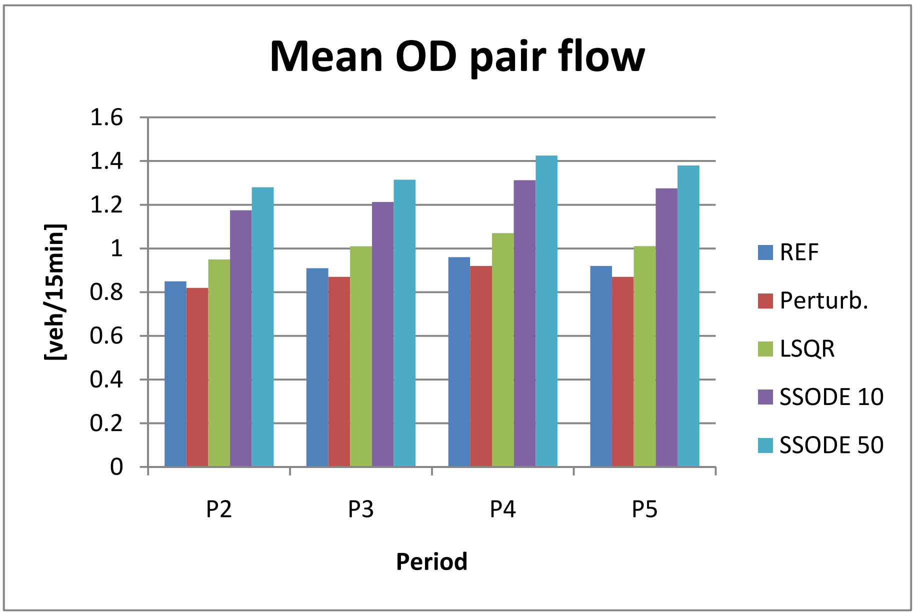


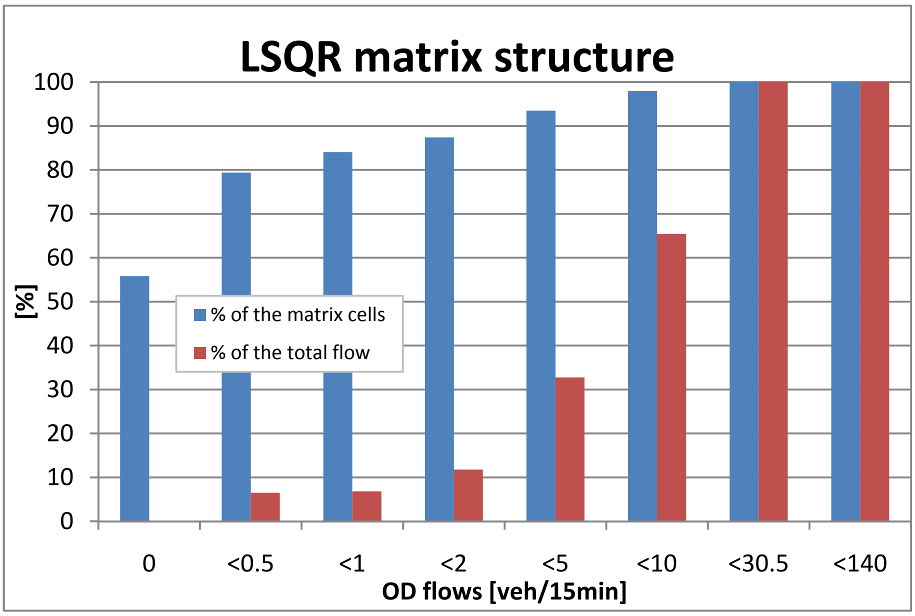
Figure 5-33 Matrices comparisons



Cells analyze of the different matrices presents a satisfactory correlation between results of the OD estimation using LSQR approach and REF matrix. Concerning SSODE approach, we can observe a large augmentation of flow for several OD pairs. This increased demand has effects (augmentation) on mean volume of traffic and number of trip per period.

To analyze deeper the structure of the obtained matrices, Figure 5-34 presents the proportion of cells dependent on OD flows values.

Figure 5-34 Matrices structure comparison



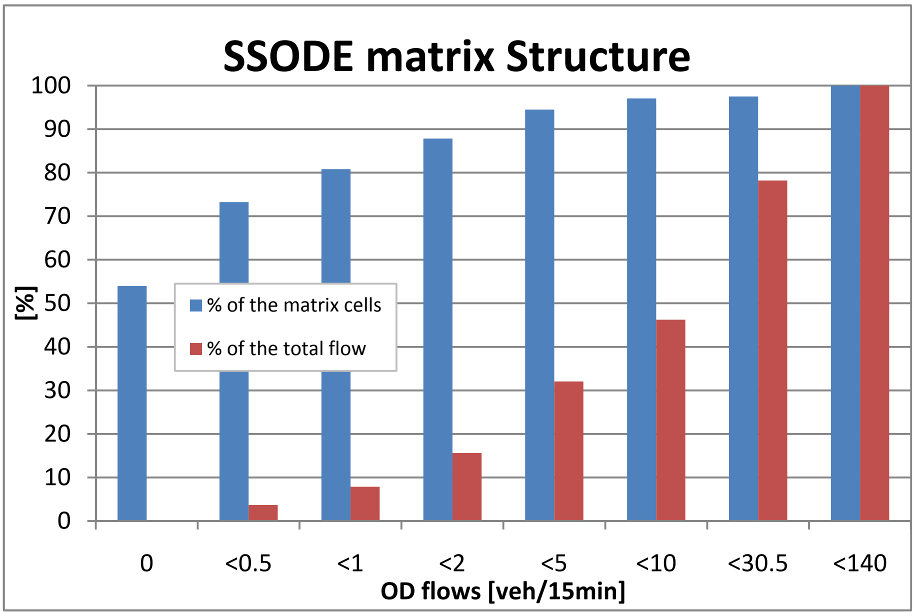
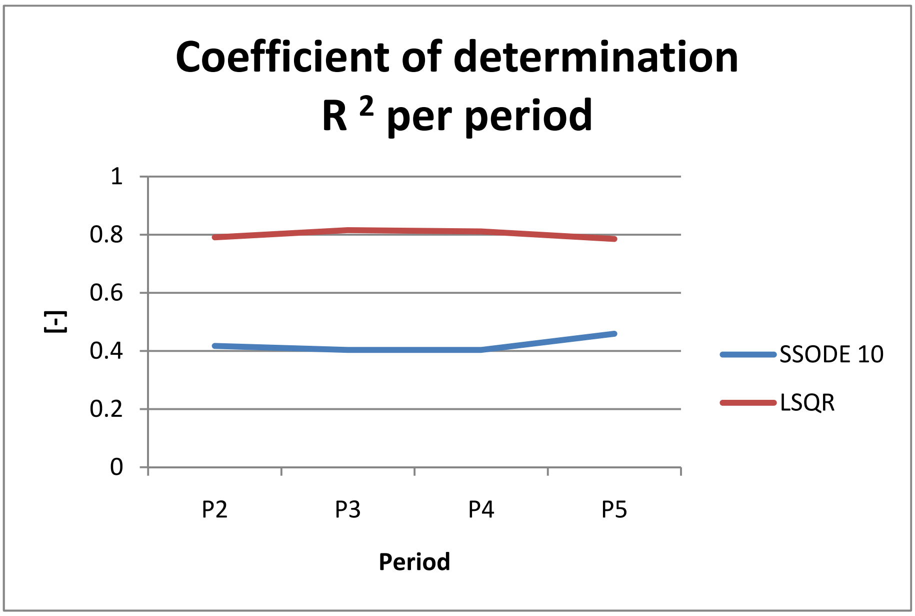


Figure 5-34 illustrates differences of the structure of the matrix obtained using LSQR and SSODE approach. It confirms the generation of large flow by SSODE approach for some cells (2-3% of the number of cells), but these trips represent more than 20% of the total number of trips. Concerning the rest of the structure of the matrices, structures are similar, particularly for small flows.

Figure 5-35 presents the coefficient of determination, R^2 obtained per period based on reference and estimation OD flows using both methods (LSQR and SSOED).

Figure 5-35 ***Coefficient of determination on OD flows par period***



The coefficient of determination confirms results already presented in Figure 5-22 and Figure 5-27 (08-11 case). The fitting is more satisfactory using methodology based on LSQR algorithm than SSODE approach.

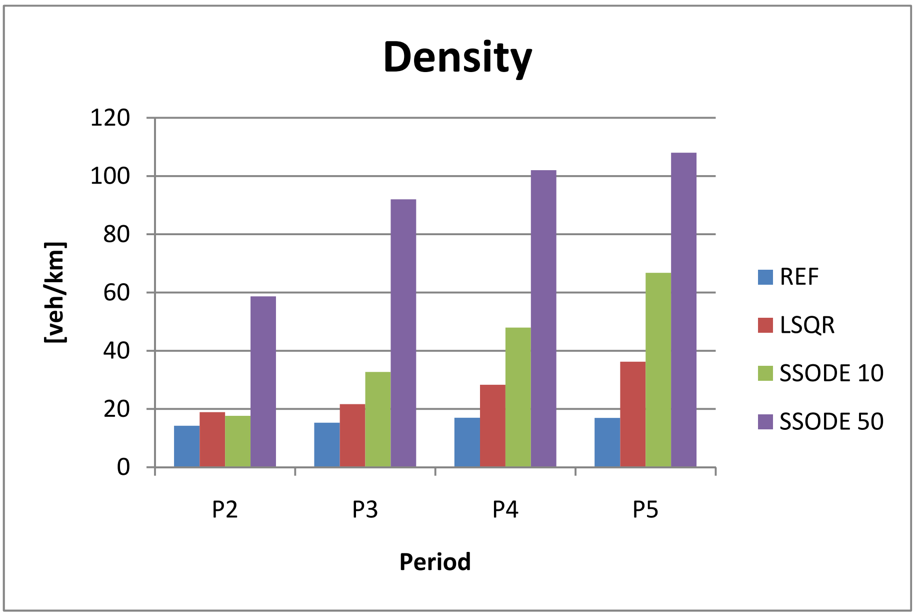
5.5.4 Assignment evaluation of outputs

After evaluation of the raw outputs of the OD estimation processes, a further step is needed to validate the methodology (as explained in chapter 4.2, Box 4 in Figure 4-10). Indeed, goal of OD estimation is to evaluate demand to be used by models for traffic study. Keeping this in mind, OD matrices obtained using SSODE and LSQR approach are assigned by a traffic model and outputs are analyzed. As explained in 4.2.6, the model used is a microscopic approach with Stochastic Route Choice algorithm for route choice and calibration parameters of the SIMLO study. In this way, the model does not use assignment method already applied in any of the OD estimation processes.

- **Aggregate indicators**

First, the analyses focused on aggregate data which could be extracted from the microscopic simulation for the whole network. Density, trip length, distance travelled, average speed and number of stop are presented in Figure 5-36.

Figure 5-36 Aggregate microscopic results



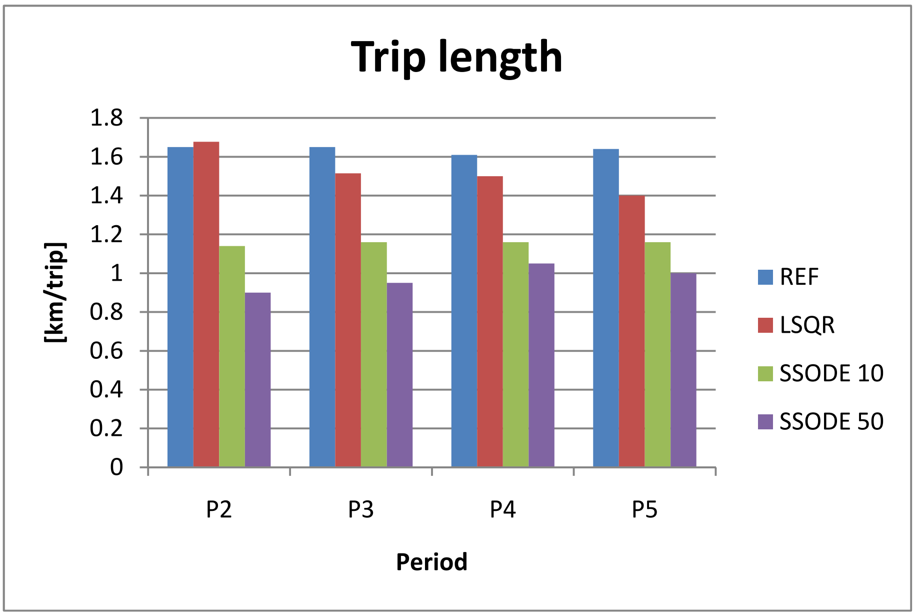


Figure 5-36 Aggregate microscopic results

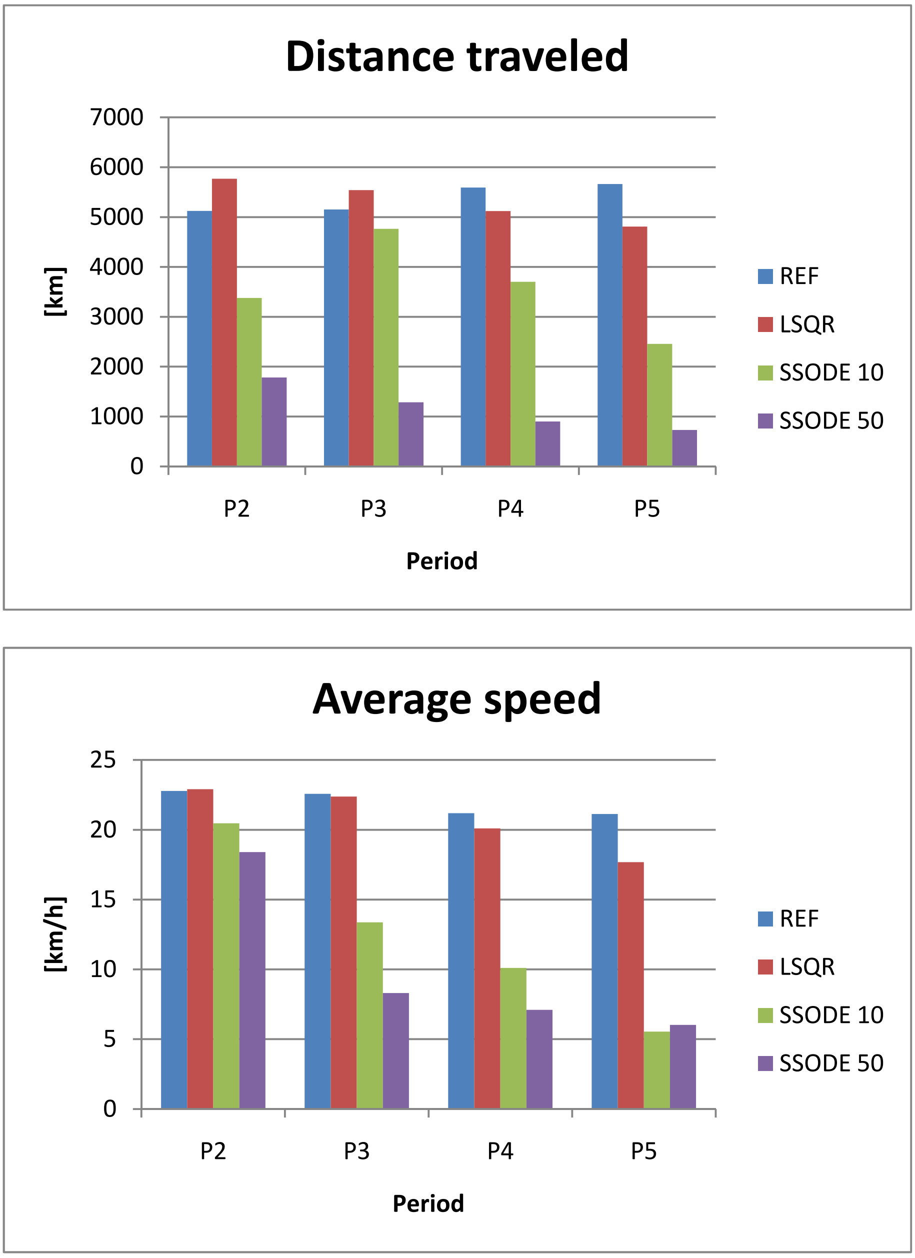
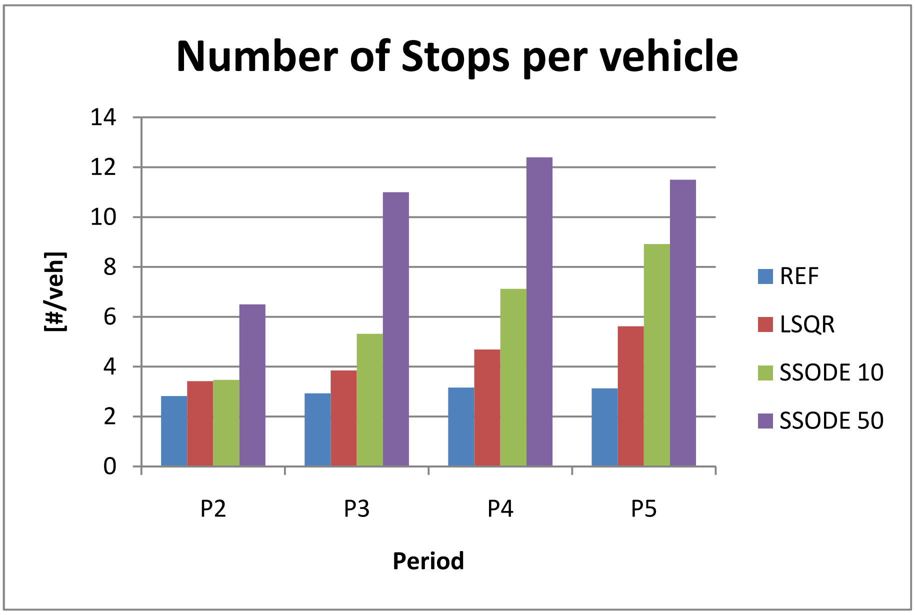


Figure 5-36 Aggregate microscopic results



Graphs in Figure 5-36 present the global behaviors of the estimated OD matrices in a microscopic model. Even though LSQR results are not perfect (mainly due to congestion in the second half of the study period), they are closer to the REF case than results obtained from static OD estimation process (SSODE). Indeed, due to the presence of large OD flows, already discussed in chapter 5.5.1, microscopic model has difficulties to assign the total demand without creating serious traffic jams. This phenomenon is measurable by the augmentation of the density and the number of stop through time periods and by the diminution of the distance travelled and the average speed in the network.

SSODE approach generates numerous smaller trips compared to trip length observed in the REF matrix. This phenomenon could be explained by limitation linked with the static approach. Indeed, sequential estimation of the OD matrix by time period leads to different assignment of the traffic into the network (compare to assignment of the demand in one simulation through several time intervals). Therefore, this difference in assignment generated slightly different traffic counts and the adjustment process has no other choice then the creation of various small trips to fit the targeted traffic counts for each time interval.

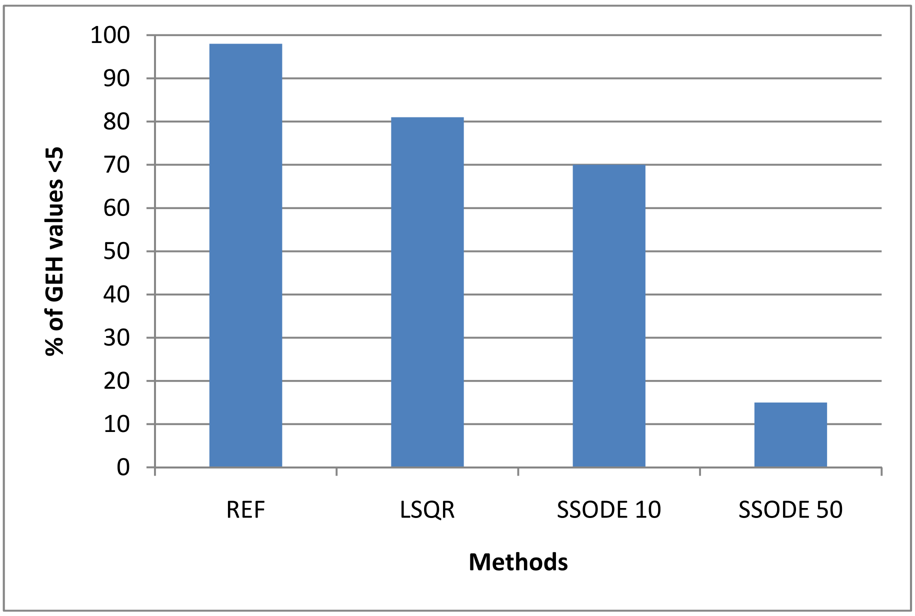
- **Disaggregate indicators**

Second, after aggregate, data, disaggregate information area analyzed to assess detailed indicators.

GEH[11] indicator informs about the fitting of the assignment of the demand with traffic count data. This indicator is evaluated to assess the repartition of the estimated demand into the network.

