Simulation of traffic conditions requires accurate knowledge of travel demand. In a dynamic context, this entails estimating time-dependent demand matrices, which are a discretised representation of the dynamic origin-destination (OD) flows. This problem, referred to as Dynamic Demand Estimation (DDE) in literature, seeks for the best possible approximation of OD flows which minimises the error between simulated and available traffic data [1], [2]. Traditional DDE models solve two optimization problems, according to a bi-level formulation: in the upper level, time-dependent OD flows are corrected in order to replicate the observations, while in the lower level a dynamic traffic assignment problem is used to ensure equilibrium principles.

Since DDE problem is usually underdetermined because of the high number of unknown variables [3], many researchers have dealt with the critical issue of decreasing the number of decision variables. The advantage is twofold: first, the objective function becomes smoother [4] and, second, the computational time is usually proportional to the number of OD pairs [5]. Additionally issues have been addressed, among the others, to the nonlinear relation between link and demand flows [6] and congestion phenomena [7], pointing out how having a reliable a-priori knowledge of the demand (*a-priori seed matrix)* is of paramount relevance in order to achieve good results[8].

From an analytical point of view, since researchers refer to OD estimation as the "*inverse assignment problem*"(*Cascetta, 2009*) [9], we might expect that the progress in DDE models and dynamic traffic assignment models (DTA) follows parallel tracks. On one hand, the most established DTA models take as input macroscopic dynamic OD matrices, which are fully compatibles with the standard DDE formulation, which is focused on providing realistic congestion patterns[10]. However, in the last decades many researchers developed utility-based DTA models, which consider both the utility of performing an activity and the disutility of travelling. Microscopic agent-based DTA focus on generating comprehensive activity patterns [11], while flow based models stress the correlation between morning and evening commute, hence their effect on congestion [12]. In this case, DDE research is poor, and only few works are available for estimating comprehensive demand patterns constraint to reproducing realistic traffic conditions [13]. The IDEAS (Improving Demand Estimation with Activity Scheduling) exploits the new opportunities related to pairing utility-based DTA and DDE models, filling this gap. The proposed formulation addresses, at least, the following shortcomings:

1) Reducing the number of decision variables and generating a smoother problem by exploiting the relation between utility and dynamic user equilibrium (DUE).
2) Generating activity-based Demand matrices, compatibles with macroscopic simulation based DTA.
3) Reducing the localism of the general DDE formulation.

Methodology:

The main difference with respect to the standard formulation is in the lower level. We assume that the DTA model performs the equilibrium through the utility maximization theory. For each considered activity, users are assumed, in this study, to maximize their utility as following[12]:

$$U(t,r) = U_A(t) + U_T(t,r) \qquad (1$$

Where $U(t,r)$ is the total utility of the traveller with actual arrival time *t* and route *r*, which is the sum of the utility of performing an activity U_A and the (dis-)utility of travelling U_T. Many simulation based DTA assume an exogenous departure time, hence the equilibrium is based only on travel time and route choice. This can be considered as a special case in which the first term is equal to zero, and the only decision variable is the route choice. In this model, we propose to include a scheduling based formulation to calculate $U_T(t,r)$, as the one proposed by Small [14]. In essence, the disutility of travelling is expressed as function of the difference between actual arrival time *t* and preferred arrival time τ, meaning that equation 1 estimates *t* for a specific vale of τ. Intuitively, we might consider τ the average value of *t* for a given OD pair. Figure 1 shows the modelling framework for the proposed model, where the dark grey area represents the utility-based extension:

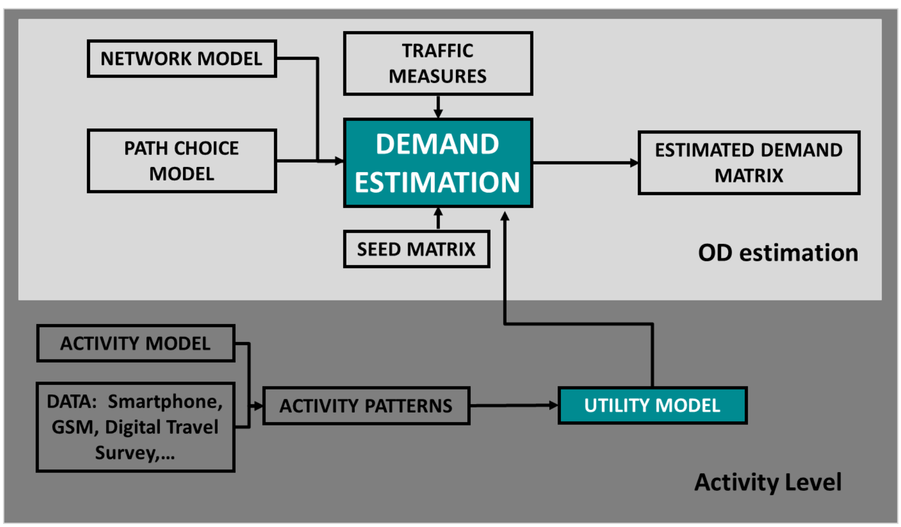

Figure 1; Relationship between utility model and dynamic demand estimation

We can now formulate our model as showed in equation 2:

$$(\mathbf{x_1}(\boldsymbol{\tau},\boldsymbol{N}) \dots \mathbf{x}_{\boldsymbol{k}}(\boldsymbol{\tau},\boldsymbol{N})) = \underset{\boldsymbol{\tau},\boldsymbol{N}}{\operatorname{argmin}}\left[z_1(\mathbf{d_1} \dots \mathbf{d}_{\boldsymbol{k}}, \mathbf{x_1}(\boldsymbol{\tau},\boldsymbol{N}) \dots \mathbf{x}_{\boldsymbol{k}}(\boldsymbol{\tau},\boldsymbol{N})) + z_2\left(\boldsymbol{f}_{\mathbf{1}}^{s} \dots \boldsymbol{f}_{\boldsymbol{k}}^{s}, \hat{\boldsymbol{f}}_1 \dots \hat{\boldsymbol{f}}_k\right)\right] \qquad (2a$$

Subject to

$$(\boldsymbol{f}_{\mathbf{1}}^{s} \dots \boldsymbol{f}_{\boldsymbol{k}}^{s}) = \max_{\boldsymbol{t}} U\left(\boldsymbol{t}(\boldsymbol{\tau},\boldsymbol{N})\right) \qquad (2b$$

Where

- **d**/**x** are the starting/estimated demand values;
- $\boldsymbol{f}^s/\hat{\boldsymbol{f}}$ are the simulated/observed link flows;
- *z* is the estimator, which measures the error between the current and target values;

- *k* is the simulation time period;
- **N** are the demand values for each OD pair;
- $\boldsymbol{\tau}$ are the preferred arrival times;
- $\boldsymbol{t}$ are actual arrival times for each OD pair.

In equation 2a, only link flows have been considered. However, many authors show that additional data can lead to a consistent improvement of DDE performances. Since this approach is an extension of the standard model (Fig.1), the same gain is available when more information is considered in equation 2a.

The lower level estimate the time dependent departure ratio for a given value of τ and a certain number of users *N*. Then, in the upper level, we check if this is consistent with the observed traffic flows. This formulation automatically decreases the number of decision variables, which is equal to the number of parameters times OD pairs, rather than simulation time periods times OD pairs. Second, if we assume different values of τ and *N* for different activities, an activity-based demand matrix is estimated. Lastly, each parameters directly affect a large number of time-dependent OD flows, meaning that the localism strongly decreases.

Proof of concept

To briefly explain this extension, let us consider the network in Figure 2. It has two origins and one common destination. The time-dependent travel time on link {O_1,a} is two times the travel time on link {O_2,a}. We adopt the link transmission model for the dynamic network loading procedure [15], and both congested/uncongested conditions are simulated. A gradient-based approach is used to estimate the demand and U_a is considered equal to zero.

