

## Towards a generic benchmarking platform for OD flows estimation/updating algorithms: design, demonstration and validation

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### Abstract

Estimation/updating of origin-destination (OD) flows and other traffic state parameters is a classical, widely adopted procedure in transport engineering, both in off-line and in on-line contexts. Notwithstanding numerous approaches proposed in the literature, there is still room for considerable improvements, also leveraging the unprecedented opportunity offered by information and communication technologies and big data. A key issue relates to the unobservability of OD flows in real networks – except from closed highway systems – thus leading to inherent difficulties in measuring performance of OD flows estimation/updating methods and algorithms. Starting from these premises, the paper proposes a common evaluation and benchmarking framework, providing a synthetic test bed, which enables implementation and comparison of OD estimation/updating algorithms and methodologies under “standardized” conditions. The framework, implemented in a platform available to interested parties upon request, has been flexibly designed and allows comparing a variety of approaches under various settings and conditions. Specifically, the structure and the key features of the framework are presented, along with a detailed experimental design for the application of different dynamic OD flow estimation algorithms. By way of example, applications to both off-line/planning and on-line algorithms are presented, together with a demonstration of the extensibility of the presented framework to accommodate additional data sources.

### Keywords

Traffic modelling, origin-destination (OD) estimation/updating, benchmarking platform.

### 1. Background and motivation

Traffic congestion has been plaguing urban and interurban transportation systems everywhere for

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4 decades. It has been widely accepted that it is not practical or feasible to attempt to counter congestion  
5 through the construction of additional capacity. Instead, smarter approaches, including traffic  
6 management and traffic control, are being followed: traffic management is a mature field with many  
7 applications and an important role in modern cities and motorway systems worldwide. One of the key  
8 inputs required for the evaluation of traffic management and policy measures are dynamic Origin-  
9 Destination (OD) demand matrices<sup>1</sup>, providing an aggregate and concise way to describe the overall  
10 demand patterns, and a practical way to load them onto a simulation model, used for the evaluation and  
11 assessment of the considered strategies. Dynamic OD matrices are also essential inputs to a wide range  
12 of traffic models, including dynamic microscopic and mesoscopic traffic simulators (Barceló, 2010),  
13 that have experienced a significant maturation, becoming suitable tools for almost any type of traffic  
14 analysis applications, and are nowadays extensively adopted both for research and practice purposes.  
15 However, there are several challenges associated with the use of OD matrices.  
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19 Normally, a prior OD flow estimate is obtained through a combination of surveys and  
20 mathematical models: see Cascetta (2009), Ortuzar and Willumsen (2011), Simonelli et al. (2012) for  
21 thorough reviews. Unfortunately, the resulting estimate is often affected by substantial errors, mainly  
22 related to the inherent complexity of the behavioural phenomena underlying demand patterns (e.g.  
23 departure time and destination choices). These errors may be mitigated by updating prior OD flow  
24 estimates, using observed traffic counts and other traffic flow measurements: that is, updated  
25 (posterior) OD flows are found using a properly specified objective function, such that they are able to  
26 fit satisfactorily available traffic flow measurements. Estimation/updating of OD flows based on traffic  
27 counts is a classical and widely adopted procedure in transport engineering, both in off-line (e.g. for  
28 medium- to long-term planning and design) and in on-line (e.g. for designing descriptive and/or  
29 prescriptive information to be disseminated in real time through Advanced Traffic Management and  
30 Information Systems ATIS/ATMS) applications. From the literature, summarized in the next section,  
31 four key difficulties in the evaluation and cross-comparison of various dynamic OD matrix  
32 estimation/updating methods can be identified (Djukic, 2014).  
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36 The first and main difficulty, as pointed out amongst others by Yang et al. (1991), Marzano et al.  
37 (2009) and Cascetta et al. (2013), is that OD flows are normally unobservable and thus it is very  
38 difficult to detect the quality of OD estimation/updating procedures based on real datasets. In this  
39 respect, a main factor is represented by the high indeterminateness of the dynamic OD  
40 estimation/updating based on traffic flow measurements, since the number of unknowns (i.e. OD flows)  
41 is much larger than the number of equations (traffic counts and possibly other network measurements).  
42 In fact, matching closely the observed traffic measurements used for OD estimation/updating is not in  
43 general a necessary indication of a good quality of OD estimation/updating. As a result, a major  
44 contradiction is that, quite frequently, sophisticated traffic models are fed with very rough and low-  
45 quality information on the time variability of traffic patterns. This leads to situations wherein it is hard  
46 for the analyst to identify whether flaws in the intended model are due to modelling mistakes, an  
47 improperly calibrated model or an unsuitable specification of the time-varying demand.  
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51 Secondly, there is no undisputed performance indicator for estimated/updated dynamic OD  
52 matrices. Instead, many candidate statistical metrics can be used to evaluate the quality of estimated  
53 OD matrices with respect to available ground-truth OD matrices (Marzano et al., 2009). The  
54 consequence of this wide range of statistical metrics is that researchers and practitioners may use  
55 different metrics according to their needs, rather than as objective assessment criteria. Few studies have  
56 focused on the evaluation of uncertainty and quality of the estimated dynamic OD matrices in absence  
57 of ground-truth OD matrices: for instance, Yang et al. (1991) introduced the maximum possible relative  
58 error (MPRE), whilst Bierlaire (2002) has proposed the total demand scale (TDS), a measure dependent  
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62 <sup>1</sup> In the following, we will refer to them interchangeably as either OD matrices or OD flows.  
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4 neither on the prior OD matrix nor on the traffic data observations, which evaluates the level of  
5 arbitrariness introduced by the prior OD matrix in the estimation process. However, such performance  
6 indicators should be used in addition to, not instead of, standard statistical metrics.  
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8 The third difficulty is that the assessment of OD estimation methods is difficult to generalize, as  
9 there are many aspects in which these methods differ. In fact, various reasons, such as familiarity with  
10 alternative OD estimation methods and selection of suboptimal parameter values, could lead to a not  
11 completely fair and informative comparison between methods.  
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13 A fourth challenge associated with the comparison of dynamic OD matrix estimation methods is the  
14 lack of consistence in the experimental design and presented results. Each researcher/developer can test  
15 their algorithms and methods under different assumptions, with different networks and traffic  
16 conditions, using different traffic data and performance indicators. Thus, even if a proposed approach is  
17 contrasted with alternative approaches, the comparison might not be completely fair and informative  
18 due to various reasons, such as familiarity with the alternatives and selection of suboptimal parameter  
19 values. As a result, one of the biggest obstacles in assessing OD estimation/updating algorithms is the  
20 lack of consistency in the presented results.  
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22 In order to solve the aforementioned challenges, a considerable opportunity is offered by an  
23 approach based on synthetic data, often used to perform “controlled” experiments in order to test  
24 systems, models or algorithms. In particular, they are well suited to verify inverse problems where,  
25 typically, the inputs to the forward problem are not measurable. In case of traffic simulation, for  
26 instance, usual questions are: “given some observed traffic, find the values of model parameters that  
27 allow reproducing that traffic” (i.e. parameter calibration) or “find the input demand that has produced  
28 that traffic” (i.e. OD demand estimation). In such examples, synthetic values for parameters or input  
29 demand are first generated, and the model itself is applied to produce synthetic traffic measurements  
30 (forward problem). Such synthetic measurements are used as input to the inverse problem, whose aim  
31 is to rediscover the values of parameters or demand that generated the synthetic measurements. Since  
32 neither model parameters nor OD demand are observable, a test with synthetic data is the only feasible  
33 way to assess the performance of the algorithms applied to solve the inverse problem, or to verify  
34 whether the problem itself or its setting are well-posed, at least in a controlled experiment.  
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36 Drawing upon such premises, this paper describes the development of a common evaluation and  
37 benchmarking framework to test methodologies and algorithms for dynamic OD flows  
38 estimation/updating. Specifically, the main objective is to provide a testing framework in which a  
39 number of algorithms can be implemented and tested under equal and “standardized” conditions.  
40 Design and implementation of the benchmarking platform – available to interested parties upon request  
41 – are very flexible and allow comparing considerably different approaches in a variety of settings and  
42 conditions.  
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44 The remainder of this paper is structured as follows. Section 2 presents a general literature review  
45 on dynamic OD flow estimation/updating. Section 3 describes design and implementation of the  
46 benchmarking framework. Section 4 outlines the experimental design process for the conducted case  
47 studies, describing the algorithmic approaches considered for testing of the framework. Section 5  
48 provides details on the setup of the platform implementing the benchmarking framework, in order to  
49 show its capabilities and characteristics, whilst Section 6 presents some selected results from the  
50 application of the platform. Finally, Section 7 provides concluding discussions and statements.  
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## 53 **2. Literature review on relevant topics**

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56 In accordance with Cascetta et al. (2013), estimation/updating of OD flows has been studied  
57 extensively first in static networks, following four main approaches: minimum information/maximum  
58 entropy (Van Zuylen and Willumsen, 1980); maximum likelihood (Bell, 1983; Cascetta and Nguyen,  
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4 1988), Generalized Least Squares (Cascetta, 1984), Bayesian (Maher, 1983). Drawing upon these  
5 broad general approaches, a number of generalizations have been proposed: examples include  
6 incorporating the treatment of congested networks through bi-level optimization (Florian and Chen,  
7 1995; Yang, 1995; Cascetta and Postorino, 2001), taking into account the stochastic nature of traffic  
8 counts (Lo et al., 1996; Vardi, 1996), estimating simultaneously OD flows and route choice model  
9 parameters (Lo and Chan, 2003), or dealing with the availability of traffic counts on multiple days  
10 (Hazelton, 2003).

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13 Dynamic OD flow estimation/updates started with the seminal contributions by Okutani and  
14 Stephanedes (1984) and Cremer and Keller (1987), which were translated into a practical generic  
15 optimization problem by Cascetta et al. (1993). Since then, dynamic OD flows estimation/updates has  
16 received a lot of attention in the literature, with continuous improvement and extension, resulting in a  
17 variety of approaches: a review of early contributions in this field is reported by Balakrishna et al.  
18 (2005), whilst Toledo et al. (2015) surveys more recent research attempts. For the purposes of the  
19 paper, it is worth mentioning some key issues.