[11] Defined in chapter 8.1 in annex

Figure 5-37 GEH results



In Figure 5-37, we can see that the LSQR demand is close to the target of 85%. Concerning SSODE approach, congested network reduce flow moving into the network and causing lack of fit of traffic count values.
As noted in chapter 4.2, assignment process differs from the creation of the REF case (microscopic DUE) and one used to evaluate outputs of OD estimation processes (microscopic SRC). Keeping this in mind, REF demand does not give 100% for the GEH due to traffic count at one location with GEH value just above five.

Travel times of three different origin destination pairs have been studied through periods to compare the fluidity of the traffic into the network based on LSQR and SSODE demand with the REF case. Three centroïds have been chosen as origin or destination. They represent main entrance or exit of the network considered and are sufficiently for apart to measure travel time of representative paths into the network. Figure 5-38 presents the position of the considered centroïds.

Figure 5-38 Travel time evaluation

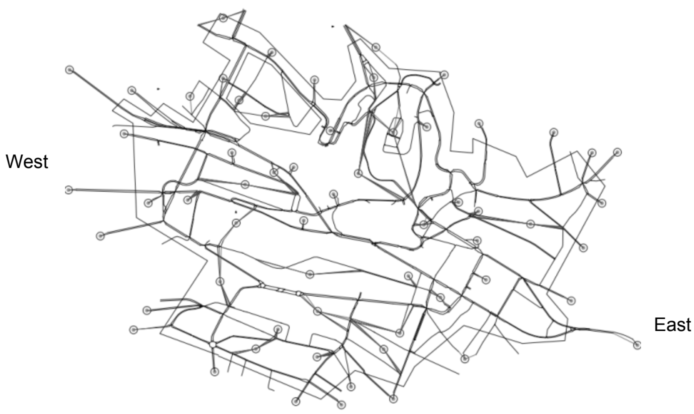
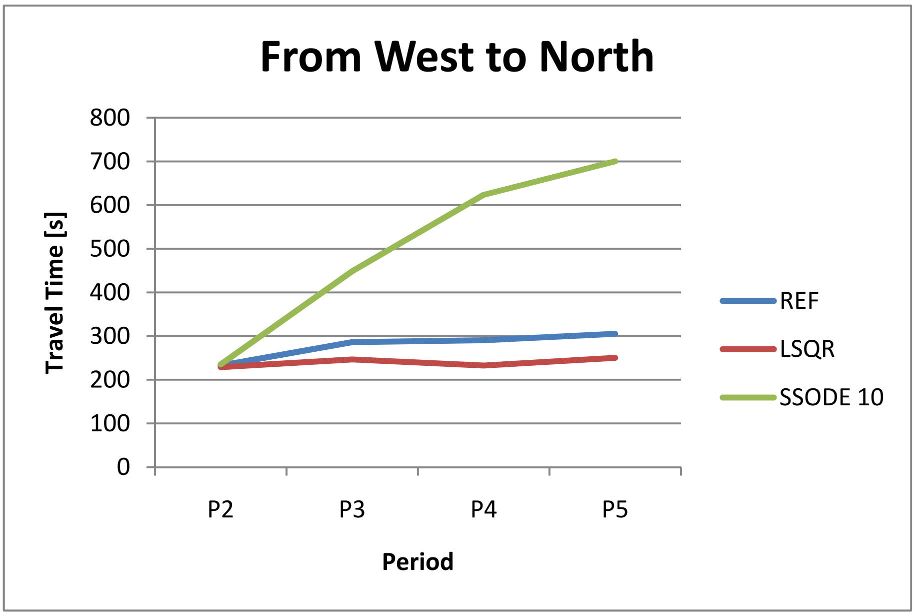


Figure 5-39 presents the different travel time measured in the network for the different OD pair for the period study.

Figure 5-39 Travel time on network



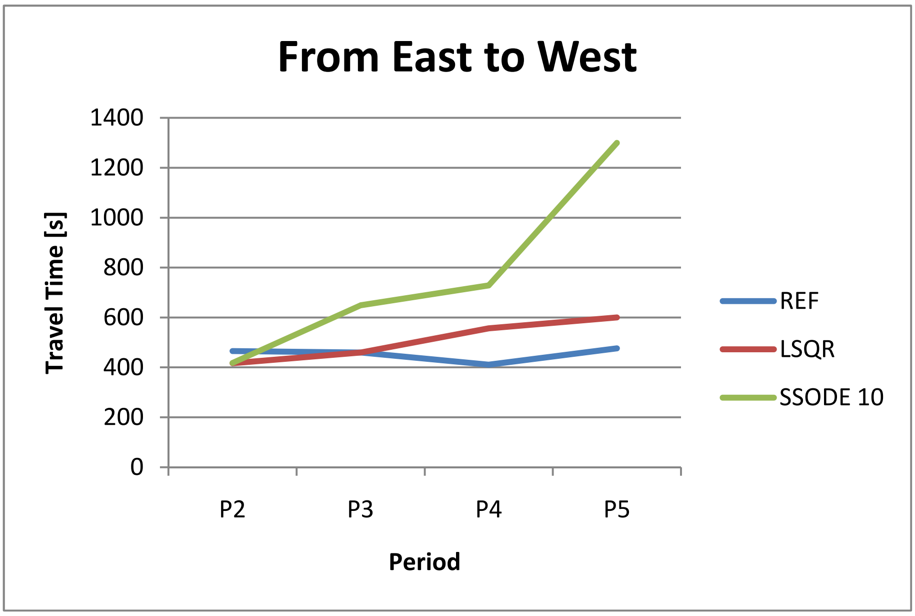


Figure 5-39 Travel time on network

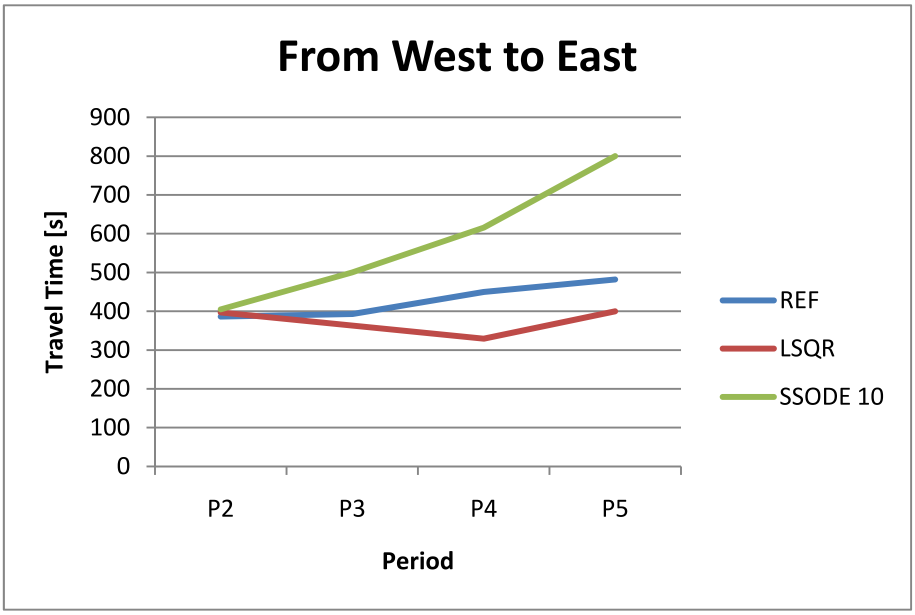


Figure 5-39, again illustrates the adequate fitting of the results obtain based on the demand estimated using LSQR algorithm and the REF case. Indeed, travel time observed to cross the network is similar for all time periods. Concerning the SSODE 10 demand, time to traverse the network is much longer than the REF case. This highlights traffic difficulties (congested areas) in the network which are not satisfactory for detailed dynamic analyses (congestion level too high to reproduce representative traffic flows and paths into the network).

5.6 Practical applications

After verification of the good implementation and working of the proposed methodology, the outputs of the approach have been compared with common method (SSODE) to present improvement added for demand estimation. Afterward, to illustrate practical applicability of the method and its outputs, different traffic scenarios have been elaborated.

5.6.1 Scenario 1, "Parking extension"

To analyze effect of network modification on the OD estimation process, attraction pole has been adapted based on new constraints in the city center. Indeed, the capacity of the "Parking du Flon", used by drivers of various shops and cinemas has been increased. Therefore, during rush hour, more vehicles are converging to this destination centroïd.

Due to difficulties for the city to measure the effect of the modification, a new OD estimation is performed. This process is based on known initial OD matrix (REF case) and optimal detection layout configuration (35 traffic counts, presented in chapter 4.2.3) added to one extra detector on the parking ramp to represent increase in the attraction. Therefore, time varying flow values for this detector (red dot in Figure 5-40) are presented in Table 5-5.

Table 5-5 ***Ramp detector flows - Sce 1***

Period	P1	P2	P3	P4	P5	P6
Traffic flow	80	100	150	151	100	80

First, based on initial demand and this new detector configuration, analysis consists of evaluating the effect on OD flows and estimating traffic counts. The green dot on Figure 5-40 presents main origins that contribute to the flow increase at the parking. Centroïds presented in Figure 5-40 are realistic solution of the proposed application. Indeed, these origins are main entrance of the network from South, East and West, close to the parking area.

Figure 5-40 ***Parking effect and map - Sce 1***

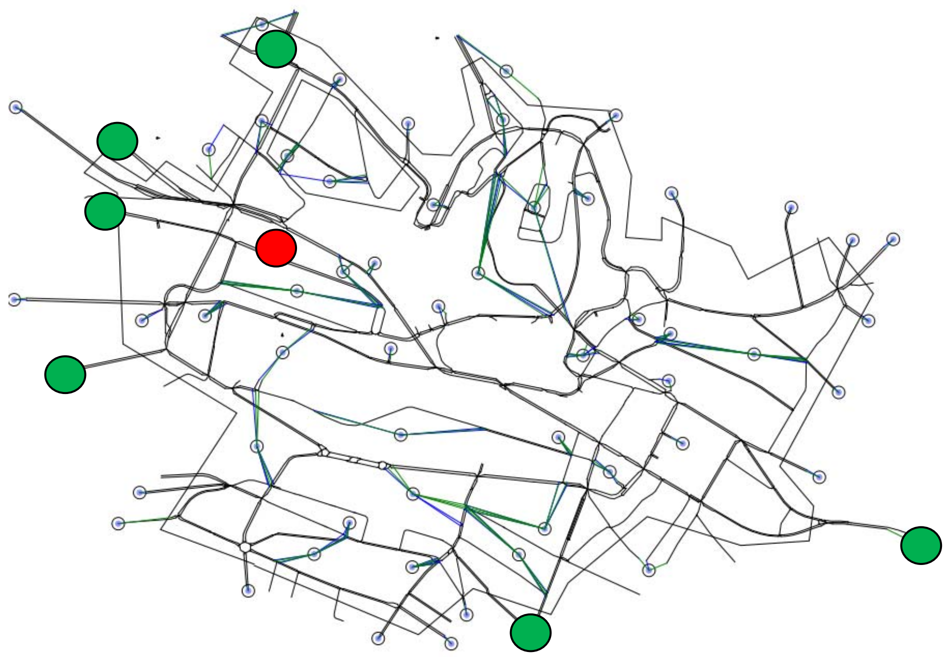
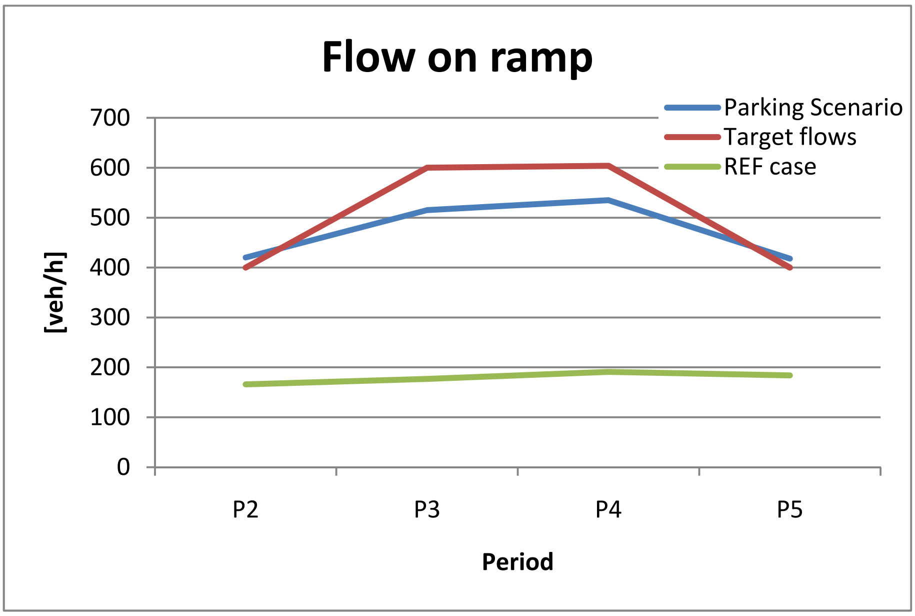


Figure 5-41 presents flows obtained after the OD estimation process on the new detector (Parking scenario) compared to the target (Target flows) and the situation before parking extension (REF case). The results show an adequate fitting of the Parking scenario compare to the target flows.

Figure 5-41 Traffic on ramp scenario comparison - Sce 1



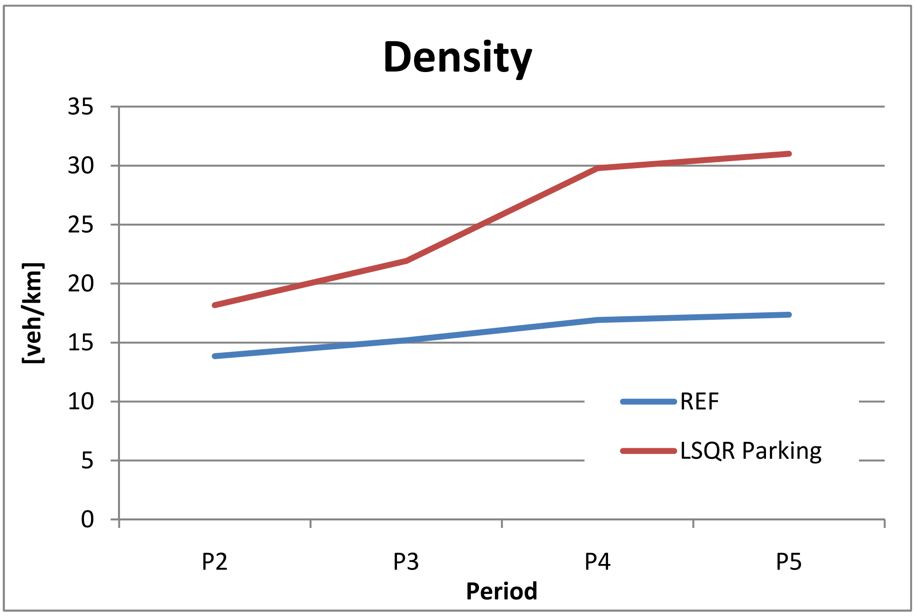
Moreover, new total number of trip per period for the concerned parking as destination is presented in Table 5-6. Augmentation of the number of trip can be observed compare to the REF case.

Table 5-6 Total number of trips for Parking destination - Sce 1

REF case	41	44	42	43
Parking scenario	119	120	145	144

After, new OD flows estimated (OD matrix), and analyzed in previous paragraph can be used to assess the effect of changes on traffic into the network. In this way, Traffic Impact Analyses (TIA) can be performed using traffic model. In our case, demand has been assign using microscopic SRC simulation (average of five replications) and results are presented in Figure 5-42.

Figure 5-42 Evaluation results - Sce 1



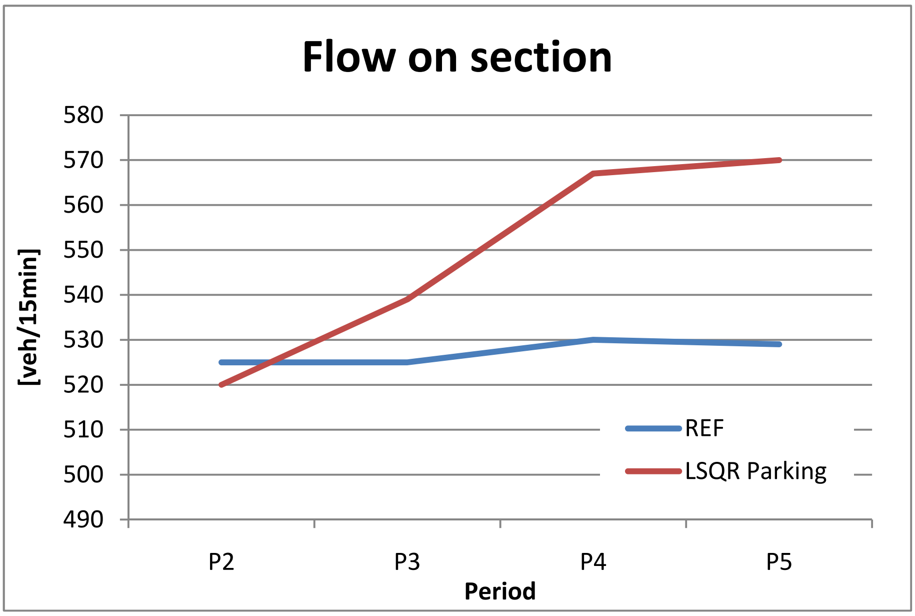


Figure 5-42 Evaluation results - Sce 1

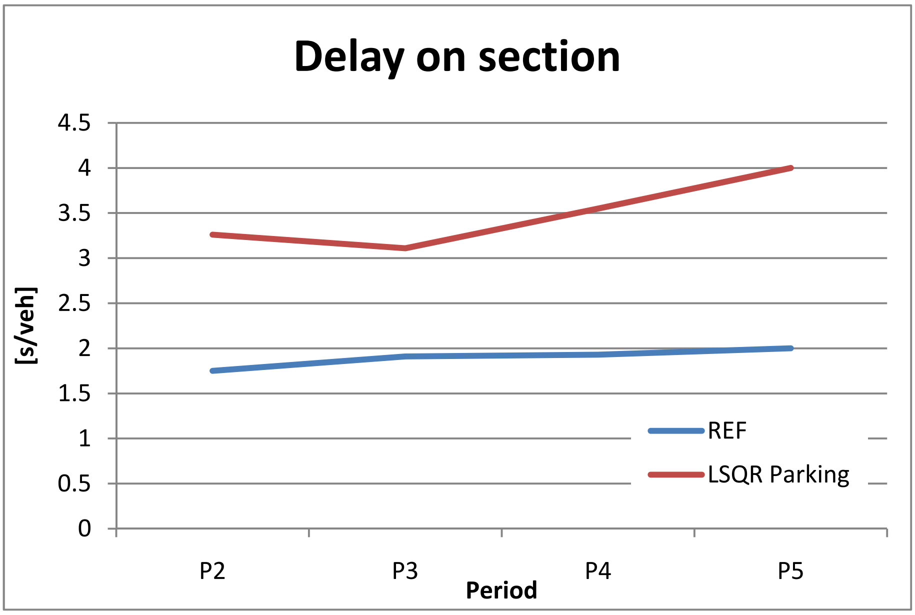
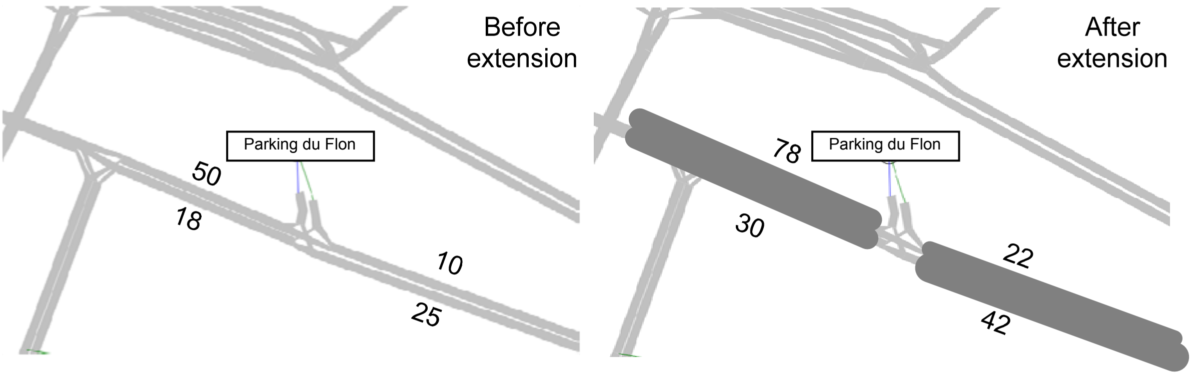


Figure 5-42 presents average density in the network, flows and delays on section around the parking area. The delays experienced near the parking area are shown in Figure 5-43. From these graphs, we can conclude that this augmentation of the mobility in the considered zone induce traffic congestion. Indeed, the density and delay illustrate that traffic flow is over saturated compare to the case without extension of parking facilities.

