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HOW IMPORTANT IS CAPTURING CONGESTION DYNAMICS IN DYNAMIC OD ESTIMATION?

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ABSTRACT

In this paper we highlight some conditions for handling congestion in dynamic origin-destination estimation. A great impact is given by the quality of the network loading model. It is shown that a too coarse queuing model may lead to confusion between demand and supply information. This is because flow measurements can correspond to two regimes, free flow and congestion. When the initial OD matrix suggests a different traffic regime at the detectors compared to reality, the measurements can also be interpreted incorrectly. The result is that flow-based dynamic OD estimation may result into wrong estimates of the real traffic states.

KEYWORDS

Dynamic OD estimation, congestion, Dynamic Network Loading

INTRODUCTION

Traditional OD estimation methods use traffic counts, since they are the most common data measures available in practice. However, these counts contain aggregate information about multiple OD flows, i.e. there can be many combinations of these flow fractions that result in the same link flow values and the set of possible solutions usually grows with the size of the network, and the travel alternatives available for each OD pair, while it usually reduces by increasing the number of detectors. A way to solve this issue is to add extra information to the counts, traditionally in the form of a prior estimate of the OD matrix, or by including route information, for instance through route choice models or travel times, or using route information sources (e.g., floating car data, automatic vehicle identification systems).

However, the underdeterminedness issue due to multiple OD flows is not the only factor causing a deviation between the estimated and real OD matrix in congested networks and for a within-day dynamic context. Due to congestion phenomena, traffic counts can be interpreted wrongly, as the same number of vehicles can be observed under light conditions of traffic (low density and high speeds), and during heavy traffic (high density and low speeds). The

scope of this study is to show, through some clarifying example, how identifying and modeling accurately congestion dynamics is necessary for the reliability of the OD estimation.

THE WITHIN-DAY DYNAMIC OD ESTIMATION PROBLEM

Key issue in the estimation of an OD matrix is the identification of the origin-destination pairs whose flow portions use a particular link in which traffic is monitored. The common ground is the relationship between any origin-destination flow distributed on each (used) route alternative and each link flow in the network. Mathematically speaking, OD estimators can be formulated in a general way as follows:

$$\mathbf{x} = \arg \min_x \left[\sum_j f_1(x_j, \hat{x}_j) + \sum_i f_2(y_i, \hat{y}_i) \right] \quad (1)$$

where f_1 and f_2 are distance with f_1 measuring the similarity between the estimated OD matrix elements x and the elements \hat{x} of the a priori matrix, and f_2 measuring the similarity between the estimated and observed link counts, respectively y and \hat{y} . By definition, the vector of link flows U_a satisfies the relationship:

$$y_i = \sum_{j \in J_i} A x_j = \sum_{j \in J_i} B(x) P(x) x_j \quad (2)$$

where A is the assignment matrix, which controls the fraction of flows from any OD pair j which uses link i . This matrix can be further subdivided into a crossing fraction matrix B and a route fraction matrix P (see also Cascetta, 2001). The elements of this crossing fraction matrix express the proportion of a route flow that passes a link in time, thus describing the spatio-temporal propagation of the route flows throughout the network. The elements of route fraction matrix P express the proportion an OD flow choosing a certain route in time. Both are calculated by the lower level, in which a dynamic OD matrix estimated in the upper level is assigned using a traffic loading model taking the route proportions from the output of an assignment model. The output of the traffic model, in terms of link flows, is then used to derive a relationship between the measurements and the OD flows. This relationship is used again in the minimization problem (1) to obtain a new estimate of the OD matrix. This process repeats until convergence is reached and the two levels are mutually consistent.

It is normal procedure in practice to consider the route and crossing fraction matrices as fixed when calculating the derivatives in the upper level (1). However, to incorporate in this level the dynamic effects of congestion, also these elements should be derivate. This error has already been addressed in past studies. Yang (1995) deals with static OD estimation, thus the crossing fraction matrix simplifies to the link-incidence matrix, which is not sensitive to the OD flows, while Lindveld (2003) decides not to use the last two terms because of computational complexity. Tavana (2001) does not find a substantial improvement compared to the standard linear relationship, but the chosen case study considers a non-congested network. In the following section we show how this simplification may affect the OD estimation results dramatically. In this study we focus exclusively on the impact of the crossing fraction, leaving to further analysis the contribution of the route choice matrix.