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21 *Non-linearity.* Research efforts have emphasized the importance of accurate modelling of the  
22 dependence of link-flow proportions on OD flows in congested networks, and of the consistent non-  
23 linear relationship between traffic measurements and OD flows, tackled with different solution  
24 frameworks. Chang and Wu (1994) were the first to attempt to formulate a non-linear relationship  
25 between OD distributions and link traffic counts under congested conditions on highway networks,  
26 using Extended Kalman filter (EKF) estimators, subsequently extended by Chang and Tao (1996) to  
27 more general networks. The influence of non-linearity of the link-route proportion matrix on OD  
28 estimation has been studied further by several authors (e.g. Flötteröd and Bierlaire, 2009; Frederix et  
29 al., 2011). In Frederix et al. (2011) the method of marginal computation is used to efficiently calculate  
30 the sensitivity of link flows with respect to OD flows, not captured by the linear approximation of the  
31 relationship between OD flows and link traffic counts. In this respect, Frederix et al. (2010) have  
32 indicated that applying a dynamic network loading (DNL) model that represents queuing properly is  
33 only a necessary condition (i.e. not sufficient) to guarantee accurate OD flow estimation<sup>2</sup>. Normally, in  
34 terms of formulation, the dynamic OD flows estimation problem for congested networks has typically  
35 been specified either as a bi-level optimization problem (Tavana, 2001; Van der Zijpp and Lindveld,  
36 2001; Zhou et al., 2003; Lindveld et al., 2003; Zhou & Mahmassani, 2006) or bypassing the complex  
37 relationship between the OD flows and traffic flow measurements by treating the assignment model as  
38 a black box (Balakrishna et al., 2007; Cipriani et al., 2011) or through proper linearization (Lundgren  
39 and Peterson, 2008; Nie et al., 2006; Flötteröd and Bierlaire, 2009). Obviously, the choice of approach  
40 implies also a consistent choice of the solution algorithm. In this respect, many more recent works  
41 (Balakrishna, 2006; Balakrishna and Koutsopoulos, 2008; Cipriani et al., 2011; Frederix et al., 2011)  
42 deal with the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm (Spall, 1992) and  
43 its recent variants/improvements (Lu et al. 2015, Antoniou et al., 2015, Cantelmo et al., 2014b,  
44 Tympakianaki et al., 2015). SPSA efficiently approximates the gradient with only two successive  
45 evaluations of the objective function, independently of the number of parameters, thus with  
46 computational time savings for large-scale problems over traditional gradient methods (e.g. finite-  
47 differences stochastic approximation, FDSA). However, SPSA is essentially a hill-climbing method,  
48 herewith at best finding a local optimum; it only uses the aggregated error between model output and  
49 observed measurements, leading to loss of the great amount of information (e.g. location and time  
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59 <sup>2</sup> Frederix et al. (2010) note that convergence is not guaranteed when prior OD flows are not close to real OD flows.  
60 Reliability of prior OD flows has been also the starting point for further research as reported in Cantelmo et al. (2014a) and  
61 Cantelmo et al. (2015), who proposed a procedure to specify proper prior OD flows, focusing on specific OD pairs in  
62 different steps or by exploiting information on aggregated demand data such as generation data by zones.

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4 interval of different measurements); in addition, noise from uncorrelated measurements is introduced,  
5 which grows rapidly with the size of the network and the number of intervals<sup>3</sup>. Other optimization  
6 techniques have been widely investigated in dynamic OD estimation, for instance Balakrishna (2006)  
7 dealt with the possible application of response surfaces techniques.  
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9 *Observability.* Drawing upon Yang et al. (1998) and Marzano et al. (2009), an important issue in  
10 dynamic OD flows estimation/updates refers to the high indeterminateness of the problem, since -as  
11 mentioned in Section 1- the number of unknowns (i.e. OD flows) is much larger than the number of  
12 equations (traffic flow measurements). In this respect, some authors tackled this issue with various  
13 approaches, for instance Flötteröd and Bierlaire (2009) and Djukic et al. (2012) explored methods to  
14 reduce the high dimensionality of OD estimation problem using principal component analysis (PCA).  
15 Cascetta et al. (2013) proposed recently a quasi-dynamic approach, providing a more effective  
16 unknowns/equations balance, shown to outperform traditional dynamic OD flow estimators. Cipriani  
17 et al. (2014) presented an application of a quasi-dynamic traffic assignment model that approximates the  
18 dynamic traffic model by steady-state intervals and applies approximate performance functions to  
19 reduce the computation burden of the estimation. Marzano et al. (2015) extend the quasi-dynamic  
20 framework to online applications, drawing upon Ashok (1996).  
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22 *Selection of measurements.* Another key issue is the selection of traffic flow measurements as  
23 inputs for dynamic OD flow estimation: indeed, in addition to link counts, also speeds,  
24 densities/occupancies and/or travel times are extensively applied (e.g. Balakrishna et al., 2007; Ashok  
25 and Ben-Akiva, 2000; Tavana, 2001). Cipriani et al. (2013) presented a preliminary analysis on the  
26 impact of different kinds of information to the estimation of dynamic OD flows, underlining the  
27 importance of using a sample of path travel time measurements, together with measures of speeds and  
28 flows on link sections. Obviously, new technologies for probe vehicle re-identification and tracking  
29 (e.g. automated vehicle identification, AVI, and automated vehicle location, AVL, systems) represent  
30 another data source of growing importance. Dixon and Rilett (2002) estimated OD flows by using OD  
31 split proportions provided by AVI data collection points. Antoniou et al. (2006) estimated dynamic OD  
32 flows by incorporating direct measurements of OD flows from AVI systems or probe vehicles. Since  
33 the direct observation of OD flows requires the location of AVI stations close to origin and destination  
34 points, Antoniou et al. (2006) relax this assumption to formulate indirect observation equation by  
35 extracting sub-paths from several connected AVI detector locations. Further, Sohn and Kim (2008)  
36 used cell-based trajectories as probe phones to estimate the average path choice proportions. Barceló  
37 et al. (2010) proposed an efficient on-line approach based on linear Kalman filtering for linear structures,  
38 subsequently extended to general networks (Barceló et al., 2013), coping with congestion effects by the  
39 use of travel times provided by new ICT technologies. Integration of route flow data into the dynamic  
40 OD demand estimation problem was tackled by researchers in terms of either turning fractions (e.g.  
41 Van Der Zijpp and Romph, 1997; Mishalani et al., 2002) and/or route flows (e.g. Sun and Feng, 2011;  
42 Asakura et al., 2000). In general, a key problem in using AVI data for OD flow estimation is the  
43 knowledge of the sampling rate, i.e. either market penetration rates or identification rates. Estimation  
44 of sampling rates, however, is a difficult problem in its own right, as these rates are essentially time-  
45 dependent and location-dependent random variables. Moreover, the inclusion of sample rates in the OD  
46 demand estimation problem could dramatically increase the number of unknowns and thus impact on  
47 the reliability of OD flow estimates. To circumvent primary difficulties associated with estimating  
48 sample rates, Zhou and Mahmassani (2007) developed an OD demand estimation framework using  
49 partial AVI data.  
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51 *Online formulations.* A specific research task in dynamic OD estimation research refers to online  
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61 <sup>3</sup> Recent extensions, such as W-SPSA (Lu et al., 2015; Antoniou et al., 2015; Cantelmo et al., 2014b), and c-SPSA  
62 (Tympakianaki et al., 2015) aim to overcome this particular limitation.  
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4 applications, wherein OD flow estimates for recent time slices together with predictions for future time  
5 slices should be provided, recursively and promptly. Online estimation was first studied by Okutani and  
6 Stephanedes (1984) and subsequently generalized by Cremer and Keller (1987), Nihan and Davis  
7 (1987 and 1989), Ashok and Ben-Akiva (1993 and 2000) and Ashok (1996), who acknowledged the  
8 importance of structural information in OD flows. Computational issues in online within-day OD  
9 estimation in large networks represent also a main issue, firstly addressed by Bierlaire and Crittin  
10 (2004) and more recently by Antoniou et al. (2009).

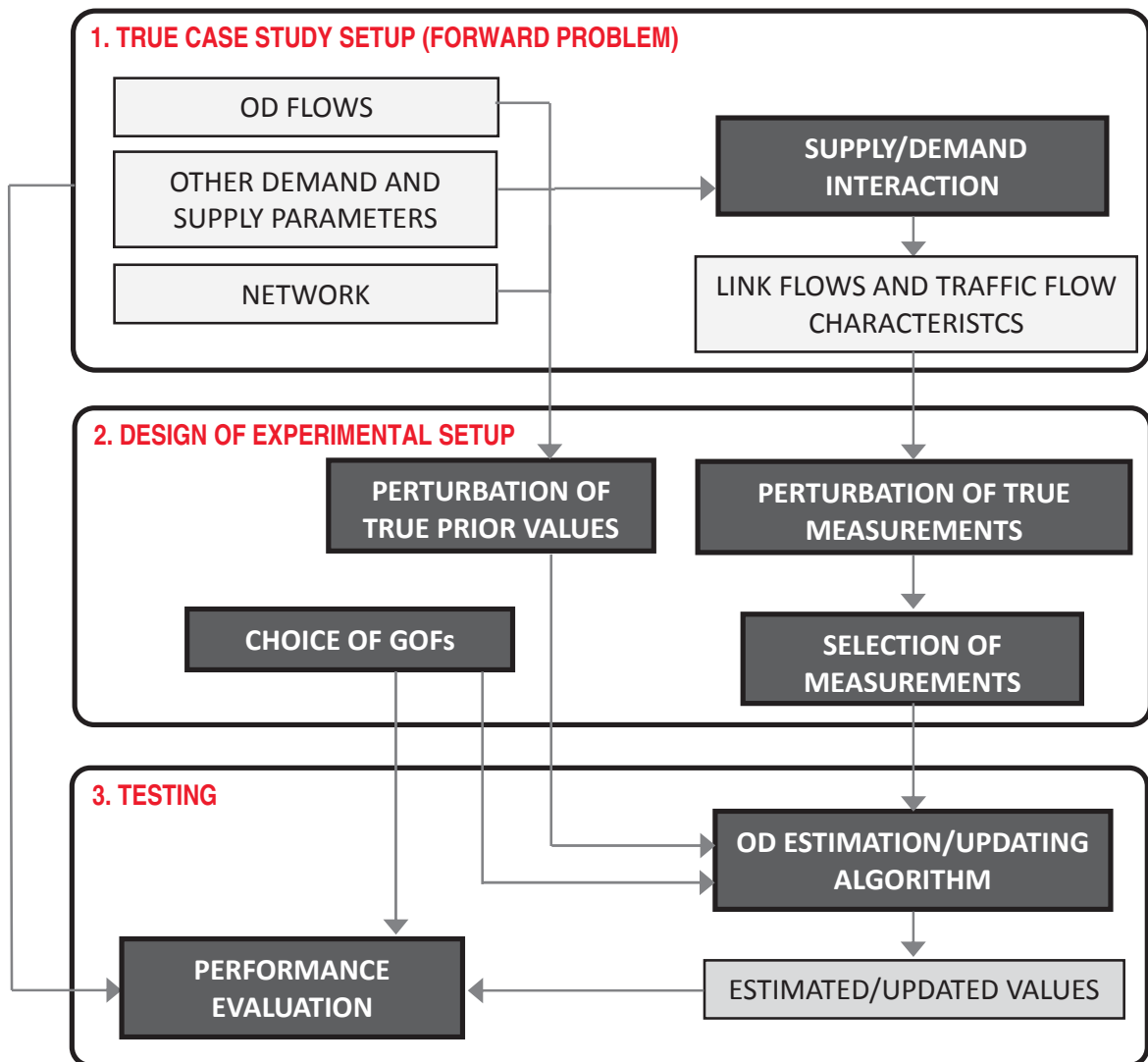
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13 Importantly, notwithstanding significant methodological contributions to the state-of-the-art, most  
14 of the aforementioned works do not provide decisive experimental evidence of their advantages over  
15 existing methods. As mentioned in the introduction, this is primarily due to the unobservability of OD  
16 flows –except in closed-form highway networks– and thus it is very difficult to detect the quality of  
17 OD estimation/updating procedures based on real datasets. In fact, matching closely the observed  
18 measurements used for OD estimation/updating is not in general indication of a good quality of OD  
19 estimation/updating itself.

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21 Therefore, the main motivation of this paper is to provide a common evaluation and benchmarking  
22 framework of methodologies and algorithms for OD flows estimation/updating, under equal and  
23 standardized conditions, based on a proper methodology pivoted on synthetic test beds, built upon real  
24 networks. For a description of synthetic test bed approaches in case of traffic simulation model  
25 parameters calibration or OD flows estimation, see respectively Ciuffo and Punzo (2014) and Marzano  
26 et al. (2009). Other applications of such approach to the field of traffic simulation can be found,  
27 amongst others, in Zhou and Mahmassani (2006), Ciuffo et al. (2008), Ossen and Hoogendoorn (2008),  
28 Vaze et al. (2009), Gao et al. (2010), Punzo et al. (2012) and Zheng and Van Zuylen (2013).