Figure 5-43 Delays on sections [s] - Sce 1



This application illustrates the practical potential of the OD estimation methodology proposed. Indeed, based on new traffic constraint (parking extension in this case) new OD matrix (time sliced OD matrices) has been estimated, origins of new trips have been identified and effects of the mobility pattern have been simulated and measured. These possibilities are huge assets for practitioners whose can gain time and money using new methodology of this study.

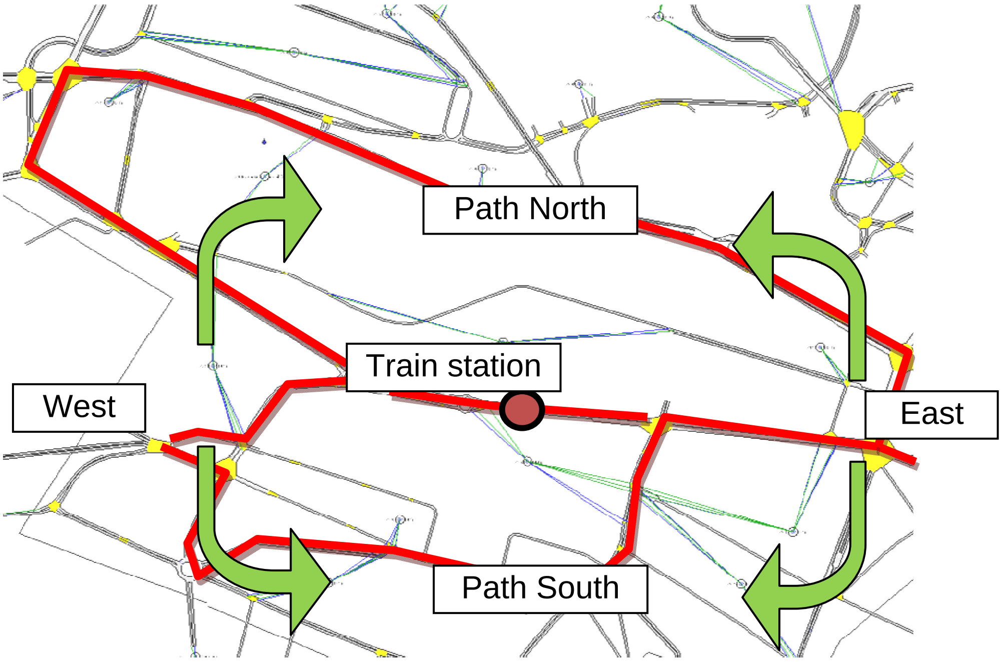
Without the proposed methodology which has performed OD estimation process and traffic model to assess traffic effects of the new demand, practitioners has to carried out a full demand estimation study based on questionnaires, surveys, hypotheses, etc. to obtained similar results. In practice, all these steps are costly and time consuming. Often educate guess are made on charges to traffic flow in proximity of the study area before carrying out a TIA. This practice does not fully assess the impact on the wide road network. Thence, the propose OD estimation process is a great asset to practitioners.

5.6.2 Scenario 2, "Train station incident"

Scenario 2 consists of evaluating the effect of supply modification on the assignment of the matrix estimated by the proposed methodology based on LSQR adjustment (LSQR), compare to the REF one. To modify locally and dynamically the supply, an incident (reducing the capacity to zero in both ways) has been created at 17h for 10 minutes on a critical link, the train station of Lausanne city (see red dot in Figure 5-44; similar to case presented in Figure 1-5).
From this new situation, traffic flows has two different possibilities to avoid the incident area using north or south routes (see Figure 5-44). Therefore, vehicle which drives from West to East or the opposite using train station corridor has to adapt dynamically their route from the "trains station" path to the "North" or "South" path. It is important to note that the "North" path induce a large augmentation of the travel time compare to "Train station" and "South" paths.

In normal conditions (without the incident), 100% of the users traveling on the East-West direction are traversing via the train station. Indeed, this route is the shortest path even in case of realistic congestion. This result is similar whatever the matrix used as input (REF or LSQR) and the time interval.

Figure 5-44 Situation and Paths - Sce 2



Taking into account the incident next to the train station, assignment of the traffic changes during the study period. Indeed, based on augmentation of the travel time on links on the "train station" path due to the incident, users switch to alternative paths with shorter travel time. Figure 5-45 presents the percentage of vehicles in the East-West direction on each of the paths for the whole period study.

Figure 5-45 Whole period Path comparison -Sce 2

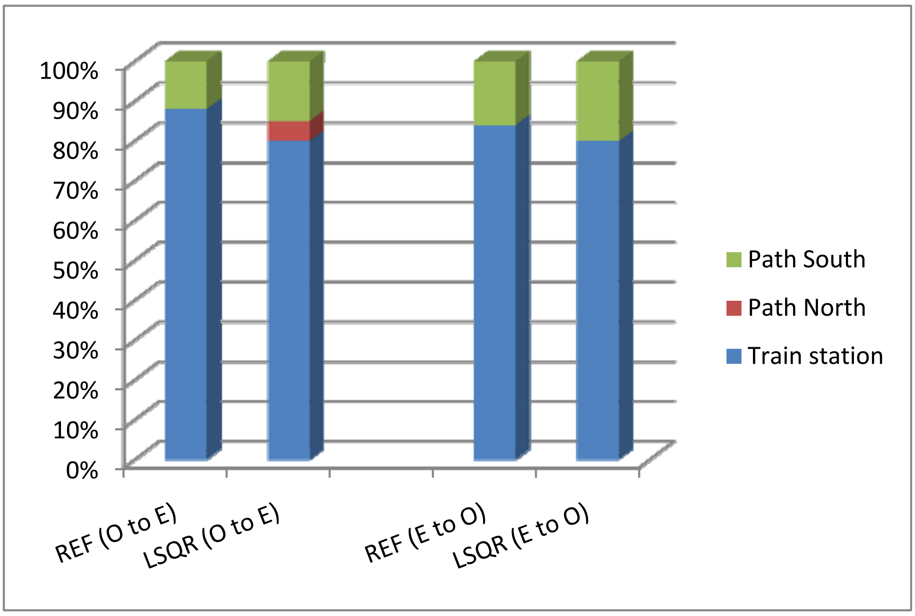
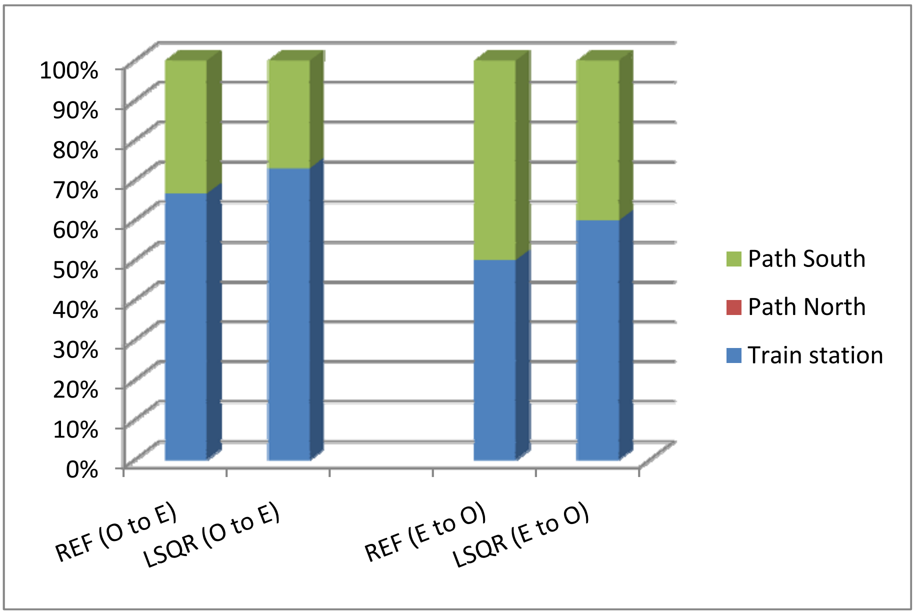


Figure 5-46 illustrates the percentage of vehicle using different paths to avoid incident area between 17h and 17h30 (the incident congested period).

Figure 5-46 17h-17h30 path comparison - Sce 2



Assessment presents satisfactory results concerning the assignment of the traffic in front of an incident for LSQR demand compare to REF matrix. Nevertheless, small differences could be observed. Indeed, these evaluations have been performed based on two different matrices. Therefore, different traffic conditions are observed. Taking into account initial congestion and the sensitivity of the microscopic simulator to path choice, difference in assignment are justified.

Nevertheless, it is an original way to assess the quality OD matrix demand and this application has shown the good behavior of the estimated matrix on realistic assignment (compare to the REF results)

5.7 Conclusions

Chapter 5 has demonstrated the capacities of the innovative proposed methodology developed and presented in chapter 3. Indeed, after verification of the implementation and that the methodology is working properly, the method has been applied on real data set to illustrate its applicability to deal with realistic data input of large urban area. Afterward, method has been compared with the common approach used by practitioners for OD estimation (SSODE). Results present satisfactory performance for the new method compared to the SSODE. Indeed, OD flows estimated and assignment of these demands using traffic simulator have shown a satisfactory fitting for LSQR approach, contrary to SSODE one. Finally, different scenarios have demonstrated the applicability of the method on realistic practical case studies and have highlighted assets of the approach in practical context.

6 Conclusions and Recommendations

Demand assessment is indispensable input for any transportation study and its quality has a large influence on analyses' outputs. In this context, the goal of this research was to develop an innovative dynamic methodology for the matrix estimation process in an urban area.

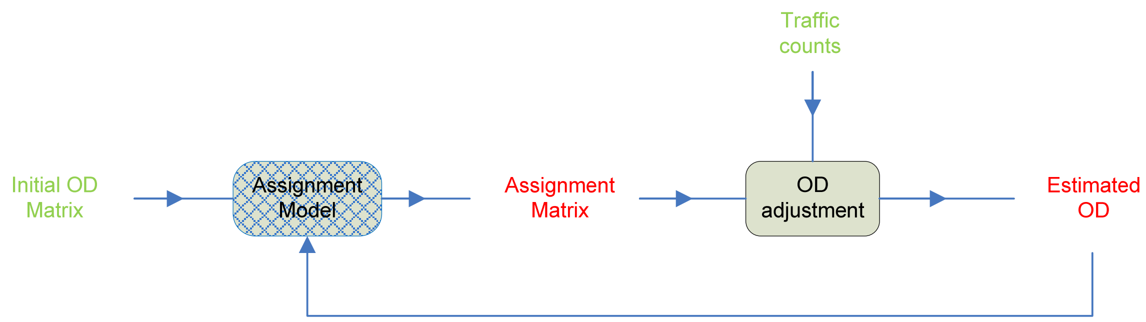
6.1 General conclusions

The methodology developed is innovative in various aspects. Based on traffic count data, the dynamic origin-destination estimation process modifies initial, inexact OD demand. The proposed method is comprised of a heuristic bi-level approach. Assignment of the initial demand is performed by a mesoscopic simulation based on the Dynamic User Equilibrium to model detailed dynamic traffic patterns. OD flow adjustment is executed by an efficient least square solution which takes into account dynamic aspects of the flow propagation and traffic counts. Based on different outputs and indicators selected, this method presents robustness and consistency.

The proposed methodology can be considerate as an improvement of the State of Practice of dynamic OD estimation for several raisons. First, the developed approach is fully implemented in well-known commercial software and does not need external resources to perform dynamic demand estimation. Second, adapted detection layout allows decrease the global computation time and therefore reduce delay to obtain relevant outputs for detail traffic studies. Finally, sensitivity analyses on a-priori initial demand has shown the low influence of this input (keeping this input consistent) on the final results and the realistic scenarios have been solved in a satisfactory manner with this tool.

Figure 6-1 presents a succinct description of the OD estimation process implemented in this research. Inputs are written in green, outputs in red. Dashed box is the assignment process. During this research, AMSUN Meso has been used to perform detailed and realistic assignment of the traffic. Nevertheless, any other tool could be easily employed to assess the assignment matrix needed for the OD adjustment algorithm.

Figure 6-1 **OD estimation process description**



This research has shown the importance of input data for the OD estimation process and mainly the detection layout configuration used for traffic count data. Indeed, OD flows must be intercepted by detectors to be estimated. Therefore, choice of the vehicle intercepted is crucial to adjust most influencing flows. Sensitivity analysis has shown that adding detectors does not necessarily improve OD estimation output and that low importance flows could be ignored to increase the efficiency of the detection layout configuration and decrease the computation time.

Applying OD estimation in urban areas presents several challenging aspects. High numbers of attraction poles (buildings, shops, parking, etc.) lead to large OD matrices and low flow per OD pair. Moreover, signalized intersections and large numbers of feasible path choices induce complex traffic patterns. To tackle these particularities, a mesoscopic model has been chosen to perform traffic assignment. The selected model allows detailed dynamic simulation and takes into account all characteristics of the urban context (traffic lights, route choice, etc.) without numerous calibration parameters. Moreover, a LSQR algorithm has been selected to adjust OD flows. Its capacity to deal with a large matrix and its ability to constrain outputs make this least square solution the better-adapted tool for urban applications.

Results obtained using the proposed methodology has demonstrated various resources. Parallel comparison with the most common approach for OD estimation has shown: first, the ability of the method to generate OD flows close to the actual demand, compared to sequential static approach. Second, the utilization of the obtained demand by a dynamic traffic model has established its aptitude to reproduce realistic assignment patterns. This second aspect is the final goal of demand estimation and represents an indispensable feature for the developed methodology.

Finally, applicability and example of the utilization of the proposed method has been presented using two different realistic scenarios by means of the commercial AIMSUN software (in which the proposed methodology is implemented as a plug-in). From the results and conclusions of these applications, the author has confirmed the benefits added by the proposed method for transportation study. The proposed approach is applicable in a real situation to solve realistic problems.

With these conclusions, the objectives established in the introductory chapter of this research can be considered as fully realized.

6.2 Practical recommendations

The acquired experience and conclusions of this research lead to several recommendations associated with the process of OD matrix estimation, and particularly applied to an urban context.

First, one particularity of the OD estimation problem is its under-determination aspect. It means that the process is looking for a solution which satisfies the given conditions, but has number of conditions (traffic counts and initial OD matrix) smaller than the unknown values. Keeping this in mind, a lot of different OD matrices can satisfy defined constraints and all those solutions are consistent with the problem. Moreover, real OD matrices are usually unknown. Therefore, it is difficult to discuss about the quality or representability 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 to obtain favorable outcomes.

Second, it is important to note that the different issues of the process are linked with the inputs used. The quality (representativeness, level of detail, etc.) of the initial OD matrix obtained by studies and/or investigations could be very different depending on the cases studied. Moreover, it has been shown that detection layout configuration also has a large influence on the results. The issue is not to add extra detectors to intercept flows but to use a minimal number of traffic counts in optimal places. Therefore, the author suggests putting specific efforts in data collection to guaranty efficient computation and good results.

Finally, the proposed methodology is an iterative, bi-level process which needs several iterations to converge to an optimal solution. Different analyses performed during this research have shown that the number of iterations required to obtain satisfactory results is relatively small, usually less than 10 (dependent on the network and input data). Therefore, based on the proposed stopping criteria defined in this report, the computation time could be greatly reduced for practical application.

6.3 Proposition of further researches

Throughout this work, different axes of research have been highlighted several times that would be interesting to develop further. Some of the promising areas include:

- Mesoscopic simulator used for demand assignment generates path choice in a deterministic way. Therefore, assessment of the utilization of a stochastic model to take into account traffic distribution presents a challenging area of research to observe the effect on the demand estimation outputs.

- Results obtained based on the proposed methodology have highlighted the importance of the input data to perform relevant and efficient OD estimation. A further research could consist of the development of a methodology to obtain satisfactory results from the approach in case of lack of input data (low quality or missing initial OD matrix, non-optimal detection layout, etc.).

- Proposed methodology is using initial OD matrices and traffic counts as exclusive input for estimation of OD flows. The possibility of including other types of measurement (i.e. speed, travel time, etc.) could be assessed to improve the accuracy of the estimation (incorporated at assignment of the traffic and adjustment of the flows levels)

- Methodology proposed has been compared with the most used approach, the sequential static OD estimation process. A similar study that evaluates results obtained compared to other dynamic approaches for OD estimation note the position of the method in the dynamic demand estimation field.

- Approach presented in this research focuses on off-line estimation of the demand. Further developments to allow on-line utilization of the OD estimation could be an interesting research to apply benefits of the method in real time traffic management systems.

- To validate fully the proposed approach, other urban networks (larger, with different characteristics, etc.) and scenarios (with demand and supply modification) must be tested in further works

- Interesting axe of research is the effect on the OD estimation process of a mixed urban/freeway network. Moreover, multimodal (considering various type of users: trucks, buses, public transport, etc.) developments can increase the versatility of the approach.

- Computation optimization must be performed to improve the execution time in order to increase the efficiency of the process.

- "Manual" calibration is proposed in this approach. Development (or combines with existing methods) of an automatic calibration is an important feature which could be added to the current tool.

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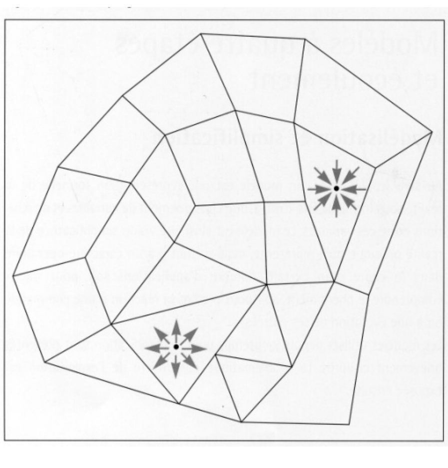
8 Annexes

8.1 The "Four Step" planning process

The "four-step" planning process is well known by traffic planners to generate traffic demands utilizing the two first steps and to assign this demand in the last two steps. It is the starting point of each traffic study and is indispensable to obtain efficient and global estimations of the demand. These steps are presented in detail in [78] and help us to place this work into the demand estimation field.

- Trip Generation
The aim of the first step is to evaluate the number of person-trips originating in, and/or ending in a given zone (geographical area with common characteristics). These trips could be to go to work or school, shopping trips, or social and recreational trips. A "trip rate" is based on zonal characteristics or a households' characteristics and help generate the number of trips.

Figure 8-1 Trip generation

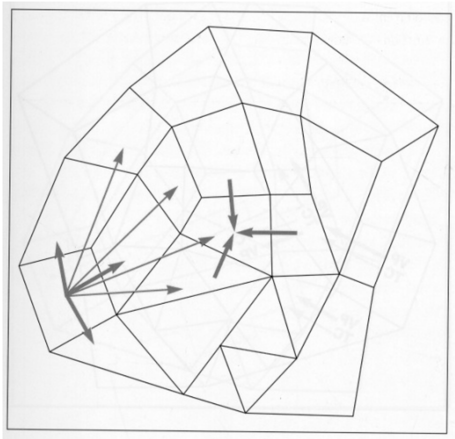


extracted from [32]

- Trip Distribution
This step consists of distributing each of the trip origins obtained in the first phase above across various destinations. Growth-factor methods, entropy-maximizing

approaches or "synthetic" models such as the "gravity" model, which is adapted from Newton's "gravitational" law of physics, are used to obtain OD flows.

Figure 8-2 Trip distribution



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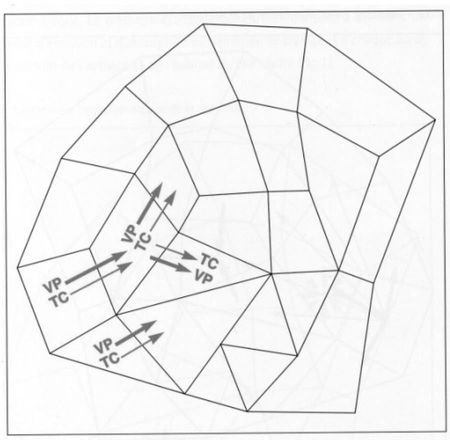
- Modal Split

Each of the origin-destination volumes obtained in the trip distribution phase are now "split" or distributed into the various alternative modes (transit or car shown as VP and TC in Figure 8-3, for instance). Factors influencing mode choice are:

- Characteristics of the trip maker (car availability, residential density, etc)
- Characteristics of the journey (trip purpose or time of the day)
- Characteristics of the transport facility (Cost, travel times, comfort, security, etc)

Modal-split models exist to achieve this step.

Figure 8-3 Modal split

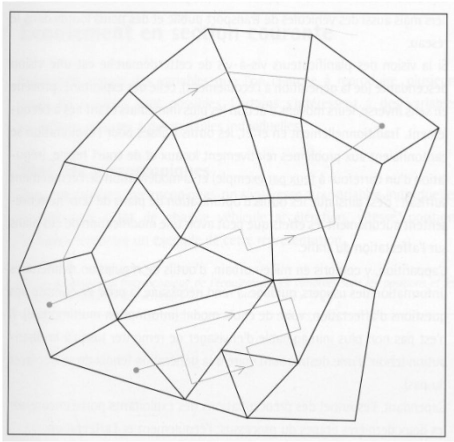


extracted from [32]

- Trip Assignment

The modal trip from a given origin to a given destination on a given mode obtained in the preceding phase is assigned to the network's links, or more precisely, routes or paths between a given origin and destination. Logit (or C-Logit) models are main the tools used to assign trips (see [30]).