The effect of congestion in the OD estimation procedure

DNL models used in OD estimation are generally classified into two main categories. The first group consists of analytical models, which describe the average behavior of traffic with macroscopic variables such as inflow rates and travel times. However, traditional analytical approaches fail in capturing the spatio-temporal effects of congestion in a network. This has motivated the development of traffic flow propagation and simulation models which have the

advantage of capturing the effects of congestion more realistically. We show this using the toy networks in Figure 1a and 1b, and by comparing the simple point-queue (PQ), spatial queue (SQ) and the Link Transmission Model (LTM, Yperman, 2006), which is a macroscopic model consistent with Kinematic Wave Theory. To show how the solution can differ if a more simplified queuing model is adopted we use LTM as reference model, i.e. we generate “virtual” loop detector data (identified by the circles in the figures) using a simple variable demand (Figures 1c and 1d). In the first network link 4 is a bottleneck, having half of the capacity of the other links. In the second case two flows converge to a section that cannot serve the peak hour traffic simulated. The estimation problem is solved using the SPSA algorithm, an optimization method that is used often for OD estimation (e.g. Balakrishna and Koutsopoulos, 2008). Details on these examples can be found in Frederix et al. (2010a).

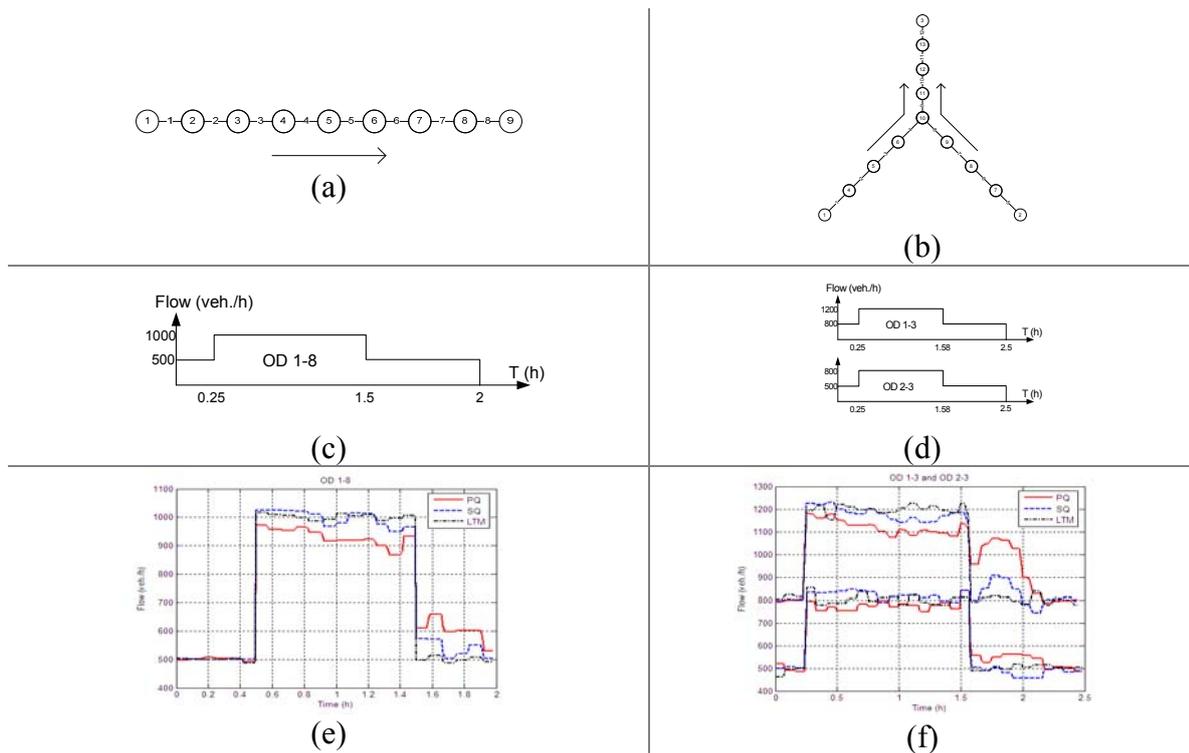


Figure 1: Toy networks adopted in this study (a,b), input demand (c,d) and estimation results using PQ, SQ and LTM models

The small deviations that can be seen in Figure 1e and 1f are the result of the stochastic nature of the SPSA algorithm. These examples indicate that the PQ and SQ models tend to confuse supply information with demand information: if in reality spillback occurs over a detector, the SQ and PQ models interpret this as a decrease of the OD flow that passes over that detector, or as a decrease of an OD flow of which no information is available. Secondly the demand information is sometimes misidentified: if a queue builds up on one link because of a merging with flow from another link, and this queue passes a detector, there may be information available about this other flow in the measurements. In conclusion, in congested networks, applying a traffic model with proper congestion spillback representation is a necessary condition for accurate OD estimation.