### 31 32 **3. Benchmarking platform: conceptual framework and methodological approach**

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34 This section introduces the main proposition of the paper, that is a common evaluation and  
35 benchmarking framework for OD flows estimation/updating methodologies and algorithms, whose  
36 main objective is to provide a test bed in which a number of algorithms can be implemented and tested  
37 under equal and standardized conditions. Specifically, a key requirement for evaluating and comparing  
38 various OD estimation/updating algorithms is to test their performances under a range of different  
39 conditions and scenarios (e.g. network sizes, demand and thus congestion levels, surveillance system  
40 characteristics, including the number and location of sensors and the type of detected information, as  
41 well as its quality, and so on) and to ensure that these conditions are consistent across experiments. The  
42 proposed design of the benchmarking framework – encompassing three main components, conceptually  
43 illustrated in Figure 1 – is generic and allows comparing considerably different approaches in a variety  
44 of settings and conditions, and is also consistent with diverse implementation platforms.

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46 The first step deals with the setup of the “true” case study, consistent with the forward problem in  
47 sensitivity analysis (recalled in Section 1): basically, a true test bed is defined in terms of OD flows,  
48 network characteristics, and any other relevant parameters related to demand and supply. Consistently,  
49 a true supply/demand interaction procedure leads to calculation of true link flows and traffic flow  
50 characteristics. In this respect, a wide range of possible traffic flow characteristics – in turn resulting  
51 into input measurements for the OD estimation/updating algorithm – can be calculated. By way of  
52 example, the practical case study that will be presented in Sections 4 to 6 is also based on using point-  
53 to-point travel time measurements and data collected using Bluetooth antennas. Therefore, this  
54 approach allows calculating all concerned variables and enables a variety of experiments and  
55 applications.



**Figure 1 – Illustrative flowchart of the proposed methodological benchmarking framework**

The second step deals with the design of the experimental setup, which consists mainly of *ad hoc* perturbations of possibly all true experimental values, i.e. OD flows, network characteristics, other demand/supply data and traffic flow measurements. This allows primarily mimicking real situations with uncertainties and/or biases in prior available estimates. In addition, a wide range of assumptions on selection of measurements can be adopted as well, so as to mimic the real and usual condition of collecting traffic flow measurements only in a few locations in the network<sup>4</sup>. Interestingly, both the initial true values in step one and the magnitude of the perturbations in step two can be combined, so as to cover diverse possible real conditions and test a heterogeneous and comprehensive range of situations. The experimental setup includes also the selection of appropriate indicators and goodness-of-fit (GOF) measures, allowing elucidating diverse aspects of the model and providing a more complete assessment of its performance. Indeed, OD flow estimation/updating algorithms are usually

<sup>4</sup> For details on the network sensors location problem – including the issues of detector positioning, qualitative appreciation of added detectors, and for quantifying the amount of information that a detector adds – the reader could refer to Yang and Zhou (1998), Simonelli et al. (2012) and Viti et al. (2014), whose algorithms and methodologies can be applied in order to select measurement locations for the benchmarking framework.

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4 formulated as an optimization problem, whose objective function exhibits a functional form expressed  
5 via a GOF (or a combination of GOFs), as will be clarified in Section 4.  
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7 The third step focuses on testing OD estimation/updating algorithms under analysis. Specifically,  
8 tested methods/algorithms are fed with perturbed setup values, calculated in the second step of the  
9 procedure, and the resulting estimated/updated values are then compared with the true underlying  
10 values defined in the first step of the procedure, based on the selected set of GOFs.  
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12 Importantly, executing the OD estimation/updating algorithm implies running in turn the  
13 supply/demand interaction, in order to ensure mutual consistency between OD flows and traffic flow  
14 measurements during and at the end of the estimation/updating procedure. In other words, a dynamic  
15 communication between the OD demand estimation methods and the traffic simulator is necessary in  
16 order to execute a traffic simulation run within the OD demand estimation algorithm, with a degree of  
17 complexity and with specific implementation issues usually dependent upon the specific tested  
18 algorithm and the underlying hypotheses (e.g. congested network, type of dynamic traffic assignment,  
19 analytic solution vs. simulation, and so on). In addition, a common situation is that an OD  
20 estimation/updating algorithm runs on a different platform/tool with respect to the supply/demand  
21 interaction, thus leading to additional implementation issues, as it will be shown in the practical case  
22 study described in Section 5.  
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25 Interestingly, the proposed benchmarking framework is able to accommodate a wide range of  
26 applications, so as to check the performance of the tested dynamic OD flows estimation methods with  
27 respect to theoretical, practical or computational challenges known in the literature (see Section 2 also  
28 for a recap of key issues), for instance:  
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- 30 • *Impacts of biased prior OD flows.* Several prior OD matrices can be tested with different degree  
31 of errors and biases, mimicking the common approach of deriving prior dynamic OD flow  
32 estimates by splitting a static prior OD matrix using an exogenously superimposed time profile.  
33 Thus, biases can occur, first of all, as a consequence of errors in estimation of the total number  
34 of trips and spatial distributions resulting from static demand modelling. Moreover, prior static  
35 OD matrices are also adjusted with traffic counts, possibly resulting in underestimation of  
36 demand when in congested conditions, because of the misinterpretation of low flow values due  
37 to traffic congestion (i.e. erroneously considered as resulting from low demand values). Also  
38 the dynamic splitting of the static prior OD matrix is source of errors, because of difficulties in  
39 observing reliable dynamic OD time profiles;  
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- 41 • *Influence of other demand parameters.* Diverse route choice options can be implemented, thus  
42 testing the effects of possible errors in route choice modelling, because route choice models are  
43 normally calibrated based on either aggregated data (e.g. link counts) and/or disaggregate path  
44 observations provided by monitored vehicles, leading in both cases to possible estimation  
45 errors;  
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- 47 • *Effects of combined types of measurements.* A variety of traffic data types can be adopted as  
48 inputs for OD flows estimation, and the proposed framework allows to analyze the combined  
49 effects of their fusion, in terms of measurement distortions/errors, collinearity, and so on;  
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- 51 • *Inherent properties of the OD flows estimation problem.* As recalled in Section 2, dynamic OD  
52 flow estimation is a highly non-linear, non-convex problem. The shape of its objective function  
53 clearly depends on diverse factors, e.g. the type of estimator adopted, the boundary conditions,  
54 and so on. In this respect, the benchmarking framework allows investigating how the structure  
55 of the objective function – and therefore the performance of the solution algorithm – changes  
56 with respect to these input factors, with important consequences in assessing the practical  
57 tractability of OD flows estimation.  
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- 59 • *Impacts of traffic simulation/assignment.* Performance of OD estimation methods depends  
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highly upon the structure and the properties of the supply/demand interaction – that is of the assignment map, defined either explicitly in analytical method or implicitly through simulation – and also upon the congestion level of the network (Frederix et al, 2013; Flötteröd and Bierlaire 2009). In this respect, the proposed benchmarking framework enables testing, on one side, a given OD estimation method with respect to different congestion levels through a proper definition of the true case study setup and of the experimental setup, and, on the other side, to compare different OD estimation methods under the same congestion level. A specific instance of this feature is proposed in Section 5.2.1.

In general, the conceptual benchmarking framework presented in this Section should be operationalized in a benchmarking platform, capable to perform comparisons between different OD estimation/updating methods in a remarkably wide range of case studies and experimental setups. Therefore, the paper presents a practical instance of implementation of a benchmarking platform based on the proposed framework, discussing the contrasted OD estimation/updating methods (Section 4), the implementation of the platform (Section 5), and the main testing results (Section 6).

#### 4. Illustration of tested OD flow estimation/updating methods

This section reports on the OD estimation/updating algorithms tested using the benchmarking framework described in Section 3 and practically implemented in the platform illustrated in Section 5. Specifically, Section 4.1 presents a general formulation of the tested (dynamic) OD estimation/updating methods, whilst Section 4.2 provides details on the specifications and on the solution algorithms.

##### 4.1 General formulation of the tested dynamic OD flow estimation methods

This subsection presents a fairly general formulation of the dynamic OD flow estimation problem. First, definitions that will be used further in formulation of selected dynamic OD demand methods are introduced. The modelling horizon has  $T$  time steps, and is divided in time intervals  $t$ , with  $t = 1, 2, \dots, T$ . The traffic demand between origins and destinations is stored in the OD vector  $\mathbf{x} = \{x_i | i \in I\}$  wherein  $I$  is the set of all OD pairs; the corresponding link flows are stored in the vector  $\mathbf{y} = \{y_l | l \in L\}$ , being  $L$  the set of links in the network. The historical or prior or seed OD vector  $\tilde{\mathbf{x}} = \{x_i | i \in I\}$  is a vector that needs to be updated. Normally, a wide range of traffic flow measurements are available, ranging from traditional link flow measurements (e.g., speed, density, occupancy) to innovative data collected by a variety of sensors (e.g. travel times collected from Bluetooth sensors, partial OD flows and travel times from GPS traces, point-to-point various traffic flow measurements between pairs of coupled sensors). Thus, let  $\hat{L} \subseteq L$  the set of monitored links, i.e. with available link traffic counts  $\hat{\mathbf{y}} = \{\hat{y}_l | l \in \hat{L}\}$  and link-based traffic flow measurements denoted as  $\hat{\mathbf{c}} = \{\hat{c}_l | l \in \hat{L}\}$ , and let  $\hat{P} \subseteq P$  be the subset of pairs of nodes/points in the network with available additional traffic flow measurements<sup>5</sup> denoted as  $\hat{\mathbf{z}} = \{\hat{z}_p | p \in \hat{P}\}$ .

From a fairly general standpoint, the dynamic OD estimation problem, combining observed link flow data and traffic flow measurements, can be expressed as:

<sup>5</sup> Notice that  $\mathbf{z}$  includes possibly node based, point-to-point based and (partial) OD based measurements. Notably, when travel time measurement are included in the estimation method, Barceló et al. (2012) show that a detection layout based on node covering instead of the usual link covering, provides richer and more sensitive data, as this layout captures higher flows and allow to exploit the identification of partial paths between detectors, as later in this paper will be shown in the case of Vitoria's network. In-depth discussions/analyses on path flow estimators have been proposed by various authors, and a basic reference could be found in Bell (1997).

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x} \in \mathcal{S}_x} \varphi(\mathbf{x}, \tilde{\mathbf{x}}, \hat{\mathbf{y}}, \hat{\mathbf{c}}, \hat{\mathbf{z}}) \quad \text{or} \quad \mathbf{x}^* = \operatorname{argmax}_{\mathbf{x} \in \mathcal{S}_x} \psi(\mathbf{x}, \tilde{\mathbf{x}}, \hat{\mathbf{y}}, \hat{\mathbf{c}}, \hat{\mathbf{z}}) \quad (1)$$

wherein  $\mathbf{x}^* = [\mathbf{x}_1^*, \dots, \mathbf{x}_T^*]$  is the unknown OD demand vector<sup>6</sup> for time intervals  $t \in 1, 2, \dots, T$ ,  $\varphi(\cdot)$  and  $\psi(\cdot)$  general functional forms and  $\mathcal{S}_x$  the feasibility set of the problem, embedding non-negativity constraints for OD flows and also other possible constraints (e.g. total production/attraction, geographical correlations, trip length distributions, and so on).