Figure 8-4 Trip assignment



extracted from [32]

These four steps are processes to estimate and assign traffic demand in a static way for long-term application (strategic or planning studies).

In our case, we skip step 1, "Trip generation" and step 3, "Modal split", because our study uses previously defined zone repartition (through initial a-priori OD matrix) and is limited to only one type of vehicle, as explained later in this report.

8.2 OD estimation State of the Art

The OD estimation problem has been treated by many researches in the literature and various approaches have been proposed for different configurations (see [54, 82] or [21]). This part presents a non-exhaustive bibliography of the domain; the most relevant papers for our topic are listed.

As already presented, two distinguished parts can be identified in the OD estimation process: traffic assignment and OD adjustment. Traffic assignment, which determines the repartition of the traffic inside the network, could be done for congested or un-congested conditions. The OD adjustment, which adapts the demand to the observed traffic counts data, could be static (flow constant during the simulation period) or dynamic (traffic volumes are changing over time period), as presented in Table 8-1.

Table 8-1 Four cases for OD estimation

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

We are going to have a look at the un-congested case and see more in details the static and dynamic estimation in congested networks.

8.2.1 Un-congested vs. congested networks

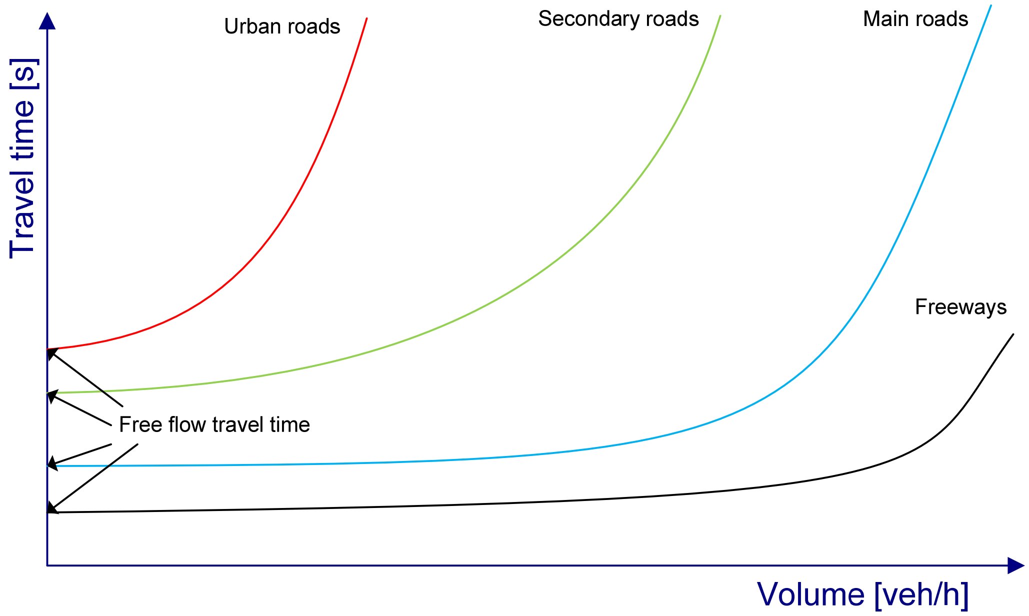
- **Un-congested**

In the early days, the simplest situation was considered. In the case of un-congested network, the route choice from an origin to a destination was made without consideration of the congestion. The travel time of a link was not dependent on the flow on it (considered like in free flow conditions). There is no consideration of the capacities for the different roads, links 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 solving of the demand estimation problem is a minimization of the “distance” between the observed data and the real data (matrix and traffic counts).
The solution was usually obtained by using standard optimization methods, Iterative Proportional Fitting (IPF), maximum likelihood, Matrix scaling, etc. Examples are presented in: [26, 29, 53]. These approaches are not very useful to work with because these models are representing non-realistic situations and not observable in reality (or for particular and rare cases).

- **Congested**

In case of a congested network (non free-flow conditions), the time necessary to cross one link is dependent on the flow (number of users) on this link; the higher the link flow, the higher the travel time (TT) on the link, i.e. more vehicles are delayed by the others. Depending on the model used, the route choice could be a function of travel cost. To evaluate this travel cost, different factors (tolls, fuel, comfort, etc.) could be considered but, usually, the main part of this cost is constituted by travel time. From this statement, to allow practical assignment, the relationship between the average speed on a link to its flow has been studied, established and is called Volume Delay functions (VDF). Figure 8-5 shows typical VDF curves on various types of roads. This representation allows the modeling of the effect of congestion on a link.

Figure 8-5 Link travel time depending on the flow



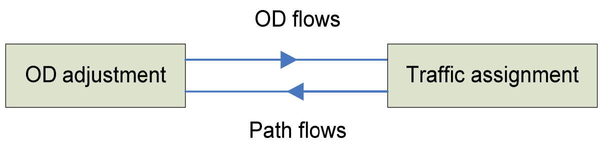
The Highway Capacity Manual (HCM, [91]) determines different volume delay functions for numerous different roads or intersections. This handbook gives these formulas depending of the road types (freeways, rural, suburban highways and urban streets), the conditions (roadway, traffic and control conditions), etc. Several groups of function have been developed to improve the accuracy and to match better with traffic and infrastructures conditions. We can cite 1985 HCM, 1994 HCM [91], BPR (Bureau Public Road), Akcelik [2] or Spiess (conical) curves [86]. A typical example of volume delay function is given by:

Equation 7 Volume Delay function

$$t = t_0.\left(1 + \alpha.\left(\frac{V}{Cap}\right)^{\beta}\right)$$

Where $X = \frac{V}{Cap}$ is the volume-to-capacity (V, traffic volume; Cap, capacity of the link), $t_0$is the free travel time, and α and β are empirical coefficients.
In this way, in a congested network, the assignment of the traffic is dependent on the travel time and vice versa. The demand estimation is dependent on the repartition of the traffic into the network, and based on the traffic flows obtained, the OD matrix could be determined. This interaction is shown in Figure 8-6.

Figure 8-6 Interaction OD adjustment - Traffic assignment



8.2.2 Fixed-point or bi-level formulations

To achieve an OD estimation; different approaches exist for solving the interaction between demand and assignment. Fixed-point and bi-level formulations are the most common ways to state the problem.

- **Fixed-point formulation**

This "equilibrium-like" model, motivated by the need to capture the interaction between the transport supply (the infrastructure) and transport demand (travelers' behavior) in various ways leads to assimilate OD estimation to a Fixed-point problem (see [26]).
A fixed-point problem is characterized by a vector $x \in \mathbb{R}^n$ such that:

$$F(x) = x$$

A fixed-point is the solution of the system of non linear equations:

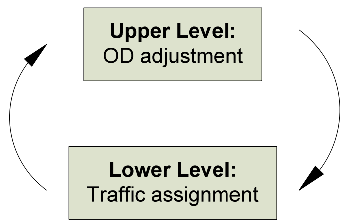
$$F(x) = 0$$

Where $F(x) = x - F(x)$
In the OD estimation case, $F(x)$ is the estimation of the OD flows x, which will lead to another OD matrix. The two different parts (presented in Figure 8-6) of the OD estimation (assignment and adjustment processes) are solved in the same process simultaneously. To find a solution for this fixed-point problem, several approaches can be found in the literature. In his paper, [61], Kaufman establishes conditions necessary for the fixed-point problem. It presents the model as an assignment mapping (link travel times estimation) and a route mapping (fastest-paths routings). The next step of this research is the development of efficient algorithms for proving convergence of the fixed-point problem. Cascetta [31] treated the OD Count Based Estimation (ODCBE) problem. It proposes different algorithms to solve the fixed-point problem: Functional iteration, Method of successive averages, and Method of successive averages with decreasing re-initialization. All these methods have been evaluated in terms of performance and to verify that they are converging to the same solution. Bierlaire and Crittin propose a generalization of secant methods ([24]). It uses several previous iterates to generate a linear approximation of the nonlinear function. It is a quasi-Newton method and the algorithm is matrix free, which is more adaptable for large-scale network.

- **Bi-level formulation**

Another approach to solve the OD estimation problem is to formulate it as a bi-level problem (presented in [43, 74] or [68]). In a bi-level formulation, two different parts of the OD estimation are executed independently, the Lower and Upper level (see Figure 8-7). An iterative approach is achieved to take into account output of the previous step.

Figure 8-7 Bi-level interaction



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

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

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.

<u>Lower level problem:</u>
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")

$$v(g) = \arg\min \sum_{b \in B} \int_0^{V_b} s_b(X).dx$$

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

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

$$v_b = \sum_{i \in I} \sum_{k \in K_i} \delta_{bk} h_k$$

Where:

$v(g)$ is the flow on link b with the trip matrix g.

h_k is the flow on the k^{th} path for the i^{th} OD pair.

I is the set of all Origin-Destination pairs in the network.

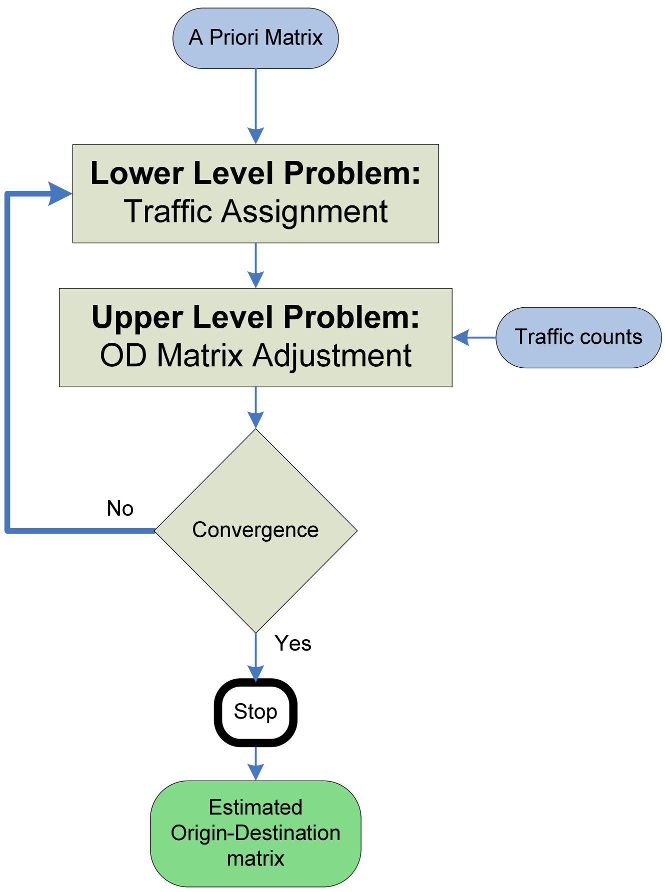
K_i is the set of paths connecting the i^{th} OD pair.

And, S_b is the function which defines the delay depending on the flow for the link $b \in B$.

In most of the literature, people describe in detail the method to solve the upper level (OD adjustment problem), which represents a bigger mathematical challenge.

Figure 8-8 shows a simplified process of bi-level approaches. From the starting point (A-priori or initial OD matrix), the iterative process (traffic assignment - matrix adjustment) is done until convergence criteria are reached.

Figure 8-8 Bi-level process for OD estimation

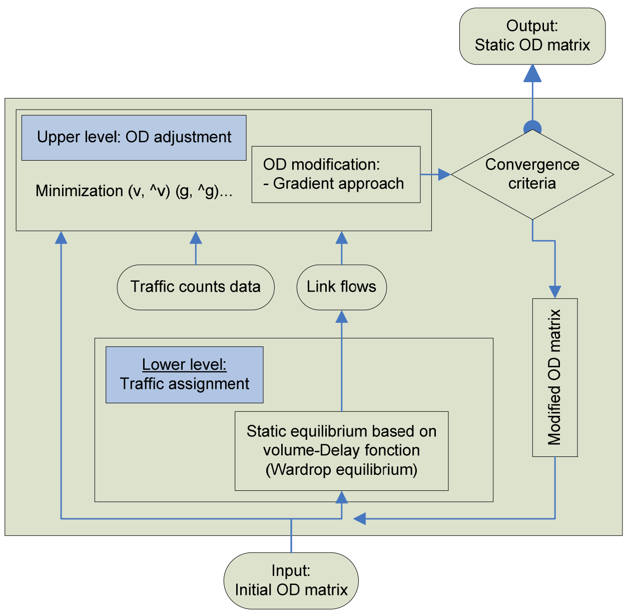


8.2.3 Static OD matrix estimation approaches

A static adjustment approach is the most common method for OD estimation. It is based on the work of several main contributors. A few of them are presented here with their work. Spiess has worked particularly in the field of matrix adjustment and his paper [87] on Gradient approach could be considered as the first congested-network approach and a reference in this domain. This paper presents a mathematical approach, which formulates a convex and non-differentiate 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 heuristic approach is using static assignment (User Equilibrium, Wardrop equilibrium [99]). The paper of Yang, Sasaki, Yasunori and Asakura [102] presents the 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 the Stackelberg leader-follower structure. Yang presents two new heuristic algorithms [101]. 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 a heuristic algorithm. Small networks are used to test the two approaches theoretically and numerically. Based on the Spiess paper, Florian proposes a Gauss-Seidel type coordinate decent method for solving the matrix adjustment problem [45]. A main feature of this analytic method is to solve two one-level optimization problems at each iteration by fixing upper and lower variables in turn such that the path information may not need to be used directly.

For instance, the methodology applied by the software EMME/2 developed by INRO ([56, 57]), which is the most commonly used method for practitioners for static OD estimation, is detailed in Figure 8-9. Based on an initial evaluation of the main traffic flow (obtained by questionnaires, studies, investigations in situ, etc.), an initial matrix origin-destination is created. This demand is assigned into the network (lower level); finding the best path between an origin and a destination (in order to minimize the global travel time) is done analytically using a static equilibrium (Wardrop equilibrium [99]) based on Volume Delay functions defined for each link and junction. Then, based on the distribution of the traffic and on actual in situ measured flows, an adjustment of the initial matrix could be done (using Gradient approach). This is an iterative process based on a convergence test and its goal is to minimize the “gap” between the estimated flows and the real flows [87]. This optimization tries to find a compromise within these two data sources and taking into account criteria (previously defined) which fix the characteristics of this compromise. Then from this step, the OD matrix, which modeled the demand of traffic on the network, is obtained.

Figure 8-9 ***Static EMME/2 approach methodology***

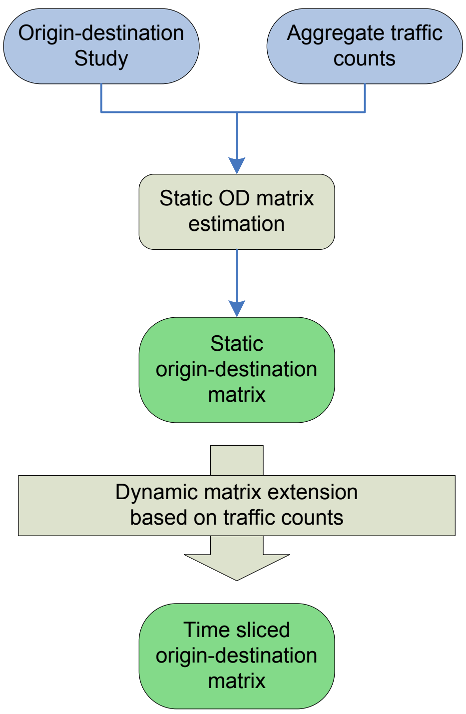


- **Approaches for dynamic demand estimation from static assignment**

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 important in an urban context, could not be obtained. Different proposals have been elaborated to obtain final "dynamic" demand even if assignment and adjustment methods are static.

- Dynamic demand extension from static estimation:
One approach is a time slicing of the matrix obtained using one initial static OD adjustment, which adapts each time slice from the available traffic counts for that period. This approach is the commonly used technique to obtained time sliced OD matrices (for dynamic analysis) from static OD estimation as presented in Figure 2-2 (see [95] and practical cases in [17, 89]). This alternative provides a time sliced OD matrix but adapts only the volume and not the structure of the demand. Figure 8-10 summaries the global and practical approach for "dynamic" OD estimation. To obtain time-sliced OD matrices, a static OD estimation approach is used and the process presented in the next paragraph is applied on results of the estimation to split and adapt the demand in different time periods.

Figure 8-10 "Dynamic" OD matrix estimation from a static approach

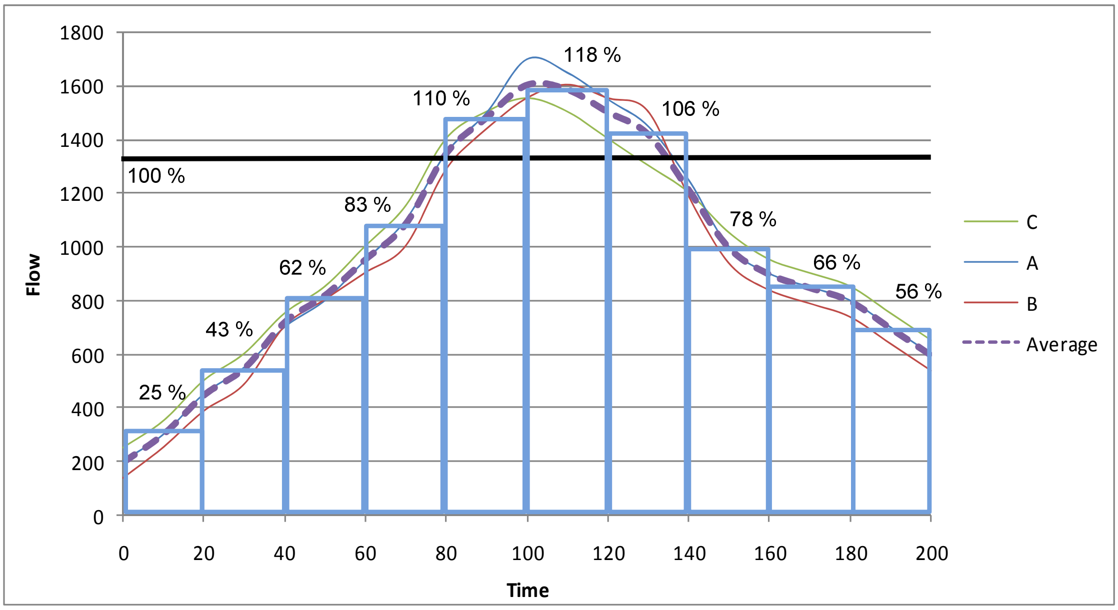


The process executes on the outputs of the static OD estimation is summarized as follows (Figure 8-11). Curves (A, B and C) represent time dependent traffic flows (in vehicle per hours) at different representative[12] points of the network. From these data, averaging is done for the whole period (dash line). From this curve, the 100%

[12] Usually, main arterials or important links of the network

line could be positioned (percentage of the highest flow e.g. 1600, depending on standards of country). A one-hour OD matrix from the static assignment, represent this 100% demand during the study period (0 to 200). A static OD matrix is divided in slices (e.g. 0 to 20) and each of these slices are scaled according to the percentage for the concerned slice (e.g. 25%, etc.). Each OD pair flow for one slice is modified by the same percentage.

Figure 8-11 Dynamic OD matrix extension

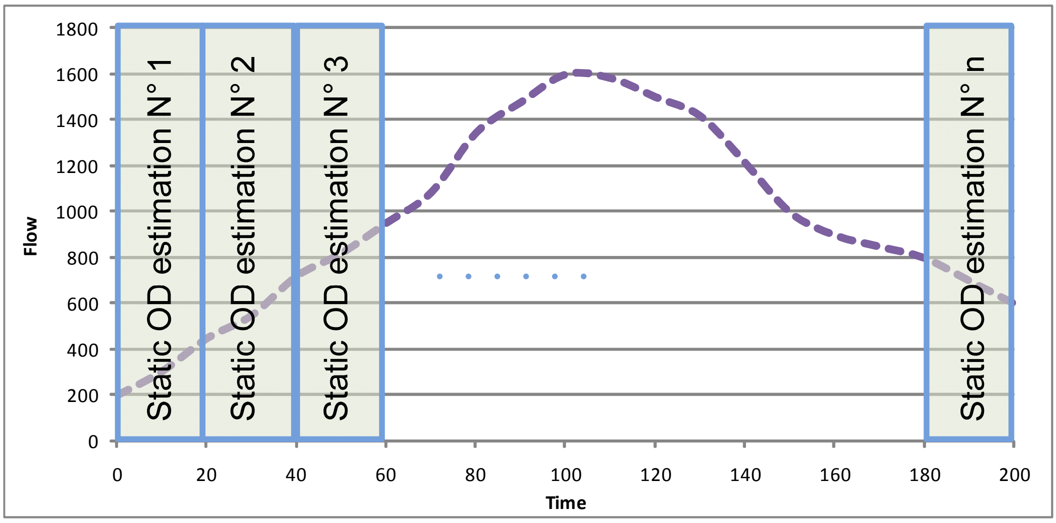


A more theoretical approach has been developed by Codina and Barcelo [39], but it is not applicable for practitioners due to its complexity.