However, even with the adoption of a more refined traffic model the result of OD estimation can still be wrong if traffic states are not identified correctly. We use again the example of Figure 1b and reprinted in Figure 2a. This time we start with a uniform initial matrix for the demand, as shown in Figure 2b. In this example demand and capacity are such that the queue

is observed only for one flow stream, spilling back on detectors 4, 5 and 6. Also in this case the OD estimation procedure confuses demand with supply information, and the resulting OD flow patterns are wrong for all three traffic models (Figure 2c). The reason for this mistake can be assigned to the ambiguity of traffic flows as input for the estimation. In fact, the same number of vehicles can be observed under free flow (low density and high speeds), and during congestion (high density and low speeds). If this regime is not identified the procedure will not identify the correct regime and will get stuck in a local optimum.

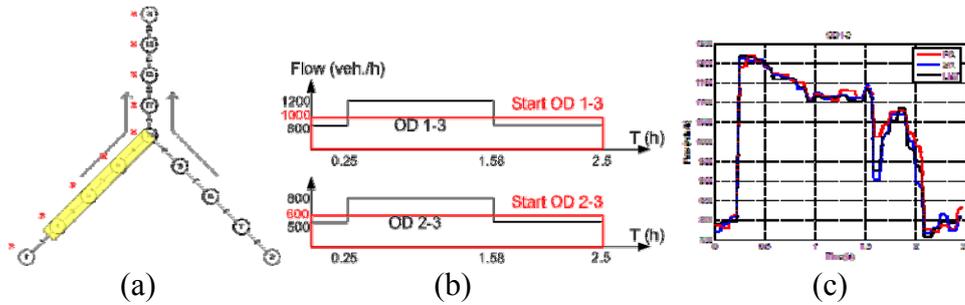


Figure 2: The example of merging flows calculated with a uniform initial OD matrix

Figure 3a shows the speed contour-plot of real data from a highway around the city of Antwerp, Belgium. If no extra information is provided, for instance through mean speeds or densities, the OD estimation procedure will provide a solution that will not reproduce the real dynamics (Figure 3b). Figure 3c shows how results correspond better to reality if density data is used in the calibration procedure. More details can be found in Frederix et al. (2010b).

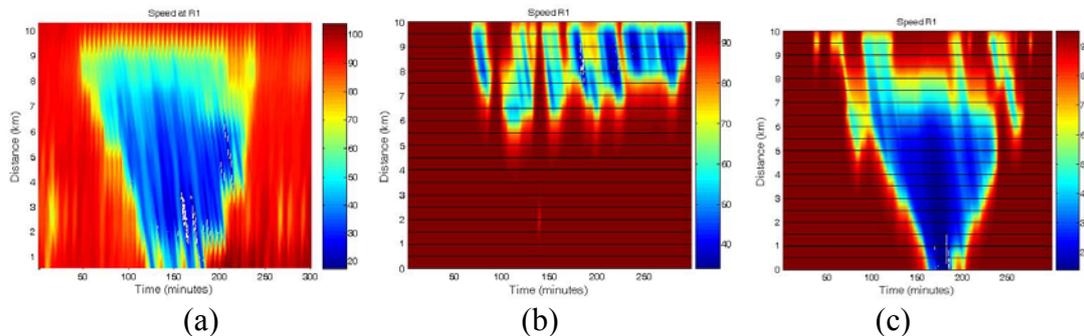


Figure 3: Real speed data (a) and OD estimation using only flows (b) and using both flow and density data to identify the correct regime (c)

Figure 3b shows that congestion regions characterized by low flows are interpreted as free-flow periods. By providing instead speed information, the solution highly improves and it reproduces the congested regions more reliably (Figure 3c).

CONCLUSIONS

In this study we had shed some light on a number of reasons that can cause a deviation between estimated and real traffic conditions due to information misinterpretation in the dynamic OD estimation. Focusing on the spatio-temporal effects of congestion we showed that the adoption of a too coarse traffic model and the use of solely traffic flow data may not be sufficient conditions to obtain the correct OD patterns. In future (and parallel) papers we suggest ways to improve these issues.

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