The dynamic OD estimation methods considered in this benchmark study is a particular, yet very common, instance of the generic formulation (1), given by:

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x} \geq 0} [f_1(\mathbf{x}, \tilde{\mathbf{x}}) + f_2(\mathbf{y}(\mathbf{x}), \hat{\mathbf{y}}) + f_3(\mathbf{c}(\mathbf{x}), \hat{\mathbf{c}}) + f_4(\mathbf{z}(\mathbf{x}), \hat{\mathbf{z}})] \quad (2)$$

wherein the four functions  $f_1$ ,  $f_2$ ,  $f_3$  and  $f_4$  express the distance between measured and modelled values as a function of different goodness-of-fit measures. An intuitive interpretation of the problem given in equation is that it searches the vector  $\mathbf{x}^*$  that is closest to the a priori estimate  $\tilde{\mathbf{x}}$ , and, once assigned to the network, produces the traffic data,  $\mathbf{y}(\mathbf{x})$ ,  $\mathbf{c}(\mathbf{x})$  and  $\mathbf{z}(\mathbf{x})$  closest to their observed values. At each iteration step or time interval  $t$ ,  $\mathbf{y}(\mathbf{x})$ ,  $\mathbf{c}(\mathbf{x})$  and  $\mathbf{z}(\mathbf{x})$  could be extracted from inputs of the traffic simulator and calculated based on running supply/demand interactions: this aspect will be described in detail in Section 5.3, and further details can be found in Yang and Bell (1998), Tavana and Mahmassani (2001), Flötteröd and Bierlaire (2009) and Frederix et al. (2011). The set of constraints depends on application of the problem as well as the desired level of accuracy, and it can include non-negativity constraints, initial condition constraints, lower and upper bound constraints to avoid infeasible solutions and restrict search space, and so on. Also, traveller's route choice or traffic assignment rules are often obtained by optimizing an objective function, which can be explicitly included in the set of constraints. This formulation results in a bi-level optimization problem, where the upper level is a non-linear non-differentiable optimization problem, whose objective function is usually defined in terms of GOFs, and the lower level is an equilibrium assignment problem. In some of the approaches tested in this paper (see Section 4), the optimization problem has been solved with an *ad hoc* version of optimization-simulation approach based on SPSA, which also evaluates the function by a mesoscopic simulation based Dynamic User Equilibrium (DUE).

A key aspect for the practical implementation of the generic formulation (2) refers to the choice of the functional form of the component functions  $f_1 \dots f_4$ . Drawing upon Cascetta (1984), a natural and straightforward choice is to assume a least square approach. However, since different traffic measurements contain very diverse values in terms of order of magnitude, a normalized mean error (NME) specification can be applied as well. Specifically, the choice of a particular NME performance measure comes from the analysis of the trend of each goodness-of-fit measure between the considered prior OD matrix and the true OD matrix, obtaining that the NME best represents the descendent direction through the desired solution. This effect can be explained by the fact that the NME is an algebraic rather than an absolute error measure, capable to balance possible instabilities of link quantities (pertaining to the assignment phase), and to capture the improvement that can be detected at network level, when the estimated matrix moves along the descent direction.

<sup>6</sup> Importantly, working with OD flows is not a strict requirement. For instance, there might be situations wherein it is more effective to separate generation profiles and distribution shares – such as in the quasi-dynamic approach by Cascetta et al. (2013) or the method proposed by Cipriani et al. (2010) (see section 4.2.2) – or to work directly with OD path flows, such as in Barceló et al. (2013) (see section 4.2.5).

## 4.2 Description of the selected dynamic OD estimation methods for the benchmark case study

Consistent with the general formulation reported in Section 4.1, Table 1 summarizes the main properties of the five selected dynamic OD estimation methods for the benchmarking case study presented in the paper, showing their diversity of input data, objective function and solution algorithm. A detailed description for each of them is reported in the following subsections.

**Table 1 - Properties of selected dynamic OD demand estimation methods**

Method	Input data				Objective function **	Solution algorithm
	prior OD	link flow	link density	travel times		
Method 1	+	+			LS	LSQR
Method 2	+ *	+	+		LS + NME	SPSA AD-PI
Method 3	+	+	+	+	NME	enhanced SPSA AD-PI
Method 4		+	+	+	NME	SPSA CG-TR
Method 5	+	+		+	LS (state - space)	Kalman filter

\* two different versions of Method 2 are implemented: the former, labelled Method 2-TD, encompasses trip distribution shares as prior OD information; the latter, labelled Method 2-OD, encompasses OD flows as prior information,

\*\* LS=least square, NME=normalized mean error.

### 4.2.1 Method 1: the LSQR method

The first tested method is the least square formulation of the dynamic OD demand estimation model (2) used by Bierlaire and Crittin (2004), given by considering only the two functions  $f_1$  and  $f_2$ . Furthermore, exploiting Ashok and Ben-Akiva (1993), deviation of OD flows from their historical estimates are assumed as state variables and deviations of link flows from historical counts as traffic measurements. The least square problem is solved through the LSQR algorithm, exhibiting computational efficiency for very large networks, analytically equivalent to a conjugate gradient method, based on bi-diagonalization procedures (Paige and Saunders, 1982). A key property of the LSQR algorithm is that the assignment matrix – very sparse in large scale networks, such as in the practical case study implemented in Section 5 – does not need to be explicitly constructed or stored. For a more detailed explanation of this algorithm the reader may refer to Bierlaire and Crittin (2004). Summarizing, Method 1 assumes the following:

- Input data: prior OD demand and link flow data;
- Solution algorithm: LSQR algorithm.

### 4.2.2 Method 2: the SPSA AD-PI method

The second tested method is formulated by adding traffic flow densities as measurements in the problem (2), with the aim of providing additional information on the traffic regime. Drawing upon the several variants of the SPSA algorithm proposed by Cipriani et al. (2010, 2011) –where the off-line dynamic OD demand estimation problem is formulated as a bi-level nonlinear optimization program without introducing assignment matrices– the proposed solution approach is a modification of the gradient-based path-search optimization method (SPSA) coupled with Asymmetric Design (AD) for gradient computation and Polynomial Interpolation (PI) of the objective function for the linear optimization. SPSA AD-PI permits to reduce the computational efforts with respect to the usual gradient-based methods: for a more detailed explanation of this algorithm the reader may refer to

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4 Cipriani et al. (2011).

5 Preliminary results using SPSA AD-PI show an interesting trade-off in the choice of the type of  
6 prior OD information in the problem (2). Indeed, on the one hand, including the distance from the prior  
7 OD matrix values in the function  $f_1$  of Equation (2) may bind too strongly the search of the solution  
8 within a neighbourhood of the prior OD matrix itself. On the other hand, removing prior demand (i.e.  
9 neglecting  $f_1$ ) would give importance only to the remaining terms of the problem (2), i.e. leading to  
10 satisfactory results only with respect to matching both link measurements and possibly to the total  
11 amount of generated trips by each origin, whilst OD flow estimates are usually poor. Thus, it is worth  
12 exploring inclusion of “structural properties” of the OD matrix as prior estimates, e.g.  
13 production/attraction by zones, geographical correlations, temporal smoothness, trip length  
14 distributions, and so on. Therefore, Method 2 will be specifically applied in the following by assuming  
15 trip distribution as prior OD values, thus labelled as “Method 2-TD”. In addition, in order to provide a  
16 direct comparison with the subsequent Method 3 (Section 4.2.3), Method 2 has been applied also  
17 considering prior OD demand instead of prior OD trip distributions, thus labelled as “Method 2-OD”.

18 Summarizing, Methods 2 assumes:

- 19 • Input data: prior OD trip distributions (“Method 2-TD”) or prior OD flows (“Method 2-OD”),  
20 link flow data and density data;
- 21 • Solution algorithm: SPSA AD-PI algorithm.

#### 22 23 24 25 26 27 *4.2.3 Method 3: the enhanced SPSA AD-PI method*

28 The previous Method 2 (Section 4.2.2) can be enriched assuming the availability of point-to-point  
29 travel times detected using Bluetooth sensors along main paths/corridors in the network. In particular,  
30 Barceló et al. (2013) has proved that a suitable Bluetooth sensor layout allows identification of the  
31 paths between sensors and therefore measurement of the associated travel times. Thus, the  
32 corresponding dynamic OD estimation problem is defined by normalized mean error functions  $f_1$ ,  $f_2$ ,  
33  $f_3$  and  $f_4$  in equation (2) and is solved by the modified SPSA AD-PI approach used in Method 2 and  
34 already described in Section 4.2.2.

35 Summarizing, the main properties of Method 3 are given as follows:

- 36 • Input data: prior OD demand, link flow data, density data and point-to-point (i.e. between  
37 Bluetooth sensors) travel time data;
- 38 • Solution approach: SPSA AD-PI algorithm.

#### 39 40 41 42 43 44 *4.2.4 Method 4: the SPSA CG-TR method*

45 As mentioned in Section 4.2.2, the computational experience showed that the presence of prior OD  
46 flow information in the general problem (2) has a twofold negative influence, because it prevents  
47 exploring OD solutions significantly different from the (biased) prior matrix and at the same time it  
48 implies high computational burden. Based on these tenets, Bullejos et al. (2014) proposed a  
49 specification of the problem (2) excluding prior information on OD flow data. Consistently, the  
50 dynamic OD estimation problem is defined by normalized mean error performance functions  $f_2$ ,  $f_3$  and  
51  $f_4$  in expression (2).

52 Furthermore, this case study focuses on exploring solution approaches capable to reduce the  
53 computational burden. For this aim, Bullejos et al. (2014) proposed a modified SPSA approach with a  
54 twofold enhancement: i.) to include a conjugate gradient strategy in the computation of the  
55 approximated average gradient, as suggested in Cantelmo et al. (2014b), because it is known that  
56 conjugate directions permit to reach the solution faster than using the basic gradient method; ii.) to use

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4 of a trust region scheme as in Osorio and Bierlaire (2010), whose main idea is to set implicitly at each  
5 iteration a neighbourhood around the current solution: indeed, avoiding matrices outside the trust  
6 region is essential to reduce the computational burden. For more detail explanation of this algorithm the  
7 reader may refer to Bullejos et al. (2014). Summarizing, Method 4 is based on the following:

- 8 • Input data: link flow data, occupancy data and travel time data;
- 9 • Solution approach: SPSA CG-TR algorithm.

#### 10 11 12 13 *4.2.5 Method 5: Kalman filter method*

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15 Barceló et al. (2013) adopted a linear state-space formulation for real-time estimation and short-term  
16 prediction of OD matrices, assuming the availability of travel times between Bluetooth sensors along  
17 the main paths connecting a subset of pairs of Bluetooth sensors in the network. Thus, Method 5  
18 exploits the travel times and counts collected, respectively, by tracking Bluetooth equipped vehicles  
19 and conventional loop detectors. Consistently, the dynamic OD estimation problem is defined as a  
20 state-space model solved by a linear Kalman filter algorithm with no assignment matrices, as proposed  
21 by Ashok (1996) and Ashok and Ben-Akiva (2000). Keeping a linear relationship between state-  
22 variables and measurements is computationally advantageous and reduces the number of state variables  
23 in the Kalman filter formulation. Further details on the mathematical formulation and on the  
24 corresponding solution algorithm are reported in Barceló et al. (2013).

25  
26 The main properties of Method 5 are:

- 27 • Input data: prior OD flows, link flow data from loop detectors, and traffic counts at Bluetooth  
28 sensors and travel times data between entry Bluetooth sensors and inner Bluetooth sensors;
- 29 • Solution approach: a linear Kalman filter, whose state variables are defined as OD path flows  
30 in the set of the most likely used OD paths<sup>7</sup>.