- Sequential static OD estimation:

Another approach to obtain dynamic demand using static estimation approaches is to do a sequential (time-sliced) static OD estimation (Figure 8-12). 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). It is estimating a continuous function with discrete approach. Static adjustment process modifies OD pair flows depending on the traffic assignment and counting values observed. The proposed solution to obtain demand variation in time is to adjust independently by the time slice. Each time slice will have a different traffic assignment and different traffic count values to achieve static OD estimation. Limitations of this approach are the total independence between consecutive time slices. For instance, a vehicle entering the network during the first time interval and detected by a traffic count in the next time interval (see chapter 8.2.4) will not be considered by this approach. In this way, there is no notion of propagation of the traffic through time periods (see [43]).

Figure 8-12 Sequential static OD estimation

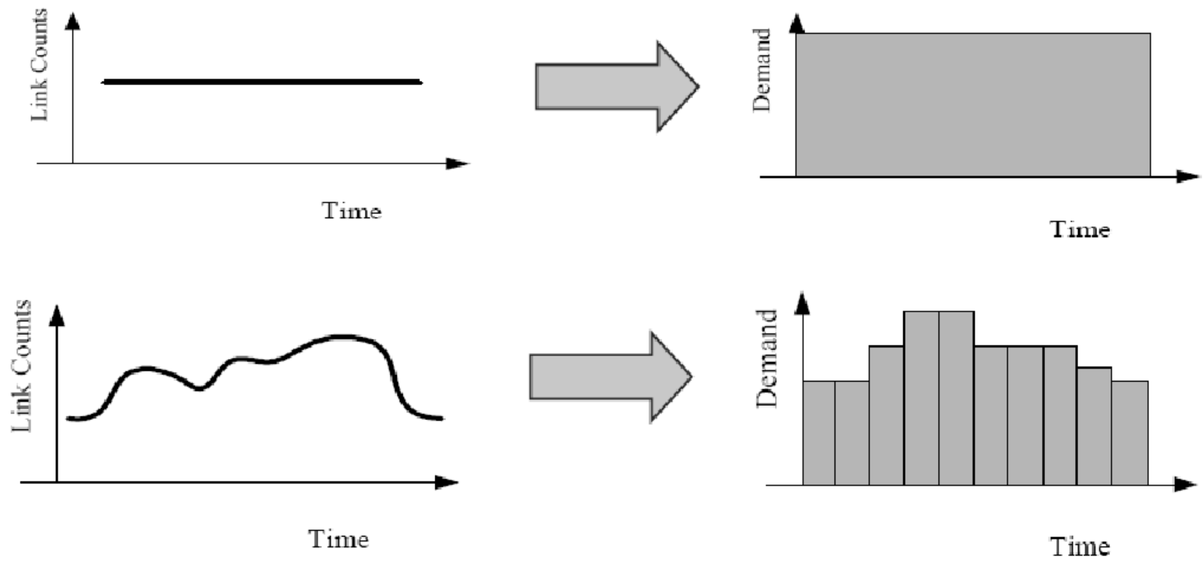


This approach is the one presented in chapter 4 and 5 as SSODE. In chapter 5.5.1, outputs of this method and comparison with the proposed approach are detailed.

8.2.4 Dynamic OD matrix estimation approaches

We have seen various approaches to proceed to the static OD estimation of demand. These approaches are efficient, but provide an aggregate value of the demand. Indeed, demand is defined for the whole time period using the same value (no variation on volume and structure). This hypothesis is very constrained and not realistic compared to the dynamic evolution of traffic in actual networks. As shown by Figure 8-13, contrary to static approach which is estimating constant demand from constant link counts, dynamic approaches are estimating a time slice demand from time varying link counts.

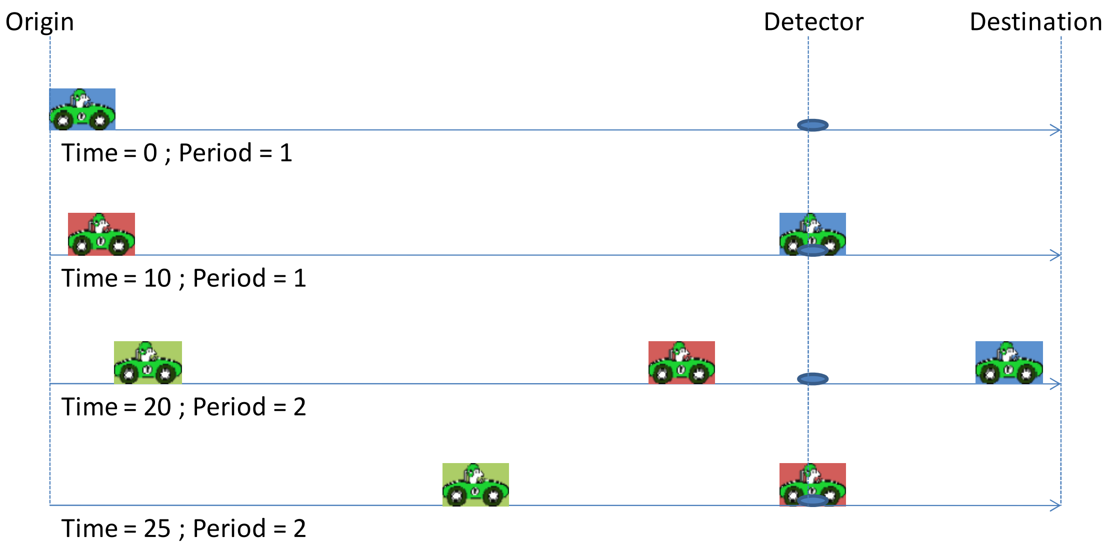
Figure 8-13 Static/Dynamic demand estimation



Dynamic aspects could be characterized by different types of variation of the demand through time: day-to-day dynamics (similitude of weekdays, weekend, holidays, etc.) or within day dynamics (dynamic during the day with usually 1 or 2 rush hours). In the real world, they are combined together. In this study, we are going to focus on the within day dynamics (main challenges of urban networks)

Dynamic approaches are more complex to take into account the evolution of traffic into the network. Indeed, time slices could be related depending on the traffic propagation. Traffic propagation is the evolution of the users into the network. In this way, a vehicle entering the network in a particular time slice could need more than one period to reach a traffic detector and then the entrance time (or period) of this vehicle and the detection time will be different. For instance, Figure 8-14 illustrates the relation between entrance time and detection time. If the duration of time slices (time intervals or periods) is 15, we can see that the blue car enters the network at time 0, period 1 and is detected are time 10, period 1. This means that the vehicle is generated by the OD matrix of the period 1 and included in the traffic count of period 1. For the red car, it is generated at period 1 (time = 10), but it passes the detector station at time 25, period 2. Therefore, this vehicle is included in the OD matrix of the first period but tallied in the traffic count of period 2. In this way, it is important that the algorithm can modify the demand of period 1, depending on the data obtain from the traffic count during period 2.

Figure 8-14 Traffic flow propagation



For this reason, and to perform a representative evolution (propagation) of the traffic through time, it is indispensable to deal with dynamic approaches. Moreover, in urban area, due to congestion or flow interruptions (traffic lights, etc), a majority of the trips take more than one time period to reach detector locations.

A dynamic OD estimation presents different challenging aspects. Demand and path evaluations must be done with time slices. The global study period is divided in N equal time intervals. From these time periods, an OD estimation must be achieved taking into account links and the relationship between them. Indeed, depending on the size of the network and its complexity (speed and distance from the origin to the destination), some vehicles could need more than one time period to reach their destination or traffic sensor, as presented previously. This statement leads to the fact that traffic counts for one time interval can be influenced by previous ones. As a consequence, demand generation (OD flows) for period n must take into account the 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 must be adapted to capture this evolution. First, traffic assignment needs to be dynamic and the OD adjustment also needs to take into account the evolution of trips in the network. An OD adjustment algorithm must be able to make a distinction between entrance time (in the network) and the time period at the location where traffic counts are measured. In this way, contrarily to static approaches, traffic counts in congested area could also be considerate for OD estimation (in static case, these detectors reflect erroneous smaller flows). Indeed, creation, and evolution of the congestion is thus represented and could influence the OD flow estimation.

The length of the time period (time-slices) must be defined taking into account network particularities. In urban networks, there are more micro dynamisms due to the influence of traffic lights. The time period must be a multiple of the light cycle and 5 to 15 minutes is good, as suggested in [43]. In our research, a study period is divided into equal 15 minutes periods.

Table 8-2 illustrates changes in the methodology used for static and dynamic OD estimation using bi-level formulation.

Table 8-2 From static to dynamic bi-level OD matrix estimation

	Static	Dynamic
Lower level	SUE[13]	DUE[14]
Upper level	Gradient	KF or LSQR[15]

State Of the Art of dynamic approaches to estimate OD matrices is presented in the following paragraphs. A more detailed review can be found in [3, 6, 41, 97]. The main contributions in the dynamic OD estimation field can be categorized based on the methodology used (see Table 8-3). The type of network tested, the way to achieve the traffic assignment and the optimization approach for the OD estimation form different groups.

- **Small networks**

The following papers are dealing with small or simple networks without traffic assignment: Okutani and Stephanedes presented two models employing the Kalman filtering theory for predicting short term traffic flow ([76]). 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 ([40]). The ordinary least squares estimator involving cross-correlation matrices, constrained optimization method, simple recursive estimation formula and estimation by Kalman filtering are analyzed to estimate accuracy and convergence properties. Comparison with static approaches is carried out on small intersection networks. Bell used the Generalized Least Squares procedure to estimate OD matrices ([13]). A simple algorithm is presented for this approach and convergence was proven. This method permits the combination of survey and traffic count data in a way that allows for the relative accuracy of two data sources. A hypothetical small network and an intersection have been tested with this method. Oneyama, Kuwahara and Yoshii worked on model that constructed a relationship between the time-dependant OD volume and traffic counts and the estimation of unique time-dependant OD matrices. The Entropy Maximizing method is used for static OD matrices estimation and extends to a time-dependent model ([77]). An extension of the previous paper presents a model using a dynamic traffic simulator to estimate the relationship between OD volumes and traffic counts ([105]). This approach has been tested on a simple and theoretical network (10 centroïds and 17 links).

This first set of papers is focusing on methodologies applied on small and/or intersection networks. The goal is to demonstrate the approach to particularly simple

[13] Static User Equilibrium or UE (Wardrop equilibrium)
[14] Dynamic User Equilibrium
[15] See chapter 3.5

cases but not to apply them on actual and complex situations with real route choice capabilities.

- **Freeway networks**

Several articles are treating freeway networks. This kind of networks offers low number of traffic signals 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 ([34]). The methodology uses the Extended Kalman Filtering algorithm and can give information without prior OD information. This model was applied on a theoretical small freeway network. No traffic signal or route choice was applied in the example. Zijpp developed a method for generating OD flows on freeway networks in which time interval boundaries are determined by analyzing time-space trajectories ([97]). 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 a 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 encircles the city with 20 entrance and exit ramps. Route choice is very limited (one way or the other) and there are no signalized intersections.

Freeway networks are challenging domains. Nevertheless, route choice capabilities and the absence of traffic lights make this special kind of network particular. Methodologies developed in these papers have not been developed for dense networks; whereas our study is focusing on dense urban areas.

In the next two papers, assignment is calculated analytically: Cascetta, Inaudi and Marquis proposed different methods using traffic counts to evaluate time varying OD flows ([28]). The combination of traffic count information and other types of data are 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 dynamic OD flows in multiple intervals simultaneously (OD flows for different time periods) and another one which calculates OD estimation sequentially (evaluating the next OD flow for a time period using 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 possibility and no traffic signals. 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 ([84]). A least squares model is used to determine the trip tables. The 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.

These approaches are evaluating the assignment matrix using analytic methods. This approach could be less accurate and not efficient (particularly in detailed dynamic context) to obtain a representative assignment compared to a heuristic equilibrium approach (DUE for instance).

The following four papers used a 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 ([55]). 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 lights. In their paper, Bierlaire and Crittin compared the Kalman filter algorithm to the LSQR algorithm (algorithm for sparse linear equations and sparse least squares) ([23]). They showed the fact that for large scale problems; the LSQR presents better performance in comparison to the other approach (diminution of the computer effort). 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 large-scale network with 627 OD pairs (25x25 OD matrix), without signalized intersections (no mention about that point in the paper). This network could also be considered as 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. Ashok developed a sequential OD smoothing scheme based on a state-space modeling concept using a DTA approach ([3]). He used a Kalman Filter solution approach to estimate the OD flows. He also discussed 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. Finally, Zhou and Mahmassani explained in [106] the potential of using a structural state space model to incorporate regular demand pattern information, structural deviations and random fluctuations. A polynomial trend filter has been developed to estimate and predict demand deviation from the a-priori estimate of the regular demand pattern. A real time DTA system and Kalman Filtering framework is used to update the regular demand pattern estimate with real time estimates and observations obtained every day. This methodology has been tested in the Irvine network described previously.

These studies are interesting approaches that used a traffic simulator to achieve assignment of the traffic. Nevertheless, they are not evaluating the methodology on real complex urban networks.

- **Urban networks**

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 ([33]). 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. Usually, OD estimation is done using data extracted from traffic measurements (traffic counts, etc.). As study by Balakrishna et al. presented a new method which allows for estimating the complex link between OD flows and traffic counts ([7]). The relationship between flows and traffic measurements are captured using an optimization approach that considers the assignment model as a black box. The assignment matrix and dynamic OD estimation are estimated mathematically in an optimization framework. Two practical cases have been analyzed. The first one is a small synthetic network constituted by four simple intersections (unsignalized) with three origins and one destination (no route choice). The second one is named the 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. Tsekeris and Stathopoulos analyzed a dynamic OD estimation for urban networks ([92]). 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, which 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 (44x44 OD matrix) with interesting RC possibilities and without traffic signals.

Finally, these last papers are applying methodology on urban networks. Nevertheless, networks considered are not complex and not dense city areas with high route choice capabilities, traffic lights density and link density and assignment is made using analytic or macroscopic approaches (limited by the level of detail provided).

Table 8-3 Dynamic OD matrix estimation in the literature

References:	Name	Type[16]	Size[17]	Ass.[18]	Opt.[19]	RC[20]	T-S[21]	#ODpair	#Link
[Okutani and Stephanedes, 1984]	Nagoya	Street	Small	-	KF[22]	No	No	<10	<20
[Cremer and Keller, 1987]	Various	Intersection	Small	-	Various	No	No	<20	<10
[Bell, 1991]	-	Street	Small	-	GLS[23]	No	No	<30	<20
	-	Intersection	Small			No	No		
[Kuwahara, Yoshii and al., 1997]	-	Streets	Small	Dyn Sim	Entropy Max	Low	No	<100	<20
[Cascetta, Inaudi et al., 1993]	Brescia-Padua	Freeway	Med	Analytic	GLS	No	No	171	54
[Chang and Wu, 1994]	-	Freeway	Small	-	KF	No	No	<30	<10
[Chang and Tao, 1996]	-	Urban	Small	Analytic (+ cordonline)	Cordonline model	Low	Yes	15	13
[Zjipp, 1996]	Amsterdam	Freeway	Large	-	TMVN[24]	No	No	<100	<100
[Ashok, 1996]	Massa Turnpike	Freeway	Med	Analytic	KF	No	No	210	<100
	I-880	Freeway	Small			No	No	20	<20
	Amsterdam	Freeway	Large			Low	No	<50	<100
[Sherali and Park, 2001]	-	Urban	Small	Analytic	LS[25]	Low	No	240	60
	Massa Turnpike	Freeway	Med			No	No		
[Hu, Madanat et al., 2001]	-	Freeway	Small	Simulator (Meso) TT	KF	No	No	<30	<10
[Tsekeris and Stathopoulos, 2003]	Athens	Urban	Med	Simulator (Macro)	MART, RMART, DIMAP[26]	Yes	No	1936	256
[Bierlaire and Crittin, 2004]	Boston	Freeway	Med	Simulator (Meso)	KF, LSQR[27]	Low	No	627	618
	Irvine	Mid	Large			Med	(No)		
[Balakrishna, Ben-Akiva et al., 2006]	Synthetic Network	Intersection	Small	-	Analytic	No	No	-	606
	Los Angeles	Mid	Med			Yes	Yes		
[Zhou and Mahmassani, 2007]	Irvine	Mid	Large	DTA Simulator	KF	Med	(No)	200	620

[16] Type of network test
[17] Size of the network
[18] Type of traffic assignment used in the OD estimation
[19] Method for OD optimization approach
[20] Route choice capabilities
[21] Traffic signal capabilities
[22] KF: Kalman Filtering (normal, adapted or extended)
[23] GLS: Generalized Least Squares
[24] TMVN: Truncated Multivariate Normal
[25] LS: Least Squares
[26] Multiplicative Algebraic Reconstruction Technique, (Revised), Doubly Iterative Matrix Adjustment Procedure
[27] LSQR: Spares Linear Equations and Spares Least Squares

8.3 GEH indicator

GEH is an indicator to evaluate the correspondence between actual and estimated traffic count flows:
Formulation:

$$GEH = \sqrt{\frac{(E^{sim} - E^{ref})^2}{(E^{sim} + E^{ref})/2}}$$

Where E^{sim} are the simulated values and E^{ref} are the measured values in the field
Note that a perfect matching gives a GEH = 0.

A GEH of less than 5.0 is considered a good match between the modeled and observed hourly volumes (flows of longer or shorter durations should be converted to hourly equivalents to use these thresholds). According to DMRB (Design Manual for Roads and Bridges), 85% of the volumes in a traffic model should have a GEH less than 5.0. GEHs in the range of 5.0 to 10.0 may warrant investigation. If the GEH is greater than 10.0, there is a high probability that there is a problem with either the travel demand model or the data.

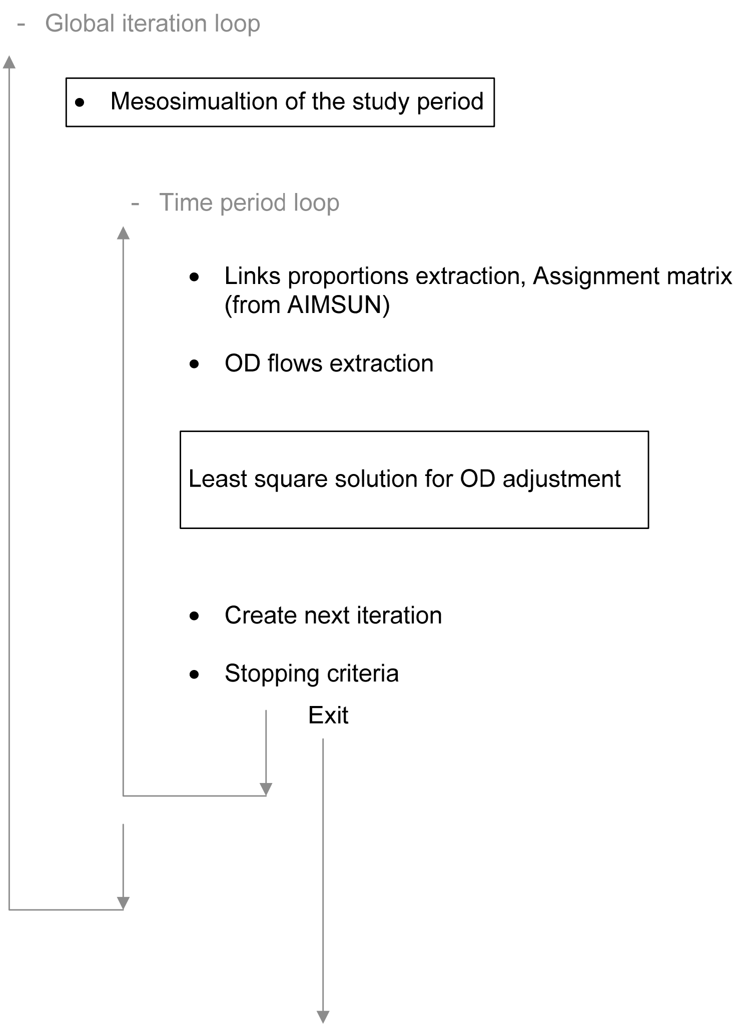
8.4 COREL traffic counts data

Table 8-4 COREL traffic counts data

	Detector ID	Link ID	Flow 1h	Link name
1	3525	170	730	Poste Ouest
2	3526	171	890	Poste Est
3	3542	173	520	Mt Repos 2 Est
4	3439	208	590	M Repos Ouest
5	3440	209	620	M Repos Est
6	3540	225	440	Rum Rep Sud
7	3541	229	1140	Mt Repos 2 Ouest
8	3431	232	770	Gare Ouest
9	3530	261	600	Tiv Est
10	3529	262	780	Tiv Ouest
11	3430	270	850	Chaudron Nord
12	3433	276	670	G pont Nord
13	3434	277	620	G pont Sud
14	3429	281	1000	Centrale Est
15	3533	330	560	Dufour Ouest
16	3532	332	490	Dufour Est
17	3428	346	630	Centrale Ouest
18	3570	353	480	Av Fr
19	3438	430	640	Baulieu Sud
20	3437	432	990	Baulieu Nord
21	3546	505	720	GE O Est
22	3545	508	680	GE O Ouest
23	3432	510	780	Gare Est
24	3539	515	880	Rum Rep Nord
25	3476	516	700	Dr St Francois Est
26	3477	517	680	Dr St francois Ouest
27	3537	533	810	La Poste Sud
28	3523	538	460	Parking Ouest
29	3522	560	1050	Parking Est
30	3441	563	780	Ruch Nord
31	3442	564	650	Ruch Sud
32	3396	567	990	Chaudron Sud
33	3535	593	570	Moderne Sud
34	3534	594	620	Moderne Nord
35	3475	600	640	GE Est
36	3527	606	550	Betu Sud
37	3528	607	1200	Betu Nord
38	3544	644	440	Pompe Ouest
39	3543	645	300	Pompe Est
40	3474	678	730	GE Ouest
41	3549	705	580	Rum O Ouest
42	3550	706	710	Rum O Est
43	3446	719	1050	Roux Est
44	3445	721	800	Roux Ouest
45	3536	740	490	La Poste Nord
46	3444	746	830	Gonin Est
47	3443	747	510	Gonin Ouest
48	3547	762	550	Vinet Ouest
49	3548	763	500	Vinet Est
50	3435	767	610	Valentin Nord
51	3436	777	460	Valentin Sud

8.5 Implementation structure

Figure 8-15 Simplified C++ implementation

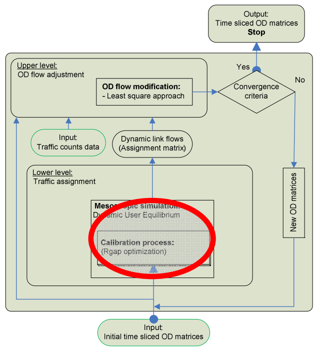


8.6 Assignment task

8.6.1 Mesoscopic simulation for Dynamic User Equilibrium assignment

The aim of this step is to determine the assignment matrix which gives the different paths choices depending on origin, destination, time interval and traffic conditions.