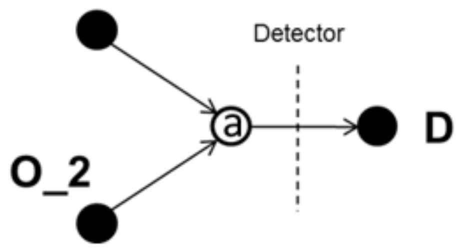

Figure 2 ; Network

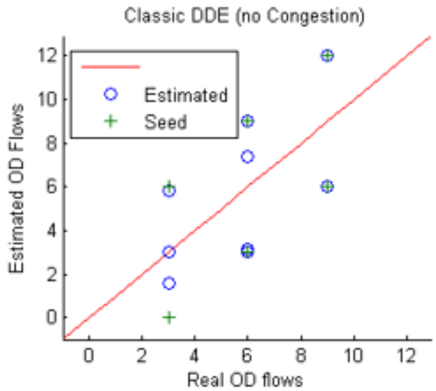

Figure 2a: Scatter plot estimated/real OD values according to the standard formulation for the uncongested case

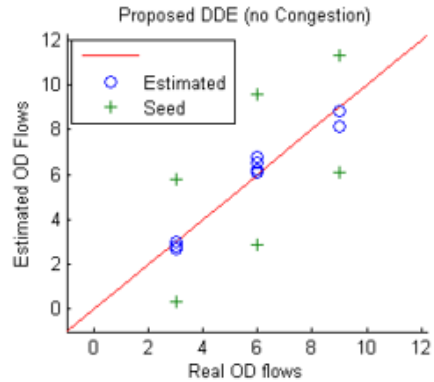

Figure 2b: Scatter plot estimated/real OD values according to the proposed formulation for the uncongested case

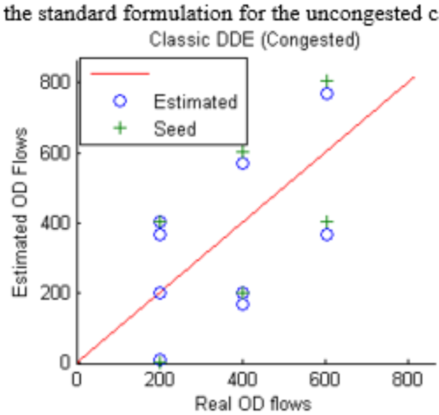

Figure 2c: Scatter plot estimated/real OD values according to the standard formulation for the congested case

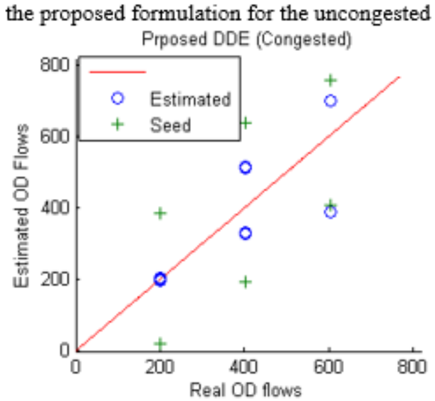

Figure 2d: Scatter plot estimated/real OD values according to the proposed formulation for the congested case

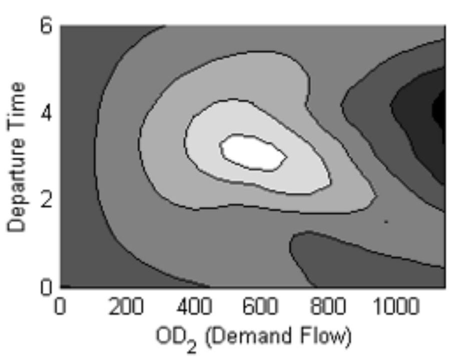

Figure 2e; Proposed Model: Solution Space for the congested case

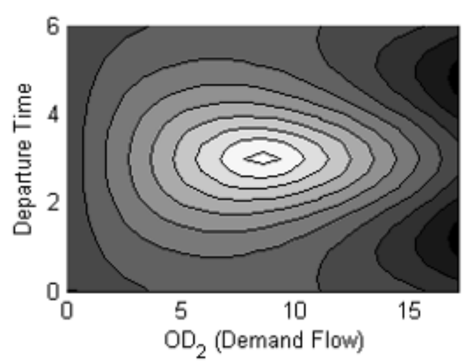

Figure 2f; Solution Space for the uncongested case

Table 1	Initial OD matrix	Standard DDE (Uncongested)	Standard DDE (Congested)	Proposed DDE (Uncongested)	Proposed DDE (Congested)
Error OD Flows	55%	44%	47%	6.5%	19%
RMSE Link Flows		0.0021	0.00019	0.25	74.59

The proposed formulation generates an extremely accurate estimation with respect to the standard bi-level approach (Table1 – Figures 2a-d). The reason is that, in this case, the solution space is smoother, as shown in figures (2e-2f) where, while keeping O_1 constant, we perform a full exploration of the solution space for O_2. The brighter area represents the optimal region. A similar visual exploration for the standard DDE is unfeasible as the number of decisional variables characterizing the traditional problem is too large.