## 31 32 33 34 35 **5. Case study: implementation of the benchmark platform and experimental setup**

36  
37 The practical implementation of a benchmarking platform, capable to contrast the performances of the  
38 OD estimation/updating algorithms described in Section 4, should follow the methodological tasks  
39 identified in the general framework illustrated in Section 3. This section follows exactly the three main  
40 steps depicted in Figure 1, that is the true case study setup (Section 5.1), the design of the experimental  
41 setup (Section 5.2) and illustrates how the interplay between the supply/demand interaction and the OD  
42 estimation/updating algorithm has been developed for testing purposes (Section 5.3).

43  
44 This setup is simply for exposition of the platform and in no way an integral (or “hard-coded”) part  
45 of it. Instead, the user applying the platform for a specific application would be free to use any type of  
46 traffic simulator, network and traffic measurement that is suitable for that application. Furthermore, the  
47 demand structure adopted by the user could be perturbed in a different way, to e.g. further obscure the  
48 structure of the initial demand, or perhaps make the demand structure perturbations dependent on the  
49 traffic state.

### 50 51 52 53 *5.1 True case study setup*

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55 First, a specific supply/demand interaction approach should be defined in terms both of theoretical

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59 <sup>7</sup> Usual approaches require a total path enumeration resulting impractical for large network, but a detailed analysis of  
60 equilibrium solutions shows that only a reduced number of paths are significantly used and that most of them show a  
61 stability across time intervals in a DUE, therefore the reformulation of the problem in terms of these paths, what we call the  
62 most likely used paths, provides a formulation of reasonable size even for large networks.

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4 assumptions (e.g. macro/meso/micro, equilibrium/network loading, and so on) and practical  
5 implementation (e.g. commercial software vs. in-house built functions). In this respect, without loss of  
6 generality, the mesoscopic Aimsun traffic simulator (TSS, 2013) has been chosen in this study. The  
7 choice of simulator is not an inherent part of the presented platform, and indeed only a factor in the  
8 case study. Any type of traffic simulators can be used, including open-source traffic simulators, whose  
9 open-source nature might actually simplify the process of developing the interfaces to the platform. In  
10 this respect, an important feature that any simulator has to exhibit for inclusion in the benchmarking  
11 platform is the numerical stability of its results, i.e. small OD flow perturbations should lead to small  
12 consistent variations in simulation outputs: this is indeed a necessary condition to ensure fair  
13 comparison amongst results using different methods/algorithms.  
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15  
16 In terms of test beds, three different networks have been modelled:  
17

- 18 • A small network used primarily for debugging and verification purposes;
- 19 • A medium-size network from Eixample, the central business district of Barcelona,  
20 consisting of 120 origin centroids, 1227 nodes (grouped in intersections), 130 destination  
21 centroids, 2800 links and 1469 OD pairs;
- 22 • A larger network from the city of Vitoria (Spain), depicted in Figure 2, including 57  
23 centroids, 3249 OD pairs, 2884 nodes and a modelled network of about 600 km,  
24 corresponding to 5799 links. This network resembles a reasonable sized real-life network,  
25 with representative congestion levels and route choice dimension, as found in many large  
26 urban areas.  
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30 For the sake of brevity, the paper reports results related only to the Vitoria network; however, other  
31 case studies using this benchmarking platform are reported in Barceló et al. (2013), Bullejos et al.  
32 (2014), and Cantelmo et al. (2014b). Consistent with the true case study setup described in Section 3, a  
33 true model has been assumed as ground-truth together with a true OD matrix. The corresponding true  
34 link flows and all other concerned traffic flow characteristics have been derived from assignment of  
35 true OD matrix using the aforementioned mesoscopic Aimsun traffic simulator. Specifically, a  
36 Dynamic User Equilibrium (DUE) has been applied, based on a mesoscopic simulation for the network  
37 loading phase and on a Method of Successive Averages (MSA) for OD paths and OD path flows  
38 computation; convergence is defined upon a gap function, and results rely on a proper calibration of the  
39 model. Additionally, applying a DUE instead to a DTA has the advantage of smoothing out the  
40 inherent stochasticity of route choice through the iterative process.  
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43 The simulation period refers to the afternoon hourly peak period, divided into 15-minutes time  
44 intervals plus another additional warm-up time interval, leading to 5 time intervals overall. The trips for  
45 vehicles that departed at a given time interval between some of the OD pairs are not necessarily  
46 completed within the same time interval, due to congestion on network or to the distance between OD  
47 pairs, thus resulting in 4 lagged time intervals and very sparse assignment matrices. All these decisions  
48 are user-defined input parameters to the platform, so they would be determined by the user specifically  
49 for each application. Similarly, the complication of stochasticity (e.g. due to the stochastic route choice  
50 models in a specific traffic simulation algorithm) should be treated by the specific calibration  
51 algorithms (which are exogenous to the platform) that are being considered and is not a factor in the  
52 operation of the platform itself. Anyway, if a DUE is used instead of a DTA, these effects would also  
53 be smoothed out, as noticed above.  
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## 58 *5.2 Design of experimental setup*

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60 The second main implementation task is to provide a comprehensive design of the experimental setup  
61 in terms of perturbation of true OD flows (Section 5.3.1), choice of traffic flow measurements and  
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locations with corresponding initial perturbations (Section 5.3.2), and choice of GOFs (Section 5.3.3).

### 5.2.1 Perturbation of true OD flows

In general, and consistent with the general formulation (2) of the tested OD estimation/updating algorithms, a prior OD flow estimate should be provided as input. Generally, the quality of such prior estimate, in terms of both demand level and patterns, is a key element affecting the performance of the estimation/updating algorithms, even more relevant for congested networks. Therefore, selecting proper perturbations of the true OD flows in order to derive the historical OD flow estimates to be provided as inputs for the OD estimation/updating algorithm is a crucial task. In this respect, three different prior OD flow scenarios have been chosen for the case study presented in this research, mimicking various sources of errors, specifically:

- **Low-demand scenario (D7):** this scenario addresses situations wherein, for instance, prior OD flow estimates result from out-of-date surveys. In detail, the low-demand scenario is defined as the 85% of the true OD demand level (Section 5.1), plus uniformly distributed random fluctuations over each OD pair and departure time interval in the range of  $\pm 15\%$  of the true value, that is:

$$\tilde{x}_{ij,t}^{LD} = x_{ij,t} \cdot [0.7 + 0.3\alpha_{ij,t}] \quad \alpha_{ij,t} \sim U(0,1)$$

wherein the generic OD pair is indexed by  $ij$  and  $t$  is the time interval;

- **Medium-demand scenario (D8):** in this scenario, the prior OD demand pattern corresponds for each OD pair to the 95% of the true OD demand level, plus an uniform random component in the range of  $\pm 15\%$ :

$$\tilde{x}_{ij,t}^{MD} = x_{ij,t} \cdot [0.8 + 0.3\alpha_{ij,t}] \quad \alpha_{ij,t} \sim U(0,1)$$

- **High-demand scenario (D9):** this scenario addresses for instance situations where the prior OD demand reflects travel demand in peak-hours, when congestion occurs on network. The prior OD demand pattern is thus pivoted on 105% of the true OD demand level plus an uniform random component in the range of  $\pm 15\%$ :

$$\tilde{x}_{ij,t}^{HD} = x_{ij,t} \cdot [0.9 + 0.3\alpha_{ij,t}] \quad \alpha_{ij,t} \sim U(0,1)$$

### 5.2.2 Selection of measurement locations and perturbation of true traffic flow measurements

In order to identify realistic scenarios in terms of measurement types and locations, two different sets of sensors have been identified in the Vitoria network:

- 389 standard loop detectors, located as depicted in the left-hand side of Figure 2, providing flows, speeds, occupancies, and so on, related to all vehicles at the detected loop;
- 50 Information and Communication Technologies (ICT) sensors, located as shown in the right-hand side of Figure 2, providing automatic signature identification for a subset of the vehicles, for instance through suitable antennas to catch Bluetooth devices in discovery mode. Notably, the Bluetooth sensors are deployed following a layout strategy to optimize the capture of equipped vehicles and provide effective travel time measurements between Bluetooth sensors.

The simulation of the true scenario leads to almost 90% of the trips collected twice at least in the

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4 afternoon-peak demand scenarios, which account for 95% of the number of OD pairs and 86% of the  
5 most likely used paths identified in a DUE assignment with the true prior OD matrix. The procedure  
6 proposed by Barceló et al. (2012) returns the location for Bluetooth sensors that provide simulated  
7 travel times on these predefined and stored routes satisfying the former properties.  
8

9 In terms of perturbation of the true link flows and other traffic flow measurement, the same  
10 approach adopted for OD flow perturbation (Section 5.2.1) can be followed in developing scenarios  
11 regarding the characteristics of the surveillance system, so as to mimic measurement errors in the real  
12 world. Without loss of generality, for the sake of simplicity, error-free measurements have been  
13 hypothesized in this paper.  
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31 **Figure 2 – The Vitoria network, Basque Country, Spain: loop detector sensors layout (left) and**  
32 **ICT sensors layout (right)**  
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### 34 5.2.3 Choice of GOFs

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36 The final component of the benchmarking framework processes the outcomes of the OD demand  
37 estimations and calculates a series of performance indicators. The choice of performance indicators  
38 plays an important role in benchmark analysis of OD demand estimation methods under uncertain  
39 inputs. In this case study, we distinguish two levels of performance indicators:  
40

- 41 • *Statistical performance indicators*: a number of statistical measures can be used to evaluate the  
42 overall performance of OD estimation methods, measuring the divergence between estimated  
43 outputs (e.g. OD flows, traffic counts, travel times) and their ground-truth values. In the context  
44 of this platform, the following goodness-of-fit measures have been implemented: RMSE,  
45 RMSNE, NRMSE, GEH1, MAE, MANE, NMAE, SE, U, ME, MNE, and NME. The reader  
46 may refer for details to Hollander and Liu (2008), Ciuffo and Punzo (2010), Antoniou et al.  
47 (2014) and Buisson et al. (2014);
- 48 • *Computational efficiency*: one of the research objectives is improvement in the computational  
49 efficiency of the dynamic OD flow estimation/updating problem for real time applications. To  
50 quantify the computational efficiency, the implemented platform calculates also the CPU  
51 computational time.  
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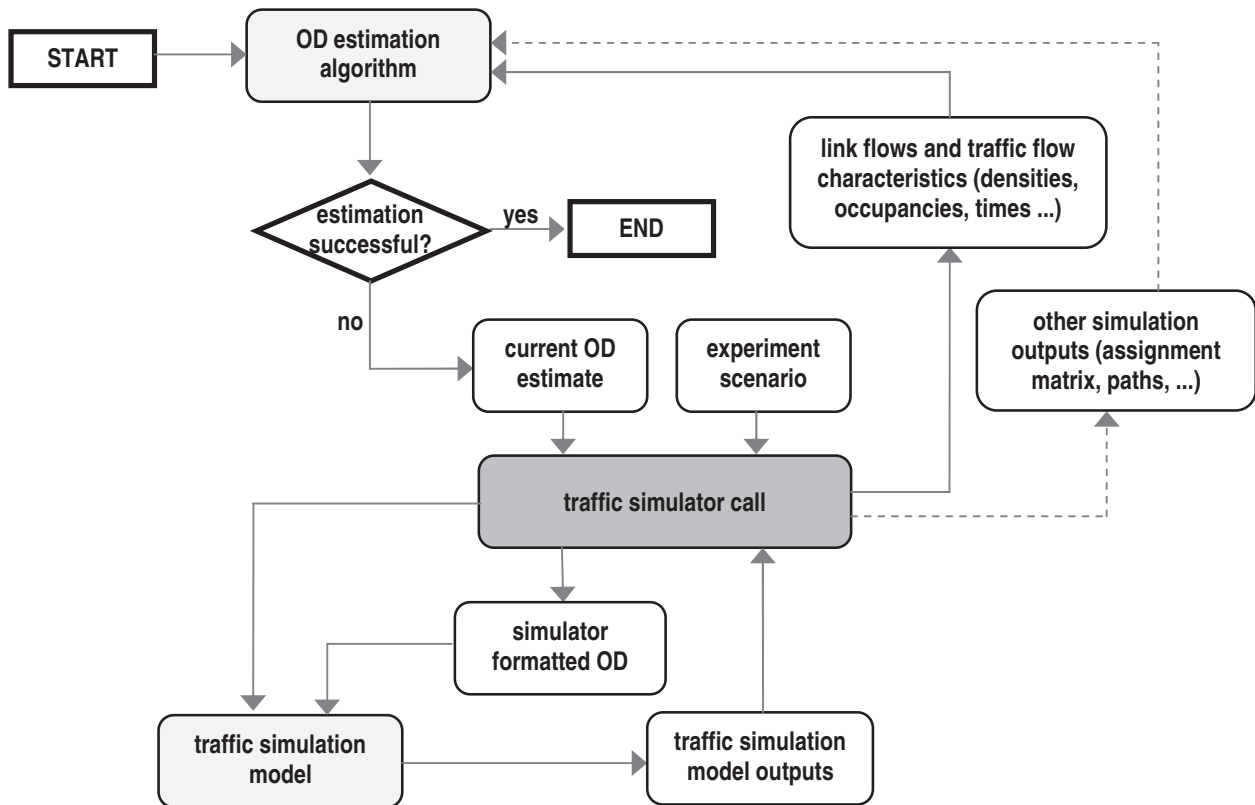
### 56 5.3 Practical implementation of the OD estimation/updating algorithms in the benchmarking platform