Figure 8-16 Presentation Mesoscopic Simulation



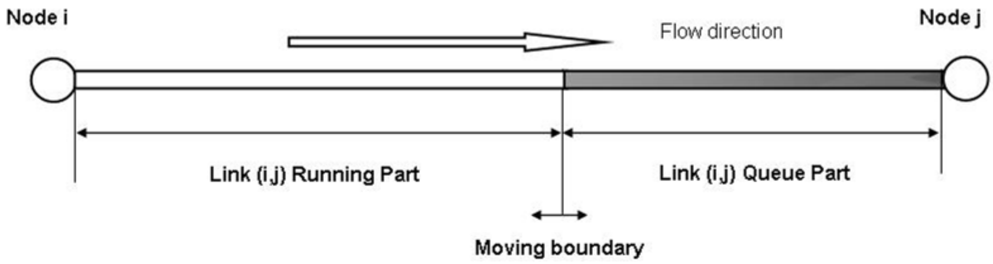
For the raisons presented in chapter 2.1.3, a mesoscopic simulator has been chosen. The simulator "AIMSUN NG" mesoscopic ([8, 12, 94]) developed by the Polytechnical University of Catalunya in Spain and commercialized by TSS (Barcelona) is designed for this task for several raisons:

- It is a well-known commercial product with developed and detailed user interface.
- Three different kind of simulators are available (microscopic, mesoscopic and macroscopic level), which is useful for process evaluation.
- API/SDK solutions are proposed (Application Programming Interface/Software Development Kit) which allows possibilities to export/import/modify all the needed information for OD estimation.
- The author has a good knowledge of this tool and LAVOC in general.
- Mesosimulator is focusing on travel time data (Rgap minimization). This feature allow reaching DUE assignment.
- LAVOC has good and continuous contacts with TSS.

- **Network loading of the AIMSUN Meso**

AIMSUN mesoscopic model is based on the event scheduling approach (as explained by Burghout and Kotsopoulos in [38]). 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.). Links are split in two parts and each part has proper rules. The boundary between parts is moving depending on the entrance and exit conditions (see Figure 8-17). 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 8-17 Link model in AIMSUN Mesoscopic



Network loading is simplified and model is event-based (entrance or exit of vehicles in a link, queuing time and space, etc.) and are focusing on flow density, speed or queues. Moreover, lane changing, car following, and gap acceptance models are simplified to reduce the number of calibration parameters.

Given that the network loading is based in a heuristic simulation approach, analytical poof 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 [48, 58]. A small value of Rgap expresses equilibrium in the network close to the Dynamic User Optimal ([35-37]).

Equation 8 Rgap function

$$Rgap(r) = \frac{\sum_{i\in I}\sum_{k\in K_i} h_k^n(r).\left[s_k^n(r) - u_i^n(r)\right]}{\sum_{i\in I} g_i^n.u_i^n(r)}$$

Where $u_i^n(r)$ are the travel times on the shortest paths for the i^{th} OD pair at time interval n for iteration r, $s_k^n(r)$ is the travel time on path k at time interval n for iteration r, $h_k^n(r)$ is the flow on path k at time n for iteration r, g_i^n is the demand for the i^{th} OD pair at time interval n, K_i, is the set of paths for the i^{th} OD pair, and I is the set of all OD pairs. Rgap value for a simulation is the maximum Rgap observed during the whole time period n of the simulation.

Practically, Rgap around 10-15 % is considerate as satisfactory (as the difference in the travel time perception by drivers).

- **Traffic assignment of the AIMSUN Meso**

AIMSUN mesoscopic simulator could perform SRC or DUE assignment. For our application, as explained previously, we are going to focus on the Dynamic User Equilibrium performed by iteration ([80]).

The approach taken in AIMSUN Meso to solve the dynamic equilibrium problem assumes that according to Friesz et al. ([49]), it can be formulated in the space of path flows $h_k(n)$, for all paths $k \in K_i$, where K_i is the set of feasible paths for the i^{th}

OD pair at time n. The path flow rates in the feasible region Ω satisfy at any time $n \in (0,N)$ the flow conservation and non-negativity constraints ([47, 48]):

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

where I is the set of all OD pairs in the network, N is the time horizon, and $g_i(n)$ is the fraction of the demand for the i^{th} OD pair during the time interval n. 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:

$$S_k(n)\begin{cases} = u_{i(n)}\ if\ h_k(n) > 0 \\ \geq\ u_{i(n)}\ Otherwise \end{cases} \qquad u(n) = \min_{k\in K_i}\{S_k(n)\}$$
$$for\ \forall k \in K_i, \forall i \in I, for\ almost\ all\ n \in (0,T)\ h_k(n) \in \Omega \quad (2)$$

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

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

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

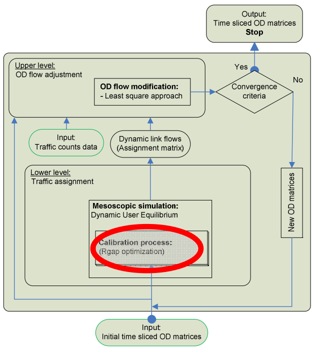
$$\sum_N \sum_{k\in K} S_k(n)[h_k(n) - h_k^*(n)] \geq 0 \quad (4)$$

Where $K = \bigcup_{i\in I} K_i$ is the set of all paths for all OD pairs. The approach taken in AIMSUN Meso solves analytically this problem at each time interval by the Method of Successive Averages (MSA, [47, 69]). 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.

8.6.2 Simulation parameters calibration

The bi-level formulation proposed uses traffic simulator to evaluate traffic assignment into the network. Traffic simulators need to be calibrated to fit the actual behavior of users into the network (see details about calibration in [18]). Reaching a representative equilibrium is dependent on the setting of the calibration parameters. During the calibration task, the lesser, the parameters to calibrate, the better and faster the equilibrium could be obtained.

Figure 8-18 Presentation Calibration Task

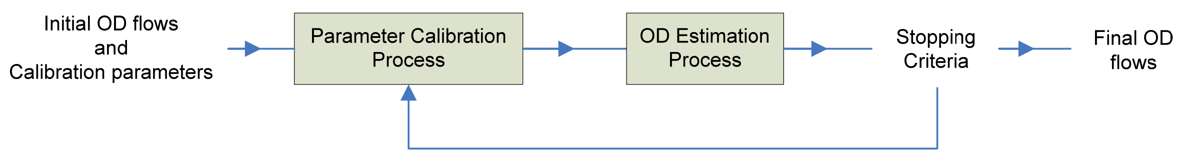


In Meso, even if behavior parameters (car following, gap acceptance, etc.) are important, mainly route choice parameters will have a strong influence on the results of the assignment problem. Due to the heuristic approach of traffic simulation, there is no representation or analytic formulation of the problem which allows finding the optimal combination of the different parameters which influence the results of the simulation. Manual calibration must be executed based on real data. Major difficulties come from the divergence between inputs (OD matrices) of the OD estimation process and control data (traffic counts), particularly for the first loops of the bi-level process where initial OD matrices could be far from the target one. Therefore, calibration will be included in the global process of OD estimation but must be carried out outside of the bi-level formulation. Indeed, if OD adjustment and calibration are done simultaneously, effects of each of them could not be identified. In this way, sequences of bi-level process and calibration task will be done to converge to optimal solution. Another approach combining OD estimation and parameter calibration is presented in [5], but is applied in microscopic model. In our case, low number of parameters does not justify the utilization of this approach.

- **Calibration process**

As presented previously, an important aspect of the calibration task is the sequential application of the process. Indeed, to avoid confusion interpretation of the effect of the calibration itself and the OD estimation task, it is crucial to split the two steps in the global methodology. In this way, a succession of OD estimation and calibration is done to converge to the final solution, as presented in Figure 8-19.

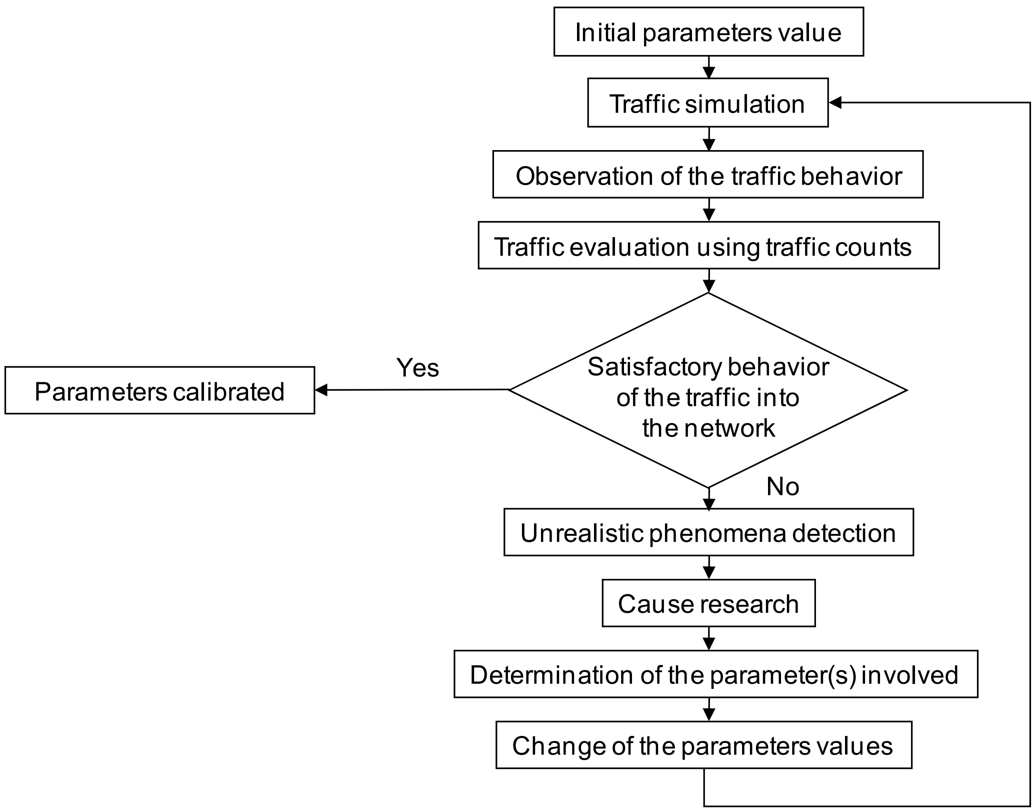
Figure 8-19 Sequence of "Calibration" / "OD estimation" task



Stopping criteria are defined depending on the gap between the actual and simulated traffic counts based on the modified OD flows during the adjustment process. Difference between the initial OD matrix and the estimated one is also considered. At the beginning of the OD estimation process, OD flows used could be far from the target. Then, calibration based on this initial demand and actual traffic counts could not be achieved in an efficient way. Calibration will be more and more relevant after several iterations of OD estimation. First calibration task will be characterized by only few loops (as presented in Figure 8-19). Using definition of stopping criteria of the Figure 8-19, accent will be more on the OD estimation part at the beginning and more on the calibration part later.

The calibration process, presented in Figure 8-20, is composed of several different steps. It could be considered as manual calibration. It is not an automatic box which provides final outputs. Indeed, the calibration is based on the experience of the user and his/her capability to "understand" the simulator.

Figure 8-20 Calibration process



The process start from **initial parameters values** which are the current values of the parameters (from experiences, previous studies or default ones). Based on those values, a simulation is performed using the **traffic simulator**. During and after the simulation, visual conciseness observation (density, traffic counts, paths…) is operated. Moreover, **traffic evaluation using traffic counts** is done by comparison of the observed flow values with the simulated ones (analyses using GEH or/and Rgap indicators -see definition in annex and in chapter 8.6.1). From this point, the step **satisfactory behavior of the traffic into the network** decides if the behavior is correct. If it is the case, parameters are calibrated and it is the end of the calibration process. If the simulation is not realistic enough, the task **unrealistic phenomena detection** identifies abnormal queues, gridlocks, extreme flows, etc. From that state, the time before the beginning of the unrealistic phenomena is analyzed to understand the cause of the problem. The next step makes the **determination of the parameters involved** that lead to this behavior. Therefore, concerned calibration parameters are modified to improve the traffic behavior.

8.7 OD adjustment methods

- **Least square formulation of the model**

The implementation of the least square formulation has been done similarly to the process described in [23]. The formulation of the model is derived from [4]. Analysis period is divided into equal intervals $n = 1, \dots, N$. The network is modeled by directed graph $(\wp, B)$, where $\wp$ is the set of nodes and B is the set of links. *TOD* is the number of OD pairs considerate. x_n is the actual OD table capturing all trips departing during time interval n and x_n^H is the associated historical OD table. The vector of deviations is denoted by $\partial x_n = x_n - x_n^H$. *TC* is the number of link b from B equipped with sensor d able to count the number of vehicles during the time period. y_{dn} is the number of vehicles crossing sensor d during time interval n and y_n the vector gathering all such counts.
The model is defined by two equations which model the evolution of the OD flows. The Transition equation captures the dynamic of the system. It is based on an auto-regressive process on the OD flows deviation:

Equation 9 Transition Equation

$$\partial x_n = \sum_{p=n-q'}^{n-1} f_n^p . \partial x_p + w_n$$

With f_n^p describes the effect of x_p on x_n and w_n is a random error. q' is the number of lagged OD flow assumed to affect the OD flow in interval $n+1$. The following assumption is made on w_n, the vector of random variables capturing the error:

$$\mathrm{E}[w_n] = 0$$
$$\mathrm{E}[w_n w_t'] = \mathrm{Q_n} \delta_{\mathrm{nt}}$$

Where $\mathrm{Q_n}$ is a [*TOD,TOD*] variance-covariance matrix and δ_{nt} is the Kronecker symbol.

The measurement equation maps the state variable onto data. It captures the relationship between the state variable (OD deviation) and the measurements (traffic counts):

Equation 10 Measurement Equation

$$y_n = \sum_{p=n-p'}^{n} a_n^p . x_p + v_n$$

Where $y_n \in \mathbb{R}^{TC}$ contains the traffic counts data from time period n, a_n^p [*TC,TOD*], the assignment matrix is the fraction of the i^{th} OD flow that departed its origin during interval p and is on sensor d during interval n (this matrix is spare because not all the OD flows are captured by all sensors on the network at each time interval). p' is the maximum number of time intervals taken to travel between any OD pair of the network. v_n is the vector of random variable capturing the error measurement on traffic count data during time period n. The following assumption is made on v_n.

$$\mathrm{E}[v_n] = 0$$
$$\mathrm{E}\left[v_n v_{n_t}'\right] = \mathrm{R_n} \delta_{\mathrm{nt}}$$

where $\mathrm{R_n}$ is a [*TC,TC*] variance-covariance matrix and δ_{nt} is the Kronecker symbol.
From Equation 10, we can obtain a formation base on deviation:

$$\partial y_n = \sum_{p=n-p\prime}^{n} a_n^p . \partial x_p + v_n$$

Where $\partial y_n = y_n - \sum_{p=n-p\prime}^{n} a_n^p . x_p^H$

In these equations, at each time interval n, f_n^p, x_p and y_n could be extracted from inputs of the simulator and a_n^p could be calculated using traffic assignment of the DUE simulation (see chapter 3.3.1).

From this model, problematic could be formulated as a least square problem (see [20]). The size of the problem is dependent on data available. Assuming that traffic count data are available for time period $1\ to\ m$.

Equation 11 Least square problem

$$\min_X \sum_{n=1}^{m} \|\Omega_n^{-1} C_n^N X - \Omega_n^{-1} z_n\|_2^2 + \sum_{n=m+1}^{N} \|\Omega_n^{-1} C_n^N X\|_2^2$$

Where:

$$X = \begin{pmatrix} \partial x_1 \\ \vdots \\ \partial x_{N-1} \\ \partial x_N \end{pmatrix}$$

$$z_n = \begin{pmatrix} O_{TOD*1} \\ \partial y_n \end{pmatrix}$$

$$\Theta = \Omega_n \Omega_n^T = \begin{pmatrix} Q_n & 0 \\ 0 & R_n \end{pmatrix} = \begin{pmatrix} P_n P_n^T & 0 \\ 0 & S_n S_n^T \end{pmatrix}$$

$$C_n^N = \begin{pmatrix} 0 & \cdots & 0 & -f_n^{n-q'} & \cdots & \cdots & \cdots & -f_n^{n-1} & I \\ 0 & \cdots & \cdots & \cdots & 0 & a_n^{n-p'} & \cdots & a_n^{n-1} & a_n^n \end{pmatrix} = \begin{pmatrix} C_n^U \\ C_n^D \end{pmatrix}$$

The solution of Equation 11 provides an estimation of the OD tables up to interval *m*. In our case, we do not consider prediction, therefore, $m = N$. Moreover, f is constant and equal to I (identity matrix), as proposed by [23].

Contrarily to the Bierlaire's paper, in this work, all time intervals are considerate during the solving process. Indeed, OD estimation in urban context is off-line and focusing on traffic peak hours. In this case, one or two hours as period study is enough to capture the full phenomena (6-8 time intervals). Nevertheless, with low modification of the implementation, larger time period could be evaluated using limited number of past time intervals in the estimation process.

8.7.1 Kalman Filtering algorithm

To adjust the OD matrix dynamically, with white and Gaussian errors in the state and measurements equations (ω_n, v_n), and if these equations are linear, Kalman Filtering (KF), propose the optimal solution to the problem and has been already proposed for OD estimation ([72] and [3, 4, 98, 100]). From this statement, author has decided to implement the Kalman Filtering algorithm to solve the least square problem of OD adjustment presented in Equation 11.

Kalman Filtering ([59, 60]) allows generating flow of the OD matrix at state $n + 1$ depending on the state n and an assignment matrix (which defines influences of OD flows on the different links). This approach takes into account dynamically the traffic evolution in the network. The filter solves Equation 11 in an iterative way. The algorithm does an estimation of a solution depending on a first "block" (time slice) of data and updates it using new data (next time slices).