The goal of IDEAS is to reproduce similar analysis for complex networks, identifying aggregate activity patterns on urban networks. This not only allows to have a more reliable calibration of the DTA model, but also to have a more realistic demand model, in which the engineer is able to observe the difference between estimated activity patterns the excepted ones.

Bibliography:

[1] E. Cascetta, “Estimation of trip matrices from traffic counts and survey data: A generalized least squares estimator,” *Transp. Res. Part B Methodol.*, vol. 18, no. 4–5, pp. 289–299, Aug. 1984.

[2] E. Cascetta, D. Inaudi, and G. Marquis, “Dynamic Estimators of Origin-Destination Matrices Using Traffic Counts,” *Transp. Sci.*, vol. 27, no. 4, pp. 363–373, Nov. 1993.

[3] V. Marzano, A. Papola, and F. Simonelli, “Limits and perspectives of effective O-D matrix correction using traffic counts,” *Transp. Res. Part C Emerg. Technol.*, vol. 17, no. 2, pp. 120–132, 2009.

[4] T. Djukic, G. Flötteröd, H. Van Lint, and S. Hoogendoorn, “Efficient real time OD matrix estimation based on Principal Component Analysis,” in *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, 2012, pp. 115–121.

[5] E. Cipriani, M. Florian, M. Mahut, and M. Nigro, “A gradient approximation approach for adjusting temporal origin-destination matrices,” *Transp. Res. Part C Emerg. Technol.*, vol. 19, no. 2, pp. 270–282, 2011.

[6] X. Zhou, C.-C. Lu, and K. Zhang, “Dynamic origin–destination demand flow estimation under congested traffic conditions,” in *Proceedings of the 91st Transportation Research Board Annual Meeting, Washington, DC*, 2012.

[7] R. Frederix, F. Viti, and C. M. J. Tampère, “Dynamic origin–destination estimation in congested networks: theoretical findings and implications in practice,” *Transp. Transp. Sci.*, vol. 9, no. 6, pp. 494–513, Jul. 2013.

[8] E. Cipriani, M. Nigro, G. Fusco, and C. Colombaroni, “Effectiveness of link and path information on simultaneous adjustment of dynamic O-D demand matrix,” *Eur. Transp. Res. Rev.*, vol. 6, no. 2, pp. 139–148, Sep. 2013.

[9] E. Cascetta, *Transportation Systems Analysis*, vol. 29. Boston, MA: Springer US, 2009.
[10] R. Frederix, F. Viti, R. Corthout, and C. M. J. Tampère, “New gradient approximation method for dynamic origin-destination matrix estimation on congested networks,” *Transp. Res. Rec.*, no. 2263, pp. 19–25, 2011.
[11] M. Balmer, K. Meister, M. Rieser, K. Nagel, and K. W. Axhausen, *Agent-based simulation of travel demand: Structure and computational performance of MATSim-T*. ETH, Eidgenössische Technische Hochschule Zürich, IVT Institut für Verkehrsplanung und Transportsysteme, 2008.
[12] Z.-C. Li, W. H. K. Lam, and S. C. Wong, “Bottleneck model revisited: An activity-based perspective,” *Transp. Res. Part B Methodol.*, vol. 68, pp. 262–287, Oct. 2014.
[13] G. Flötteröd, “Cadyts - a free calibration tool for dynamic traffic simulations,” presented at the 9th Swiss Transport Research Conference, 2009.
[14] K. A. Small, “The Scheduling of Consumer Activities: Work Trips,” *Am. Econ. Rev.*, vol. 72, no. 3, pp. 467–479, Jun. 1982.
[15] I. Yperman, “The link transmission model for dynamic network loading,” *Status Publ.*, 2007.