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58 For the purposes of the benchmarking platform, it is crucial to design how the supply/demand  
59 interaction and the OD estimation/updating algorithm interact with each other in running the  
60 experiment (i.e. step 3 of the general framework in Figure 1). Indeed, the practical implementation of  
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the general benchmarking framework illustrated in Section 3 should take into account that the optimization of the problem (2) requires sequential calls and integrated input/output exchange between the supply/demand interaction and the OD estimation/updating algorithm<sup>8</sup>. For instance, calculation of the descent direction at a given iteration  $i$  of the OD estimation/updating algorithm requires normally several evaluations of the objective function, which in turn implies running the supply/demand interaction in order to calculate model-based link flows and traffic flow characteristics to compare with observed measurements in the terms  $f_2$  to  $f_4$  of expression (2). The practical declination of this interplay requires also defining the specific characteristics of the supply/demand interaction: as mentioned at the beginning of Section 5, for the purposes of the paper, and without loss of generality, a mesoscopic traffic simulation model has been chosen.

In addition, it should be considered that normally the OD estimation/updating algorithm and the traffic simulation model run on different environments, e.g. an in-house built programming code for the former and a commercial software package for the latter. Therefore, illustratively, from a fairly general standpoint, the conceptual diagram depicting the interplay between OD estimation/updating algorithm and traffic simulator is reported in Figure 3.



**Figure 3 – Conceptual diagram of interplay between OD estimation/updating algorithm and traffic simulator within the benchmarking platform**

Notably, within the OD estimation main function, whenever a simulation run is needed the Traffic Simulator Call Function is initiated. This function converts the demand to be simulated to the Simulator

<sup>8</sup> Rigorously, this does not apply to Method 5 described in Section 4, which evaluates the GoF at the end of the simulation period and does not requires a DUE simulation call each iteration, just counts and travel times between Bluetooth sensors.

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4 Format, generates all the inputs necessary to properly run the traffic simulation models and finally calls  
5 and executes the Traffic Simulator with these inputs. From this logical diagram the main requirements  
6 of a Traffic Simulator to be used in this process become evident. The exchange of information between  
7 the proposed OD estimation procedure and the Simulator requires that it can be called in run time from  
8 the estimation algorithm as a subprogram. It also requires that the simulation output provides the inputs  
9 required by the OD estimation process and the GOFs calculations (e.g. traffic data, link flows, speeds,  
10 occupancies, OD travel times or travel times along the paths between OD pairs of ICT sensors),  
11 depending on the requirements of the specific method to test. In addition, as represented by the dashed  
12 lines in Figure 3, specific methods<sup>9</sup> to be tested could also require further additional traffic modelling  
13 data, e.g. estimates of the assignment matrices and/or set of chosen/feasible paths for each OD pair.

14  
15 From a practical standpoint, the benchmarking platform adopted in this paper is based on a  
16 combination of Aimsun as traffic simulator and Matlab (Matlab, 2013) as programming language for  
17 running the OD estimation/updating algorithms, with the calls between the two defined through  
18 Python: details of the implementation are given in the Appendix to the paper.  
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## 22 **6. Results and discussion**

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24 This section provides some<sup>10</sup> illustrative results obtained from the use of the benchmark platform  
25 described in the previous sections, with the main goal of demonstrating its potential application to  
26 various algorithms and using different traffic flow measurements. Specifically, the following  
27 applications of the methods illustrated in Section 4 are presented:  
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- 30 • Method 1 applied to demand scenarios D7 and D9 (Section 5.1), showing the effect on the  
31 estimated demand matrices and predicted link flows;
- 32 • Method 2-TD (i.e. the method illustrated in Section 4.2.2 with OD trip distributions as prior  
33 information) applied to the demand scenario D7;
- 34 • Method 2-OD (i.e. the method illustrated in Section 4.2.2 with OD flows as prior information)  
35 compared with Method 3 using the demand scenario D7;
- 36 • Methods 3 and 4 applied to the demand scenarios D7 and D9, showing the progress of the  
37 algorithms along the iterations when point-to-point travel times are considered in both methods;
- 38 • Method 5, demonstrating the potential effect of using new sensing capabilities, as travel times  
39 between the entry points to the system and the ICT internal sensors, beyond point counters for  
40 an on-line application, applied to the scenario D9.  
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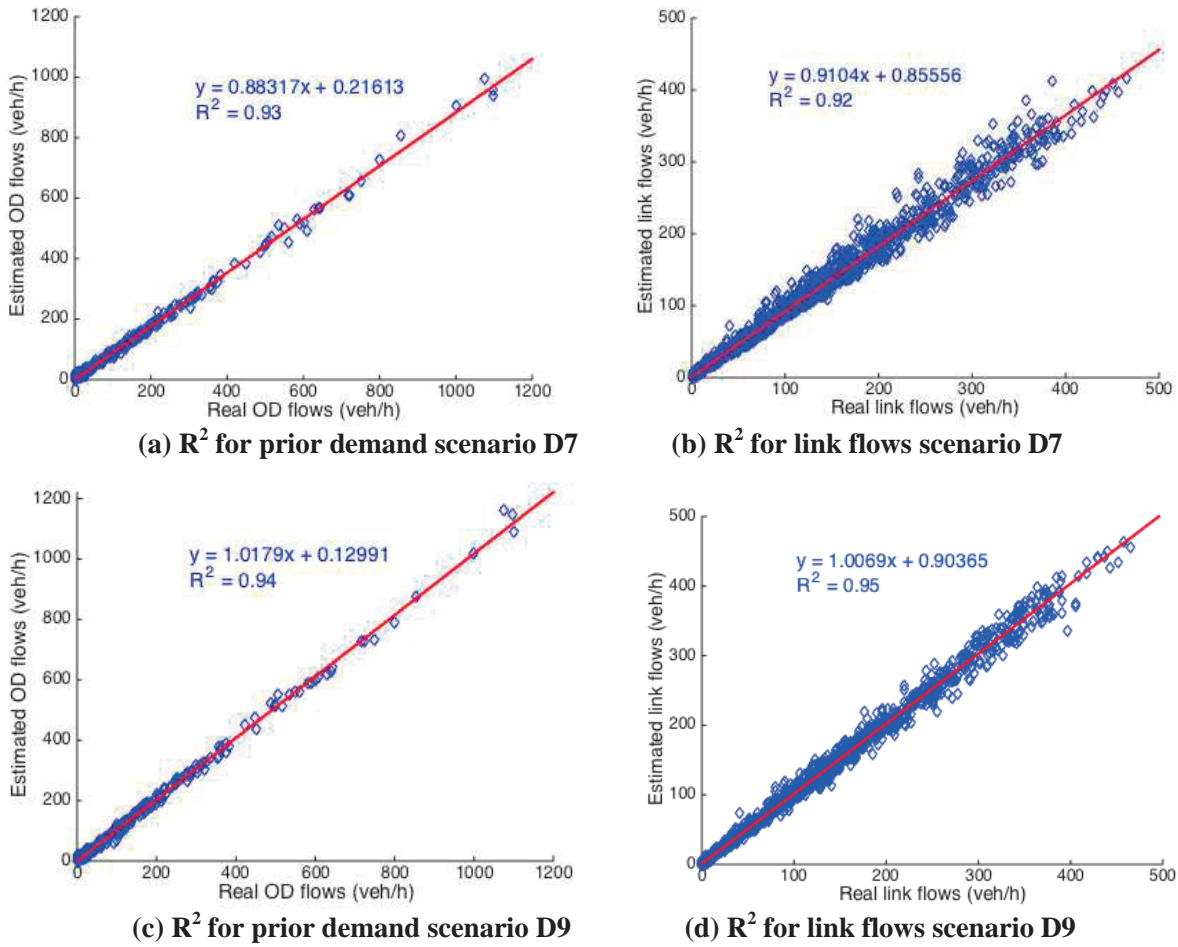
45 Figure 4 presents the performance of Method 1 using prior OD demand scenarios D7 and D9 and  
46 error-free link flow data. As discussed above, both demand scenarios are biased: on average, the D7  
47 seed matrix is biased downwards by 15%, and the D9 seed matrix is biased upwards by 5%. The figure  
48 shows the fit of the estimated OD flows, both to the true OD demand and to the link flows: as expected,  
49 a slightly better fit is obtained when the average bias in the seed OD matrix compared to the true  
50 demand is smaller.  
51

52 Scenario D7 was also used with Method 2-TD, which includes several parameters (step size,  
53 number of replications and use of information from previous iterations in the gradient calculations), set  
54 based on the results of a sensitivity analysis conducted by Cantelmo et al. (2014b). Figure 5a presents  
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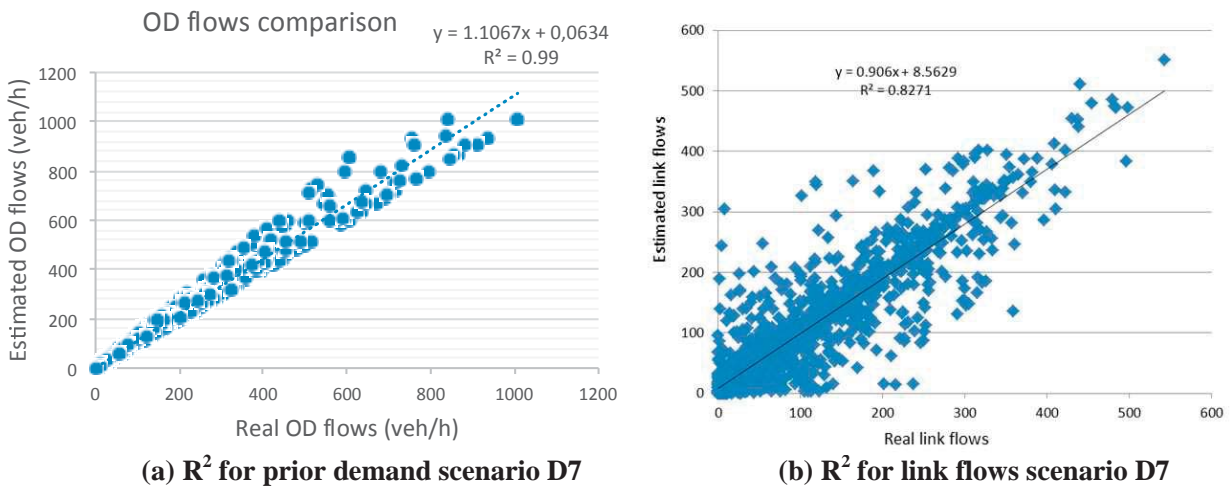
56  
57 <sup>9</sup> This is for instance the case of Methods 3 and 4, described respectively in Sections 4.2.3 and 4.2.4, for which the traffic  
58 simulator used must also be able of performing a DUE assignment and of exporting some internal information of the  
59 network structure and additional link data.

60 <sup>10</sup> As mentioned in Section 5, the presented platform is being used by several of the participants in active research, that has  
61 already led to the following publications, where the interested reader can find case studies and research aspects not covered  
62 here for the sake of brevity: Barceló et al. (2013), Bullejos et al. (2014), Cantelmo et al. (2014b), Barceló et al. (2014).  
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4 results in terms of estimated OD flows for Method 2-TD, that are comparable with those reported for  
5 Method 1 at convergence; instead Figure 5b indicates a worse fit for link flows with Method 2.  
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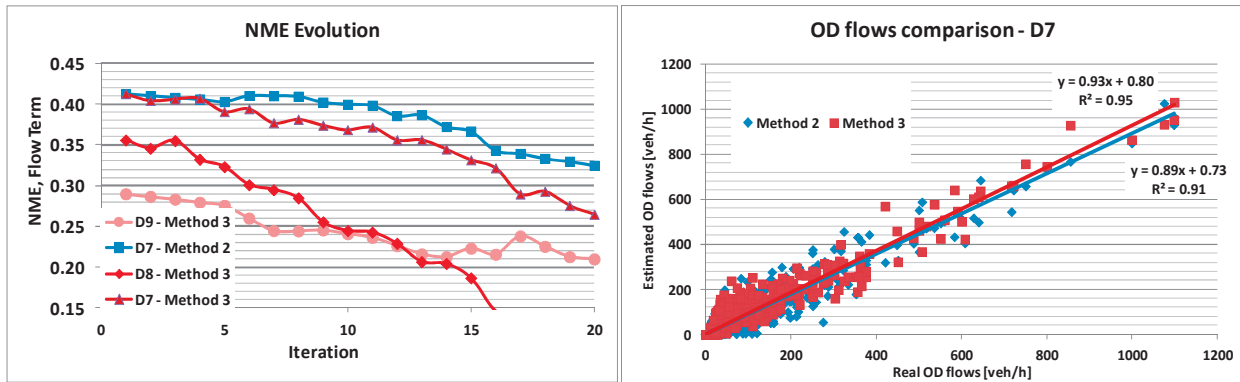


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41 **Figure 4 - Method 1 results:  $R^2$  for prior demand and for link flows - scenarios D7 (top) and D9**  
42 **(bottom)**



61 **Figure 5 - Method 2-TD results:  $R^2$  for prior demand and for link flows - scenario D7**

Method 3 extends Method 2 by the use of additional travel time information in the estimation process. Results in Figure 6 refer to comparisons with Method 2-OD (i.e. including OD flows as prior information) in order to make it comparable with Method 3. Specifically, Figure 6a shows how the flow term in the objective function evolves through iterations for both Method 3 (considering all demand scenarios D7, D8 and D9) and Method 2-OD (considering the demand scenario D7). In addition, Figure 6b compares the solutions of Method 3 and Method 2-OD at convergence for the demand scenario D7, evidencing the benefit of including a travel time term in the objective function.

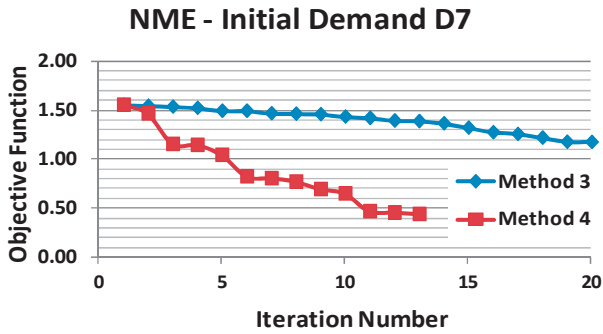


(a) evolution of function  $f_1$  for Method 2-OD and Method 3

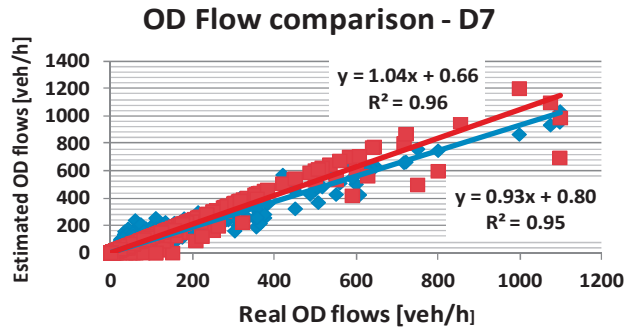
(b) true vs. estimated OD flows for Method 2-OD and Method 3

**Figure 6 – Results for Method 2-OD and Method 3**

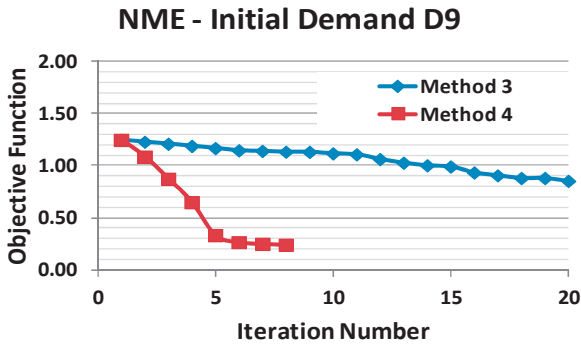
Method 4 is another variant of the basic algorithm underlying Methods 2 and 3. Its main characteristics are: i. it does not use a prior OD matrix, and ii. it exhibits a major algorithmic enhancement, consisting of approximating a stochastic conjugate gradient descent direction combined with a trust region scheme. In this respect, Figure 7 reports the results of a comparison of Method 3 and Method 4 under equal experimental conditions. Specifically, Figure 7a and 7c report the change of the objective function through iterations, respectively for demand scenarios D7 and D9. Similarly, Figure 7b and Figure 7d compare Methods 3 and 4 based on the  $R^2$  goodness-of-fit of the OD flows solution at convergence, again respectively for demand scenarios D7 and D9. In general, Method 4 shows a faster convergence than Method 3 in terms of reduction in the value of the objective function. However, in both cases, the quality of the solution in terms of coefficient of determination is similar for both methods, as shown by comparing Figures 7b and 7d, with estimation accuracy slightly magnified when the prior demand is close to the true one. Further numerical details can be found in Bullejos et al. (2014). Consequently, as shown in Figures 7a and 7c, Method 4 significantly reduces the number of iterations.



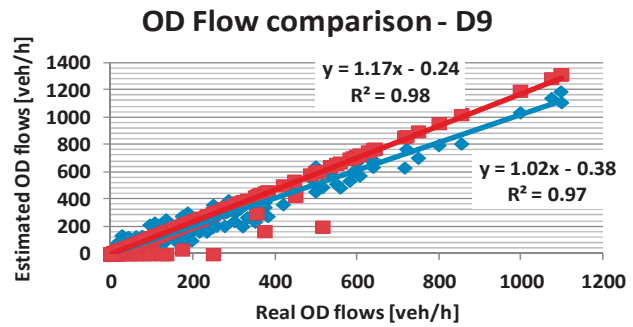
(a) OD flow evolution for Methods 3 and 4, demand scenario D7



(b) true vs. estimated OD flows for Method 2-OD and Method 3, demand scenario D7



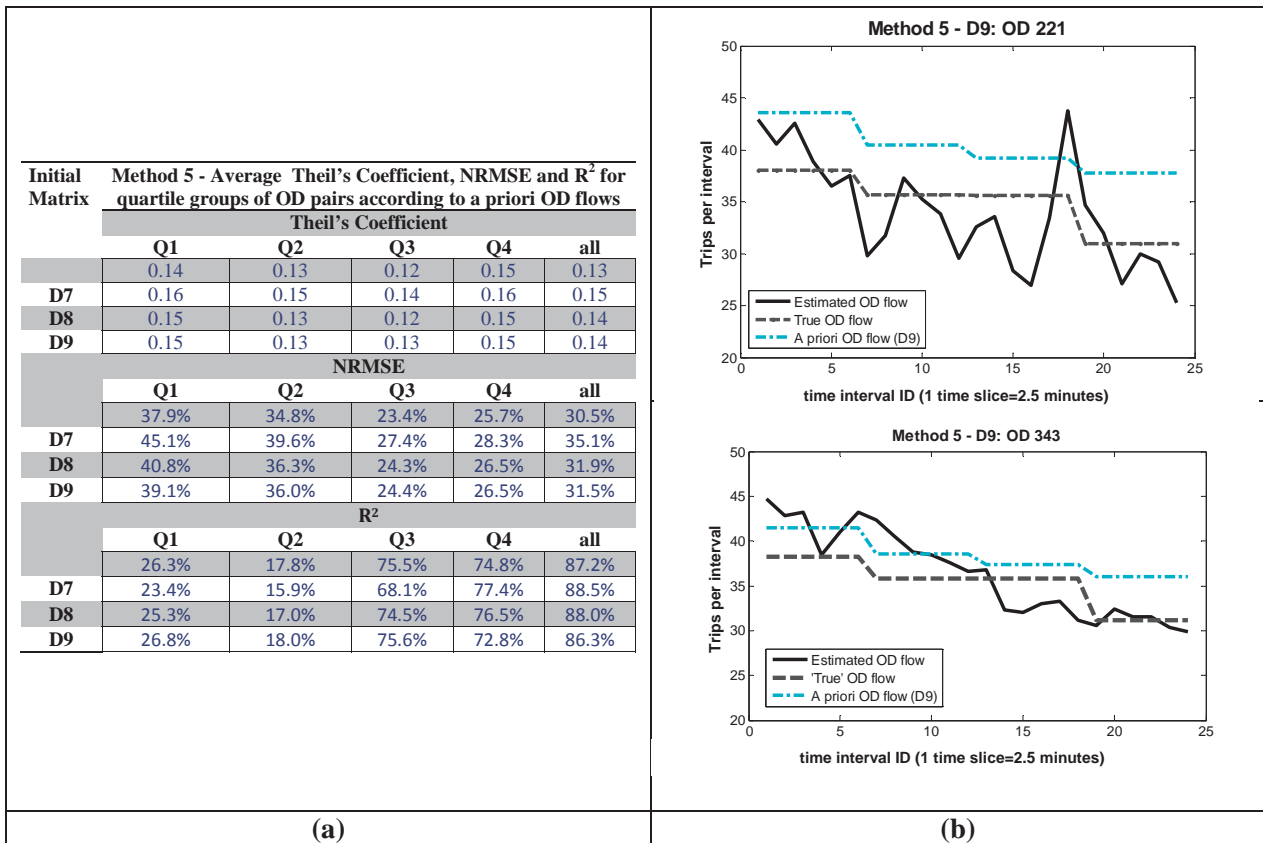
(c) OD flow evolution for Methods 3 and 4, demand scenario D9



(d) true vs. estimated OD flows for Method 2-OD and Method 3, demand scenario D9

Figure 7 - Results for Method 2-OD and Method 3

Method 5 is a Kalman filtering method suitable for on-line applications. Results for Method 5, assuming a 100% penetration of Bluetooth equipped vehicles and prior OD scenarios D7, D8 and D9, are presented in Figure 8a for selected GOF measures: Normalized Root Mean Squared Error, Theil's U coefficient and  $R^2$ . Good performance of Method 5 is reflected in high  $R^2$  fit (above 85%) that is obtained for the overall OD pairs and demand levels, but mostly for the most important OD flows (i.e. those in the 4<sup>th</sup> and 3<sup>rd</sup> quantiles). The fit of true versus estimated OD flows for all considered OD pairs (for the aggregated 1 hour period) for a scenario initialized with prior demand levels D7, D8 and D9 show coefficients of determination of the simple regression line of almost 90%, i.e. lower than the value achieved by Method 4, but the computational burden decreases from hours in Method 4 to minutes in Method 5. Figure 8b presents the evolution of estimated OD flows per departure time interval for the prior high OD demand scenario D9, demonstrating also how Method 5 is able to recover from an initial point characterized by overestimated prior OD flow with respect to the true OD flow.



**Figure 8 - Method 5 results: (a) performance indicators, (b) filtered values throughout 1h for prior OD scenario D9 (horizontal axis shows time intervals IDs, with a duration of 2.5 minutes each)**

Overall, results presented in this section show that the potential of information from advanced traffic measurements to improve OD demand estimation can be fully exploited only using OD estimation methods capable to correct for biases in spatial and temporal OD pattern given by a prior OD matrix, especially in congested networks. In this respect, the computational experiments presented in this paper prove the robustness and quality of the OD estimates exploiting AVI measurements. The computational performance of the SPSA CG-TR proposal (Method 4) solved without prior OD information and using gradients and a trust region has been substantially increased by significantly reducing the number of function evaluations and the number of iterations, converging faster in this way to better demand estimates. This OD estimation method provides an effective tool for off-line pre-processing of prior OD data producing an initial OD matrix suitable for on-line applications of methods based on, for example, Kalman filtering (Method 5). According to the published research with Method 5 using Vitoria and Eixample networks, the performance of the method in terms of goodness of fit is highly dependent on the quality of the a priori OD matrix (Barceló et al., 2013).

## 7. Conclusion

The problem of OD flow estimation/updating is one of the main problems in modern traffic management systems and Intelligent Transportation Systems deployments and it receives a large amount of attention from researchers and practitioners alike. Demand is very volatile, in the sense that

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4 it can be influenced by a number of factors, both intentional and unintentional, such as weather  
5 conditions, special events and public announcements. On the other hand, demand is in general  
6 unobservable, considering current technology. Therefore, it is rarely possible to know the “true”  
7 demand, and therefore it is difficult to know how well each approach performs in reality.  
8

9 The nature of the OD estimation problem makes it a problem that is particularly difficult to solve.  
10 In particular, OD estimation tends to deal with a large number of unknowns (thousands or even tens or  
11 hundreds of thousands) and a limited number of observations (from a few hundreds of point  
12 measurements to several hundred or a few thousands point-to-point observations, using modern data  
13 collection techniques). These properties make it particularly difficult to benchmark and compare  
14 algorithms, as the underlying conditions are often very different.  
15

16 In this paper, we motivate and present a flexible and software-agnostic platform for the  
17 implementation, validation and comparison of different OD flow estimation/updating algorithms. The  
18 structure of the platform is first presented in a general way, and then a specific implementation is  
19 described, as a blueprint for other implementations. This platform is general and can be used with any  
20 type of algorithm and traffic simulation software; furthermore, it is freely available to other researchers.  
21 A long list of algorithms are currently implemented and are being tested with this platform in a  
22 systematic and objective way, and in this paper we report on the results from some of these. We foresee  
23 (and hope) that more researchers will join the authors of this paper in contributing algorithms and  
24 results.  
25

26 In particular, the presented results demonstrate that the developed framework is capable of  
27 supporting the development, application and testing of a wide range of algorithms. First, both off-  
28 line/planning level algorithms (like the Bilevel-DUE) and on-line algorithms (like that SPSA AD-PI  
29 and the LSQR) are presented. Furthermore, the modular and open design of the framework allows its  
30 extension so that it can accommodate other characteristics of the data and the algorithms considered by  
31 the researchers. In particular, an extension of the framework is presented, which allows the  
32 consideration of additional sources of data (in this case, data from Bluetooth sensors).  
33

34 This research does not intend to claim or demonstrate the superiority of any algorithm or type of  
35 traffic data over the others, but was intended to show the potential of different algorithms and types of  
36 traffic data for dynamic OD estimation. The use of advanced traffic data to model dynamic OD demand  
37 is relatively new, and the literature still shows a lack of empirical experiments to validate their use for  
38 dynamic OD estimation. The benchmark study presented here indicates that advanced traffic data  
39 require more research efforts and new techniques to turn them into usable information.  
40

41 Like many other aspects of research, dynamic OD estimation keeps evolving, taking advantage of  
42 occurring technological and methodological advances. In this context, it is now becoming likely that  
43 demand estimation will be at some point possibly supported by big data (e.g. from social networks or  
44 cell-phone traces). Furthermore, several existing traffic simulator models are using different demand  
45 representations, e.g. explicitly describing the mobility patterns of the travellers (Balmer et al., 2008;  
46 Flötteröd et al., 2011) or taking directly input from activity based or urban simulation models, such as  
47 the coupling presented in Nicolai et al. (2011). The presented platform is extensible and can  
48 accommodate all these developments –with some straightforward extension, which has been already  
49 demonstrated in this research– thus providing a common facility for the demonstration of the  
50 incremental benefits of moving to the new paradigms.  
51

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54 MULTITUDE – Methods and tools for supporting the Use caLibration and validaTIon of Traffic  
55 simUlation moDEls ([www.multitude-project.eu](http://www.multitude-project.eu)).  
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7

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9 ([www.aimsun.com](http://www.aimsun.com)). The MATLAB function and all the requirements to replicate the OD estimation  
10 algorithms benchmarking exercise are freely available from the authors of the present paper.  
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## 9 **Appendix. Implementation of the benchmarking platform in an integrated Matlab+Aimsun** 10 **environment**

11  
12 This appendix provides details of the benchmarking platform described in Section 5, whose two main  
13 elements are:  
14

- 15 • *traffic simulator*: the mesoscopic version of the Aimsun simulation model (TSS, 2013) was  
16 used as the common traffic model. The mesoscopic model was used because it is substantially  
17 faster than the microscopic one. Thus, it allows for more elaborate testing and a richer  
18 experimental design. A default set of parameters was used in all cases;
- 19 • *OD estimation algorithm codes*: MATLAB was used to code all algorithms. This approach  
20 allowed the development of common functions to write inputs for the simulation, execute it and  
21 read simulation outputs, thus reducing the differences in run times that stem from the efficiency  
22 of these functions and lowering the workload for using the framework.  
23  
24  
25

26 A dynamic communication between the MATLAB and Aimsun software was necessary in order to  
27 execute a traffic simulation run within the OD estimation algorithm. To this aim a MATLAB function  
28 was created allowing the following logical steps:  
29

- 30 • it receives as input a traffic demand matrix generated by the estimation algorithm;
- 31 • it calls Aimsun for a new traffic simulation run with the new traffic demand and waits until the  
32 simulation ends. The actual communication of the instructions for the Aimsun call is done  
33 through Python;
- 34 • it imports the result of the simulation run as matrices in the MATLAB environment.  
35  
36

37 The MATLAB function that forms the engine for Aimsun execution and communication within the  
38 OD estimation algorithms uses the following inputs:  
39

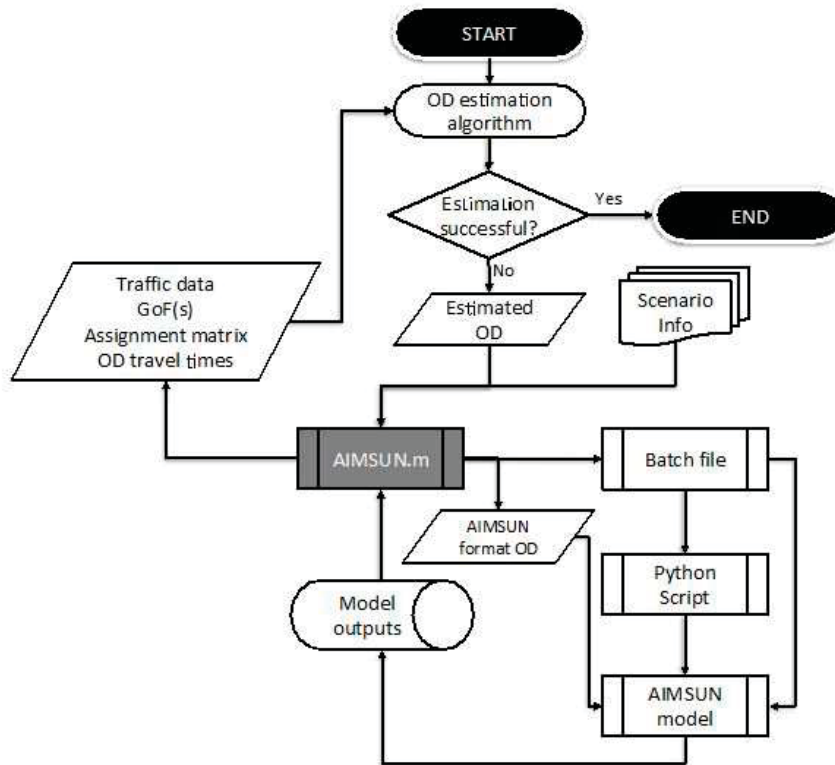
- 40 • the demand pattern to be simulated in the form of OD flows per time interval;
- 41 • the time series of traffic data to be compared with the outputs of the new traffic simulation. The  
42 user may choose the types of traffic data among counts, speeds, densities and occupancies at  
43 detectors, and the intervals to be considered;
- 44 • a subset of the OD pairs for which the average travel times are requested;
- 45 • the number of replications to carry out with the specific input.  
46  
47  
48

49 The Aimsun scenario is then simulated by creating and executing a batch file, which launches the  
50 Aimsun executable and the python script with the relevant information. When the simulation is  
51 finished, the MATLAB function collects and organizes all the outputs, and produces several relevant  
52 outputs:  
53

- 54 • an array of 12 measures of goodness-of-fit (GoF) resulting from the comparison between  
55 reference and simulated traffic data;
- 56 • a matrix with the time-dependent set of simulated traffic data;
- 57 • a matrix with the dynamic assignment matrix resulting from the simulation;
- 58 • a matrix with the average travel times between the OD pairs defined in input.  
59  
60

61 Figure 7 presents a flowchart that shows the main elements of this platform, i.e. representing a  
62  
63  
64  
65

practical instance of the general flowchart depicted in Figure 3.



**Figure 7 - Flowchart with the main elements of the AIMSUN.m MATLAB function**

Within the OD estimation main function, whenever a simulation run is needed the Aimsun call function (AIMSUN.m) is initiated. This function converts the demand to be simulated to the Aimsun format, creates the batch file to execute the requested simulations, generates the Python file with the Aimsun run flags and finally calls and executes Aimsun with these inputs. After the simulation runs have been completed, it imports the observed traffic data and the simulation outputs and calculates the GOF measures that were defined within the algorithm, assignment matrices and travel times.

The AIMSUN.m function has been developed to be compatible with AIMSUN 7 and to operate under Microsoft Windows (32 and 64 bit) and Mac OSs. The function has been developed in the framework of the MULTITUDE Project ([www.multitude-project.eu](http://www.multitude-project.eu)) and is freely available from the authors of the present paper.