Assuming that the problem is solved up to time period $m-1$, with solution X_{m-1} and variance-covariance matrix H_{m-1}. The update of these variables is made by a first step which incorporates the transition equation to obtain $\hat{X}_m$ and $\hat{H}_m$ and the second step incorporates the measurement equation to obtain X_m and H_m. After incorporation of the transition equation, the least square problem to solve becomes:

$$\min_X \left\| \left(\begin{array}{c|c} P_m^{-1} & 0 \\ \hline 0 & (\Omega_{m-1}^{tot})^{-1} \end{array} \right) \left(\begin{array}{c|c} -F_{m-1} & I \\ \hline \Omega_{m-1}^{tot} & 0 \end{array} \right) X - \begin{pmatrix} 0 \\ (\Omega_{m-1}^{tot})^{-1} z_{m-1}^{tot} \end{pmatrix} \right\|^2$$

$$F_{m-1} = \begin{pmatrix} 0 & \cdots & 0 & f_m^{m-q'} & \cdots & f_m^{m-1} \end{pmatrix} \in \mathbb{R}^{TOD*(m-1)TOD}$$

$$C_{m-1}^{tot} = \begin{pmatrix} C_1^{m-1} \\ \vdots \\ C_{m-2}^{m-1} \\ C_{m-1}^{m-1} \end{pmatrix} ; \; z_{m-1}^{tot} = \begin{pmatrix} z_1 \\ \vdots \\ z \\ z_{m-1} \end{pmatrix}$$

$$\Omega_{m-1}^{tot} = \begin{pmatrix} \Omega_1 & & 0 \\ & \ddots & \\ 0 & & \Omega_{m-1} \end{pmatrix}$$

From this formulation, KF is solved using the calculation of the four following steps:

Equation 12 Kalman Filtering, four steps

1. $\hat{X}_m = \begin{pmatrix} I \\ F_{m-1} \end{pmatrix} . X_{m-1}$

2. $\hat{H}_m = \left(\begin{array}{c|c} H_{m-1} & H_{m-1} F_{m-1}^T \\ \hline F_{m-1} H_{m-1} & F_{m-1} H_{m-1} F_{m-1}^T + Q_m \end{array} \right)$

3. $H_m = \hat{H}_m + (C_m^D)^T R_m^{-1} C_m^D$

4. $X_m = \hat{X}_m + H_m^{-1} (C_m^D)^T (R_m^{-1} \partial y_m - R_m^{-1} C_m^D \hat{X}_m)$

To inverse H_m in step 4 of Equation 12, equation is transformed in linear system solving:

$$X_m = \hat{X}_m + H_m^{-1} (C_m^D)^T \left(R_m^{-1} y_m - R_m^{-1} C_m^D \hat{X}_m \right) \Leftrightarrow H_m . dX_n = (C_m^D)^T \left(R_m^{-1} y_m - R_m^{-1} C_m^D \hat{X}_m \right)$$

With: $dX_n = X_m - \hat{X}_m$

System to solve:

$$\underbrace{H_m}_{\text{"A}} . \underbrace{dX_n}_{\text{X}} = \underbrace{(C_m^D)^T \left(R_m^{-1} y_m - R_m^{-1} C_m^d \hat{X}_m \right)}_{\text{b"}}$$

To solve this linear system, TNT library has been used. The approach is based on LU decomposition.

- **Kalman Filtering limitations and drawbacks**

As presented in chapter 5.1, due to missing observations (mainly in case of low quality detection layout leading to poor OD flow interception), KF algorithm can propose negative flows (no sense for OD estimation) and the number of OD pairs makes the problem very large. Indeed, as presented in [23], drawbacks of the KF algorithm are its inability to handle large-scale problem and its constant numerical complexity, whatever the quality of the a-priori matrix.

- **Extended Kalman Filtering**

To avoid negative flow estimation, another solution could be to use a Constraint Kalman Filtering (CKF, for instance [85]), but this approach does not deal with the cause of negative flows (need of relevant inputs) and does not address the problem of the size of the computed matrices and the computation complexity.

More details and results concerning these points are presented in chapter 5.2.

8.7.2 LSQR algorithm

Based on results using KF and first network tests (see limitation of KF, more detail in chapter 5.1), the approach could be reformulated in terms of LSQR (based on [21, 23] works) to get the computational performance required for very large networks and overcome the limitations of the Kalman Filtering approach (size of the different matrices used in the process).

LSQR is an iterative method for solving the least square problem, analytically equivalent to a conjugate gradient method, based on bi-diagonalization procedures ([25, 79]). It generates a sequence of x which decreases monotonically the associated sequence of residual's norms.

Contrarily to the KF algorithm, it is a global approach dealing with all time period at the same time. In this way, all OD tables for all time intervals within the considerate horizon must be included in a state vector. Key properties of that approach are that matrix A ($\sum_{n=1}^{m} \Omega_n^{-1} C_n^m$) does not need to be explicitly constructed or stored, only $A.x$ and $A^T.y$ need to be implemented (see Equation 13, with x and y, vectors of appropriate dimensions). This feature is attractive for large sparse problems, which is the case for solving Equation 11, given its specific structure.
As presented in the reference paper [79], this algorithm is able to find a solution with, maximum, the same number of loops as the size of the problem (number of OD pair). Nevertheless, depending on the prediction of the actual deviation by the auto regressive process, the iteration nature of the LSQR makes it converges in a few iteration and decreasing the computation time.

As presented in [25][28], u_j and l_j are bounds of the variable, with:

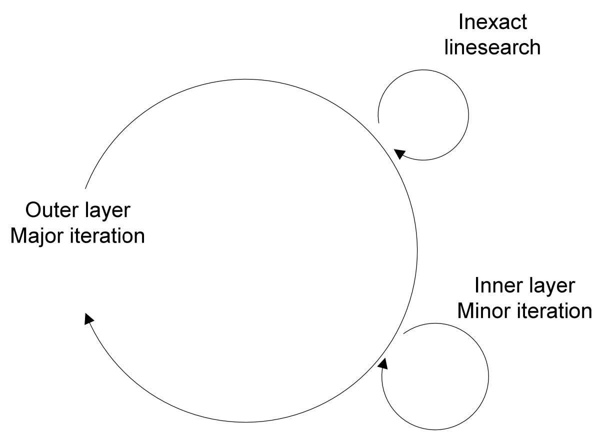
$$l_i \leq x_i \leq u_i$$

The LSQR method involves two distinct algorithmic layers:
- The outer layer handles the status of the variables taking into account their bound. This layer process called Major iteration declares each variables "free" if is strictly between its bounds or "fixed" if is at one of its bounds (using Inexact lineserach loop).
- The inner layer solves the problem by a conjugate gradient algorithm on "free" variables only, at every major iteration. This layer called minor iteration keeps constant the "fixed" variables.

In this way, three different loops are used to solve the problem: the "Outer layer, major iteration loop", using *Kout* index, the "inexact" loop for evaluation of fixed variables, using index *Iexact*, and the "inner" loop which solves the optimization problem on "free" variables (using *iinner* index).

Figure 8-21 presents the different loops executed in the global LSQR process.

Figure 8-21 LSQR algorithm loops



Therefore, the formulation of the least square problem is identical (Equation 11) but the solving approach is different (see [25] for more details). The problem is defined as:

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_2^2$$

When A is large and sparse, and the LSQR solution is given by:

Equation 13 LSQR formulation

$$X_m = LSQR\left(\sum_{n=1}^{m} \Omega_n^{-1} C_n^m, \sum_{n=1}^{m} \Omega_n^{-1} Z_n \ , X_{m-1}\right) = LSQR(A, b, \bar{x})$$

[28] To simplify comprehension of the paper, index used and defined in [25] has been respected. It could different from one, described in Table of symbols. Extracts of the paper are presented in chapter 8.7.2 in annex.

The Projected Gradient Framework[29] presented in [25], has been implemented to achieve LSQR algorithm approach:

Step 1: Initialization.

$Let\ x^{(0)}\ be\ a\ feasible\ point. Set\ k = 0.$

Step 2: Major iterations.

Step 2.a: $Compute\ g^{(k)}, the\ gradient\ of\ Q\ at\ x^{(k)}$.

Step 2.b: $Compute\ the\ active\ set\ at\ x^{(k)}\ and\ check\ if\ x^{(k)}\ is\ a\ solution$

$Define\ the\ set\ I^{(k)}\ as\ the\ set\ of\ indices\ j\ between\ 1\ and\ n\ such\ that$

$$\left[x_j^{(k)} = l_j\ and\ g_j^{(k)} > 0\right] or \left[x_j^{(k)} = u_j\ and\ g_j^{(k)} < 0\right]$$

$$If\ I^{(k)} = \{1, \dots, n\}\ or\ if\ k \geq 1\ and\ I^{(k)} = I^{(k-1)}. then\ STOP\ with\ x^* = \ x^{(k)}$$

Step 2.c: $Find\ the\ GCP$

$$\left(x_C^{(k)}, I_C^{(k)}\right) = INEXACT\left(x^{(k)}, g^{(k)}, I^{(k)}\right)$$

Step 2.c: $Attempt\ to\ solve\ the\ problem\ in\ the\ space\ of\ the$ "free" $variables$.

$If\ I_C^{(k)} = \{1, \dots, n\}, define\ x^{(k+1)} = x_C^{(k)};$

$Else\ compute$: (Minor iteration)

$$\left(x^{(k+1)} S^{(k+1)}\right) = LSQR\left(x_C^{(k)} \{1, \dots, n\} \setminus I_C^{(k)}\right)$$

$Increment\ k\ by\ one\ and\ go\ to$ step 2.a

The Inexact linesearch has been chosen for the estimation of the bounds that are active at the solution. Indeed, this approach does not require the *GCP*. $x_C^{(m)}$ to be an exact minimizer of the piecewise quadratic q(t).

Full details of the algorithm implementation in the AIMSUN plug-in are presented in [25]. Figure 8-22 and Figure 8-23 are reproduction of the formulation of the algorithm as presented in the reference paper [25]. They illustrate different steps of the Minor iteration loop and Inexact linesearch (part of the C++ code is reproduce in chapter 8.8 in annex).

[29] Index used are defined in [25].

Figure 8-22 Minor iteration in LSQR algorithm

2.1. Minor Iterations: Solving the Subproblem in the Free Variables

For solving the restricted least squares subproblem, we have chosen to use a variant of the LSQR algorithm [23]. This variant differs from the original algorithm in the following points.

(1) It is applied only in the subspace of the free variables, the fixed variables remaining, by definition, fixed.

(2) The iterations are stopped as soon as one or more of the free variables violate their bounds.

(3) The starting point is not necessarily the origin, which may well be infeasible, but a feasible point given by the current major iteration.

Its formal description otherwise follows that of [23].

More precisely, assume that $J^{[0]} = J^{(k)}$ is the set of free variables at major iteration k. A starting point $x^{[0]} = x^{(k)}$ is also given. We also assume, without loss of generality, that

$$J^{[0]} = \{1, \ldots, p\}. \tag{3}$$

We then partition the vector $x^{[0]}$ into two parts:

$$x^{[0]} = \begin{pmatrix} y^{[0]} \\ z^{[0]} \end{pmatrix}, \tag{4}$$

where the vector $y^{[0]}$ contains the first p components of $x^{[0]}$ (the free part), while $z^{[0]}$ contains the last $n - p$ components (the fixed part). The subproblem then reduces to finding a new vector y of free variables solving

$$\min_{y \in \mathbf{R}^p} \tfrac{1}{2}\|By - d\|_2^2, \tag{5}$$

where the matrix $B \in \mathbf{R}^{m \times p}$ contains the first p columns of A and where

$$d = b - Ax^{[0]}. \tag{6}$$

We also assume that the stopping rule parameters ATOL and BTOL are given, according to [23].

RESTRICTED LSQR.

Step 1: Initialization.
Given $x^{[0]}$ and $J^{[0]}$, compute $y^{[0]}$ and d from (4) and (6). Also define

$$\begin{aligned} \beta^{[1]}u^{[1]} &= d, \\ \alpha^{[1]}v^{[1]} &= B^t u^{[1]}, \\ w^{[1]} &= v^{[1]}, \\ \bar{\phi}^{[1]} &= \beta^{[1]}, \\ \bar{\rho}^{[1]} &= \alpha^{[1]} \end{aligned} \tag{7}$$

and set $i = 1$.

Step 2: Minor iterations.

Step 2.a: Bidiagonalization.
Set

$$\begin{aligned} \beta^{[i+1]}u^{[i+1]} &= Bv^{[i]} - \alpha^{[i]}u^{[i]}, \\ \alpha^{[i+1]}v^{[i+1]} &= B^t u^{[i+1]} - \beta^{[i+1]}v^{[i]}. \end{aligned} \tag{8}$$

Step 2.b: Orthogonal transformation.
Compute

$$\begin{aligned} \rho^{[i]} &= \left(\bar{\rho}^{[i]2} + \beta^{[i+1]2}\right)^{1/2}, \\ c^{[i]} &= \bar{\rho}^{[i]}/\rho^{[i]}, \\ s^{[i]} &= \beta^{[i+1]}/\rho^{[i]}, \\ \theta^{[i+1]} &= s^{[i]}\alpha^{[i+1]}, \\ \bar{\rho}^{[i+1]} &= -c^{[i]}\alpha^{[i+1]}, \\ \phi^{[i]} &= c^{[i]}\bar{\phi}^{[i]}, \\ \bar{\phi}^{[i+1]} &= s^{[i]}\bar{\phi}^{[i]}. \end{aligned} \tag{9}$$

Step 2.c: Update.

Compute the maximum feasible step from $y^{[i-1]}$ along $w^{[i]}$:

$$\lambda^{[i]} = \min_{j=1,\ldots,p} \lambda_j^{[i]}, \tag{10}$$

where

$$\lambda_j^{[i]} = \begin{cases} \dfrac{l_j - y_j^{[i-1]}}{w_j^{[i]}} & \text{if} \quad w_j^{[i]} < 0, \\ \dfrac{u_j - y_j^{[i-1]}}{w_j^{[i]}} & \text{if} \quad w_j^{[i]} > 0, \\ +\infty & \text{otherwise}. \end{cases} \tag{11}$$

If $\lambda^{[i]} \leqslant \phi^{[i]}/\rho^{[i]}$ then set

$$y^{[i]} = y^{[i-1]} + \lambda^{[i]} w^{[i]}, \tag{12}$$

efine $S^{[*]}$ as the set of indices of the variables that are at their bounds at $^{[i]}$ but not at $y^{[i-1]}$, and go to step 2.e. Else set

$$y^{[i]} = y^{[i-1]} + \frac{\phi^{[i]}}{\rho^{[i]}} w^{[i]}, \tag{13}$$

$$w^{[i+1]} = v^{[i+1]} - \frac{\theta^{[i+1]}}{\rho^{[i]}} w^{[i]}. \tag{14}$$

Step 2.d: Stopping criteria.

If

$$\|r^{[i]}\| \leqslant \text{BTOL}\,\|d\| + \text{ATOL}\,\|B\|\,\|y^{[i]}\|$$

or (15)

$$\|B^t r^{[i]}\| \leqslant \text{ATOL}\,\|B\|\,\|r^{[i]}\|,$$

where

$$r^{[i]} = By^{[i]} - d, \tag{16}$$

then define $S^{[*]} = \varnothing$ and go to step 2.e.

Else increment i by one and go to step 2.a.

Step 2.e: Return to the n-dimensional space.
Set

$$x^{[*]} = \begin{pmatrix} y^{[i]} \\ z^{[0]} \end{pmatrix} \tag{17}$$

and STOP.

As in [23], the scalars $\alpha^{[i]}$ and $\beta^{[i]}$ are chosen in (7) and (8) to normalize the vectors $v^{[i]}$ and $u^{[i]}$ respectively.

For a given problem (1)–(2) and for a consistent choice of ATOL and BTOL, we will refer to the application of this algorithm, starting from $x^{[0]}$ with the indices of the free variables $J^{[0]}$ and computing the result $x^{[*]}$, by the statement

$$(x^{[*]}, S^{[*]}) = \text{LSQR}(x^{[0]}, J^{[0]}), \tag{18}$$

where $S^{[*]}$ is the set of indices of the free variables that hit one of their bounds in step 2.c. $S^{[*]} = \emptyset$ therefore means that a feasible unconstrained solution has been found in the space of the free variables, and $S^{[*]} \neq \emptyset$ means that one or more bounds have been hit before any of the optimality conditions of step 2.d is satisfied.

Figure 8-23 Inexact Linesearch in LSQR algorithm

INEXACT LINESEARCH.

Step 1: Minimization in the first interval.

Given an initial point $x^{\{0\}}$, the gradient $g^{\{0\}}$ of Q at this point, and the corresponding active set $I^{\{0\}}$, compute the line coordinate of the minimizer of q in the first interval by

$$t^{\{0\}} = \frac{\|d^{\{0\}}\|^2}{\|Ad^{\{0\}}\|^2}, \tag{38}$$

where $d^{\{0\}}$ is given by (29). Also set $l = 0$ and compute $\alpha^{\{0\}}$, the line coordinate of the first breakpoint, from (31) and (32).

If $t^{\{0\}} \leqslant \alpha^{\{0\}}$, then STOP with

$$x^{\{*\}} = x^{\{0\}} + t^{\{0\}} d^{\{0\}} \tag{39}$$

and $I^{\{*\}} = I^{\{0\}}$.

Else compute the line coordinate of the last breakpoint as

$$t^{\{1\}} = \max_{j \notin I^{\{0\}}} \alpha_j^{\{0\}}, \tag{40}$$

where the $\alpha_j^{\{0\}}$ are again computed by (32), and set $l = 1$.

Step 2: Check if the decrease in q is sufficient.

Compute

$$x^{\{l\}} = P[x^{\{0\}} + t^{\{l\}} d^{\{0\}}], \tag{41}$$

and define $S^{\{l\}}$ as the set of indices of the bounds that are violated at $x^{\{0\}} + t^{\{l\}} d^{\{0\}}$.

If

$$q(x^{\{l\}}) \leqslant q(x^{\{0\}}) + \mu d^{\{0\}t}(x^{\{l\}} - x^{\{0\}}), \tag{42}$$

then STOP with $x^{\{*\}} = x^{\{l\}}$ and $I^{\{*\}} = I^{\{0\}} \cup S^{\{l\}}$.

Step 3: Safeguarded quadratic interpolation.

Compute $\lambda^{(l)}$, the line coordinate of the minimizer of the univariate quadratic that interpolates $q(0)$, $q'(0)$, and $q(t^{(l)})$, from

$$\lambda^{(l)} = -\frac{q'(0)}{2\left[q(t^{(l)}) - q(0) - q'(0)\right]}. \tag{43}$$

Then set

$$t^{(l+1)} = \max\left[\alpha^{(0)}, \frac{t^{(l)}}{100}, \min\left(\lambda^{(l)}, \frac{t^{(l)}}{2}\right)\right]. \tag{44}$$

Increment l by one and go to step 2.

We will refer to the application of this last algorithm to determine $x^{(*)}$ and $I^{(*)}$ from $x^{(0)}$, $g^{(0)}$, and $I^{(0)}$ by the statement

$$\left(x^{(*)}, I^{(*)}\right) = \text{INEXACT}\left(x^{(0)}, g^{(0)}, I^{(0)}\right). \tag{45}$$

The inner iterations of this procedure (denoted by superscripts of the form (l)) are also called *GCP iterations*.

ATOL and BTOL, variables of the stopping criteria of the Inner loop and μ, υ used in the Inexact linesearch loop have been defined as proposed in the paper (see paper [79] for more detailed definition).

8.8 LSQR C++ code

Following lines are extracted from the global C++ code implemented for LSQR algorithm. This part concerns the Bidiagonalization and Orthogonal transformation of the Minor Iterations (solving the sub problem in the free variables, [25]).

```
//Bidiagonalization (8)
CalD << "Inner loop, Bidiagonalization Box2" << endl << endl;
AxMix (v, Bv, Aa, TOD, TC, period, Qe, Re, x, Bn);

if (Time ==1) time(&temps_act);
if (Time ==1) CalD << "*ap Ax Bv*    " << ctime(&temps_act);

if (Ecrit ==1) Dis(Bv, &CalD, "Vecteur Bv (=B*v)  [TC+TOD] : ", TODTC);
Mult1M(u, au, TC+TOD, AlphaI, iin);
Add(Bv, au, Bvau, TC+TOD, TC+TOD);


Norme(Bvau, Beta, iin+1, TODTC);
CalD << "             Beta[" << iin+1 << "] =norm(Bv-au): " << Beta[iin+1] << endl;
Unit(Bvau, u, Beta, iin+1, TODTC);
if (Ecrit ==1) CalD << "Vecteur u[" << iin+1 << "] =Bv-au/Beta [TC+TOD] :";
if (Ecrit ==1) Dis(u, &CalD, "", TODTC);

CalD << "-------" << endl;

//AlphaI ; v
AtxB (u, Btu, Aa, TOD, TC, period, Qe, Re, x);

if (Time ==1) time(&temps_act);
```

```
if (Time ==1) CalD << "*ap Atx Btu*  " << ctime(&temps_act);
if (Ecrit ==1) Dis(Btu, &CalD, "Vecteur Btu    [Var] : ", Var);

Mult1M(v, bv, Var, Beta, iin+1);
//Dis(bv, &CalD, "Vecteur -bv    [Var] : ", Var);
Add(Btu, bv, Btubv, Var, Var);
//Dis(Btubv, &CalD, "Vecteur Btubv   [Var] : ", Var);

Norme(Btubv, AlphaI, iin+1, Var);
CalD << "             AlphaI[" << iin+1 << "] =norm(Btubv): " << AlphaI[iin+1] << endl <<
endl;
Unit(Btubv, v, AlphaI, iin+1, Var);
CalD << "Vecteur v[" << iin+1 << "] =Btubv/AlphaI [Var] :";
if (Ecrit ==1) Dis(v, &CalD, "", Var);


//Orthogonal transf. (9)
CalD << "Inner loop, Orthogonal transf. Box3" << endl << endl;
//Cal << "Inner loop, Orthogonal transf. Box3" << endl;

R[iin] = sqrt(Rb[iin]*Rb[iin]+Beta[iin+1]*Beta[iin+1]);
CalD << "             Ro [" << iin << "]: " << R[iin] << endl;
C[iin] = Rb[iin]/R[iin];
CalD << "             c [" << iin << "]: " << C[iin] << endl;
s[iin] = Beta[iin+1]/R[iin];
CalD << "             s [" << iin << "]: " << s[iin] << endl;
Teta[iin+1] = s[iin]*AlphaI[iin+1];
CalD << "             Teta [" << iin+1 << "]: " << Teta[iin+1] << endl;
Rb[iin+1] = -1*C[iin]*AlphaI[iin+1];
CalD << "             R- [" << iin+1 << "]: " << Rb[iin+1] << endl;
O[iin] = C[iin]*Ob[iin];
CalD << "             O [" << iin << "]: " << O[iin] << endl;
Ob[iin+1] = s[iin]*Ob[iin];
CalD << "             O- [" << iin+1 << "]: " << Ob[iin+1] << endl << endl;

//Update
//Calcul de Delta (10 et 11)
time(&temps_act);
CalD << "Inner loop, Update, Delta Box4   " << ctime(&temps_act)  << endl;
//Cal << "Inner loop, Update, Delta Box4" << endl;

DeltaMin[iin] = 0;
int indDelta = 0;
if (Ecrit ==1) Dis(w, &CalD, "Vecteur w   [Var] : ", Var);
for (jK = 0; jK < Var; jK ++)
{
if (w[jK]<0) Delta[iin] = ((limitB-ydxh[jK]) - ydx[jK][iin+1]) / w[jK];
if (w[jK]>0) Delta[iin] = ((limitH-ydxh[jK]) - ydx[jK][iin+1]) / w[jK];
if (w[jK]==0) Delta[iin] = 10000000000;

if (jK == 0) DeltaMin[iin] = Delta[iin];
if (DeltaMin[iin] > Delta[iin])
{
DeltaMin[iin] = Delta[iin];
indDelta = jK;
}
}
CalD << "      DeltaMin [" << iin << "]: " << DeltaMin[iin] << " , pour indice : " << indDelta
<< endl;

//Test Delta Box5
CalD << "O/R [" << iin << "]: " << O[iin]/R[iin] << endl << endl;
if (DeltaMin[iin] <= O[iin]/R[iin])
{
time(&temps_act);
CalD << "Inner loop, Update, Box5                    " << ctime(&temps_act) << endl;
CalD << "DeltaMin <= O/R, Sorti Minor loop (*9*)" << endl << endl;
Cal << "DeltaMin <= O/R, Sorti Minor loop (*9*)" << endl << endl;
CalD << "#lg   Ind.   ydx(iin=0)     ydx(iin=1)     ..." << endl;
for (jK=0; jK<Var; jK++) ydx[jK][iin+2] = ydx[jK][iin+1]+DeltaMin[iin]*w[jK];
       // (12)
if (Ecrit ==1) Dis(ydx, &CalD, /*&Cal,*/ "Matrice ydx  (13) [Var, iin+3] (last colonne): ",
Var, iin+3);

for (jK = 0; jK < Var; jK ++) xFlow[jK] = ydx[jK][iin+2] + ydxh[jK];
if (Ecrit ==1) Dis(xFlow, &CalD, "xFlow (ydx) : [Var]", Var);
```

```
OutIinner:
                                                //Point OutIinner
//Creation du new S   (12+)
Sn=0;
for ( jK=0; jK<TODperiod; jK++ )     S[jK][1] = 1;
for (iK=0; iK<Var; iK++)
{
if ( ydx[iK][1] == 1 )
{
if ( ydx[iK][iin+2] <= limitB-ydxh[iK] && ydx[iK][iin+1] >= limitB-ydxh[iK] || ydx[iK][iin+2]
>= limitH-ydxh[iK] && ydx[iK][iin+1] <= limitH-ydxh[iK] )
{
       S[ydx[iK][0]][1] = 0;
       Sn= Sn+1;
}
}
}
if (Ecrit ==1) Dis(S, &CalD, "Matrice S   [TOD*period, 2] (12+): ", TOD*period, 2);

CalD << "Sn, new fixed (aux limits, # de 0) (12+): " << Sn << endl << endl;
goto Point3;
}
else
{
time(&temps_act);
CalD << "Inner loop, Update, Box6   " << ctime(&temps_act)  << endl;
CalD << "DeltaMin > O/R (*10*)" << endl << endl;
Cal << "DeltaMin > O/R (*10*)" << endl << endl;
for (jK=0; jK<Var; jK++)
{
ydx[jK][iin+2] = ydx[jK][iin+1]+(O[iin]/R[iin])*w[jK];            //(13 et 14)
w[jK] = v[jK]-(Teta[iin+1]/R[iin])*w[jK];
}
if (Ecrit ==1) CalD << "Matrice ydx[" << iin << "] (=iin) [Var, iin+3] (13): (last colone)";
if (Ecrit ==1) Dis(ydx, &CalD, "", Var, iin+3);
for (jK = 0; jK < Var; jK ++) xFlow[jK] = ydx[jK][iin+2]+ydxh[jK];
if (Ecrit ==1) Dis(xFlow, &CalD, "xFlow (ydx) : [Var]", Var);

if (Ecrit ==1) CalD << "Matrice w[" << iin+1 << "] [Var, iin+3] (14): ";
if (Ecrit ==1) Dis(w, &CalD, "", Var);
}
//Stopping criteria (15, 16)
float dn =0, yn =0, Btrn =0;                                          //Variable pour
stopp criteria
time(&temps_act);
CalD << "Inner loop, Stopping criteria Box7   " << ctime(&temps_act)  << endl << endl;
//Avec r = By-d
for (jK=0 ; jK < Var ; jK++) ydxb[jK] = ydx[jK][iin+2];
if (Ecrit ==1) Dis(ydxb, &CalD, "Vecteur ydxb [Var] :", Var);
AxMix (ydxb, Bydxb, Aa, TOD, TC, period, Qe, Re, x, Bn);
if (Ecrit ==1) Dis(d, &CalD, "Vecteur d [TOD+TC] : ", TODTC);
for (jK=0 ; jK < TODTC ; jK++) r[jK] = Bydxb[jK]-d[jK];
if (Ecrit ==1) CalD << "Vecteur r[" << iin << "] [TC+TOD] (=B.ydx-d): ";
if (Ecrit ==1) Dis(r, &CalD, "", TODTC);

//Calcul de norme de r
Norme(r, rn, iin, TODTC);
CalD << "rn [" << iin << "]: " << rn[iin] << endl;
//Calcul de norme de d
Norme(d, dn, TODTC);
CalD << "dn: " << dn << endl;
//Calcul de norme de y (ydx)
float SQ = 0;
for (iK=0 ; iK < Var ; iK++)  SQ = SQ + ydx[iK][iin+2]*ydx[iK][iin+2]; yn = sqrt(SQ);
CalD << "yn: " << yn << endl;
//                                              //Calcul de norme de B               Norme
euclidienne (2)
CalD << "Bn (Norme euclidienne de B): " << Bn << endl << endl;
AtxB (r, Btr, Aa, TOD, TC, period, Qe, Re, x);
if (Ecrit ==1) Dis(Btr, &CalD, "Vecteur Btr   [Var] : ", Var);

//Calcul de norme de Btr
Norme(Btr, Btrn, Var);
CalD << "Btrn: " << Btrn << endl << endl;

CalD << "ATOL*||d||+ATOL*||B||*||ydx|| (pour r): " << ATOL * dn + ATOL * Bn * yn << endl;
CalD << "ATOL*||B||*||r|| (pour Btr): " << ATOL * Bn * rn[iin] << endl << endl;
```

```
if (rn[iin] <= (ATOL * dn + ATOL * Bn * yn) )
{
Sn = 0;
for (jK = 0; jK < TODperiod; jK ++) S[jK][1] = 1;
time(&temps_act);
CalD << "Cond. rn < ATOL..., -> S=0 et sortie Iinner (*11*)   " << ctime(&temps_act)  << endl
<< endl;
Cal << "Cond. rn < ATOL..., -> S=0 et sortie Iinner (*11*)" << endl << endl;
goto Point3;
}
if (Btrn <= (ATOL * Bn * rn[iin]) )
{
//S = Vide (indices=1, all free)
Sn = 0;
for (jK = 0; jK < TODperiod; jK ++) S[jK][1] = 1;
time(&temps_act);
CalD << "Cond. Btrn < ATOL..., -> S=0 et sortie Iinner (*11*)   " << ctime(&temps_act)  <<
endl << endl;
Cal << "Cond. Btrn < ATOL..., -> S=0 et sortie Iinner (*11*)" << endl << endl;
goto Point3;
}
else
{
iin = iin+1;
iinTT ++;
time(&temps_act);
CalD << "iin = iin+1 (=" << iin << "), goto Bidiagonalization (*12*)   " << ctime(&temps_act)
<< endl << endl;
Cal << "iin = iin+1 (=" << iin << "), goto Bidiagonalization (*12*)" << endl << endl;
goto Point2a;}
```

8.9 Initial Matrix / Traffic counts quality data

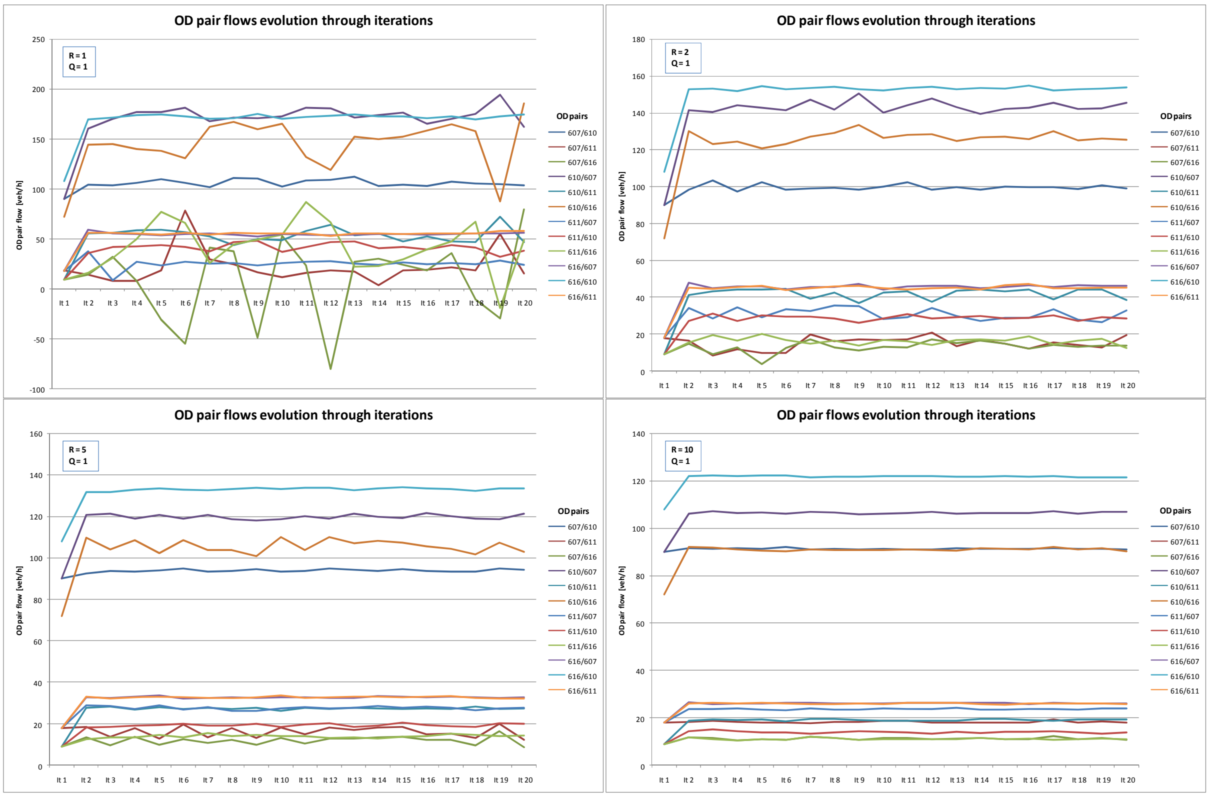
As formulated in Equation 9 and Equation 10 (Transition and measurement) includes an error term, respectively w_n and v_n, to take into account the precision of the model and the measurements. These errors must be white and Gaussian according to the definition of the Least square solution ([59]) and must be evaluated depending on the inputs quality of the process. Error settings have been tested using KF algorithm but similar results can be obtained for LSQR algorithm.
Following assumptions are made on w_n and v_n

$$\mathrm{E}[w_n] = 0 \qquad\qquad \mathrm{E}[v_n] = 0$$
$$\mathrm{E}[w_n w_t'] = \mathrm{Q_n}\delta_{\mathrm{nt}} \qquad\qquad \mathrm{E}[v_n {v_n}_t'] = \mathrm{R_n}\delta_{\mathrm{nt}}$$

where $\mathrm{Q_n}$ is a [*TOD,TOD*] variance-covariance matrix, $\mathrm{R_n}$ is a [*TC,TC*] variance-covariance matrix and δ_{nt} is the Kronecker symbol.

w_n represents the confidence related to the evolution of the model (from state at time n to $n+1$) and v_n is linked with the measurement data (in our case, error is assumed equal for all the OD pairs and for all counting). The ratio w_n/v_n is giving the way you trust in the model and/or the measurement. A low ratio signifies a better confidence in the measurement then in the transition model.
As you can observed in the following plots (Figure 8-24), theses error terms have a strong influence on the results of the filter (R = 2 means $\mathrm{R_n}$ = 2xI, etc.). In the four graphs presented, only values of error terms have changed.

Figure 8-24 OD flows depending on R/Q ratio



Depending on the setting of the error terms, oscillations of the results could be quite large. For low OD pair flows (as explained previously), resolution could easily lead to solutions with negatives flows (see R=1; Q=1). It is therefore, very important to have a clear idea of the quality of the inputs (measurement and model) to fix this ratio depending on the existing inputs.

Objective evaluation of w_n and v_n is primordial to obtain realistic behavior of the filter, but estimation of the optimal setting may need empirical assumptions and evaluations.

RECHERCHE EN MATIERE DE ROUTES DU DETEC — ARAMIS RPT

Formulaire N° 3 : Clôture du projet

établi / modifié le:	3 juillet 2009

Données de base

Projet N°:	**2006/016**
Titre du projet:	Interaction entre macrosimulateur et microsimulateur de trafic
Echéance effective:	3 juillet 2009

Chef de projet

Nom:	Dumont	Prénom:	André-Gilles
Service ou entreprise:	EPFL – LAVOC		
Rue et N°:	Station 18		
NPA:	1015	Email:	andre-gilles.dumont@epfl.ch
Lieu:	Lausanne	Téléphone:	+41 21 693 23 89
Canton, pays:	Vaud – Suisse	Fax:	+41 21 693 63 49

Textes:

Résumé des résultats du projet:

Cette recherche vise à développer une méthodologie novatrice permettant la détermination de matrices origine destination (OD) dynamiques adaptées au trafic dans un réseau urbain. Ce type de réseau est caractérisé par un grand nombre de pôles de trafic, de choix de routes potentiellement complexes et de nombreux carrefours à feux.
L'analyse des méthodes existantes a permis d'identifier plusieurs déficiences, principalement concernant le faible niveau de détail de l'assignation du trafic mais aussi des lacunes dans l'approche dynamique.
La méthode proposée se fonde sur une approche heuristique à deux niveaux. L'assignation de la demande initiale est opérée par un simulateur mésoscopique du trafic basé sur un Equilibre Dynamique de l'Usager afin de modéliser en détail des situations de trafic dynamiques sans pour autant nécessiter de nombreux paramètres de calibrage. L'ajustement des flux OD est mis en œuvre à l'aide d'une approche aux moindres carrés efficace qui prend en compte les aspects dynamiques de la propagation des véhicules et des comptages de trafic. L'algorithme LSQR a été sélectionné pour ses aptitudes à gérer de grandes matrices et sa capacité à s'adapter aux spécificités du domaine des transports.
Une analyse comparative avec l'approche la plus couramment utilisée pour estimer les matrices OD (approche séquentielle et statique) a mené aux conclusions suivantes : premièrement, la méthode génère des flux OD proches de la demande réelle. Deuxièmement, l'utilisation de la demande obtenue avec un modèle de trafic dynamique a montré ses aptitudes à reproduire des assignations de trafic réalistes. Finalement, l'applicabilité de la méthode a été démontrée par la résolution de deux situations de trafic complexes et concrètes à l'aide du logiciel de simulation AIMSUN dans lequel la méthodologie proposée a été implémentée en tant que plug-in: le cas d'une modification d'un parking au Flon et celui d'un incident à la gare de Lausanne.

Atteinte des objectifs:	L'objectif principal était de développer une nouvelle approche pour l'estimation de la demande. Outre un état de l'art détaillé dans le domaine de la simulation de trafic, la recherche a mis en évidence les faiblesses des approches actuellement utilisées (macro de type EMME2). Sur cette base, une nouvelle approche a été développée et testée sur deux cas pratiques. Les objectifs fixés ont été atteints.
Déductions et recommandations:	Les résultats de la recherche apportent aux gestionnaires de réseaux routiers une nouvelle approche pour l'estimation des flux de trafic. La méthode classique d'établissement statique des matrices OD peut être complétée et, dans certains cas remplacée par l'approche dynamique que cette rechercher a développé. Le recours à un outil de simulation du trafic est indispensable. Le niveau méso s'est avéré particulièrement adapté au réseau urbain démontrant ainsi l'objectif de comparaison entre outils macro et méso/microscopiques.
Publications:	[1]. Bert, E. *Dynamic Urban Origin-Destination Matrix Estimation Methodology. LAVOC*. 2009. Lausanne, EPFL, PhD thesis. [2]. Bert, E., et al. *Mesoscopic Simulator Data to Perform Dynamic Origin-Destination Matrices Estimation in Urban Context*. in *ISTS 08*. 2008. Queensland, Australia. [3]. Bert, E., E. Chung, and A.-G. Dumont. *Approach for Dynamic Origin-Destination Matrices Estimation in Urban Context*. in *ITS in Europe*. 2008. Geneva, Switzerland. [4]. Bert, E., E. Chung, and A.-G. Dumont. *Dynamic Origin-Destination Matrices Estimation Method for Urban Networks*. in *7th STRC (Swiss Transport Research Conference)*. 2007. Ascona, Switzerland. [5]. Bert, E., E. Chung, and A.-G. Dumont. *Dynamic Urban Origin-Destination Matrix Estimation Methodology. Submitted to IET Journal*. 2009. [6]. Bert, E., E. Chung, and A.-G. Dumont. *Exploring the Use of Dta for Origin-Destination Matrix Estimation*. in *6th STRC (Swiss Transport Research Conference)*. 2006. Ascona, Switzerland. [7]. Bert, E., E. Chung, and A.-G. Dumont. *Urban Dynamic Origin-Destination Matrices Estimation*. in *15TH World Congress On ITS*. 2008. New York.

Appréciation de la commission de suivi:
Cette appréciation de la commission de suivi remplace l'ancienne évaluation technique détachée.

Evaluation:	Le projet s'est déroulé selon le programme prévu et la commission de suivi a été informée du contenu scientifique et technique au travers de plusieurs séances. Les résultats finaux répondent aux objectifs fixés initialement. Au cours du projet, le sujet a été adapté en fonction de l'analyse des besoins et de l'état de l'art. Ainsi le projet s'est centralisé sur une méthodologie pour l'estimation des matrices origine/destination dynamiques. En conséquence, un nouveau titre est retenu qui illustre mieux le contenu du rapport. On notera que le travail mené a abouti à une thèse de doctorat acceptée par l'EPFL.
Mise en oeuvre:	Les développements présentés par ce rapport apportent plusieurs pistes pour la pratique dans l'étude de trafic. Des recommandations sont faites sur l'estimation de la demande mais également sur le nombre et le positionnement des capteurs de trafic. Pour une centrale de gestion du trafic cette méthode peut permettre une estimation de la demande en temps réel.
Besoin supplémentaire en matière de recherche :	Aucun besoin direct et immédiat de recherche supplémentaire n'est proposé. Néanmoins le rapport suggère neuf axes de recherches futures particulièrement intéressants et utiles pour le domaine des transports.
Influence sur les normes:	Les normes actuelles ne proposent pas de méthodes pour l'estimation de la demande trafic. Comme il s'agit d'une approche innovante qui s'applique au cas par cas, il parait prématuré de proposer une normalisation de la méthodologie.

Président de la commission de suivi:

Nom:	Maillard	Prénom:	Patrick
Service ou entreprise :	RGR – Robert Grandpierre & Rapp SA		
Rue et N°:	Av. Ruchonnet 12		
NPA:	1003	Email:	maillard@rgr-sa.ch
Lieu:	Lausanne	Téléphone	+41 21 614 04 40
Canton, pays:	Vaud – Suisse	Fax:	+41 21 614 04 41

Signature du président de la commission de suivi: