Estimation of O-D Demand for Dynamic Assignment with Simultaneous Route and Departure Time Choice

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Abstract - As congestion not only results in the dispersion of O-D demand over multiple routes, but also in peak-spreading, use of dynamic traffic assignment (DTA) models as a means to predict the impact of new infrastructure should take account of departure time choice in addition to route choice. Departure time choice may be modelled simultaneously with the choice of routes in a utility maximisation framework. In such a model, each traveller has a preferred departure- and arrival time, deviation from which results in a certain disutility. Departure-time choice can be viewed as route-choice in a suitably defined hypernetwork. The combination of departure time choice and route choice in a single framework is called the Dynamic User Optimum Departure time and Route choice (DUO-D&R) assignment. Where the DUO assignment needs a dynamic Origin-Destination (O-D) matrix with fixed departure times, the DUO-D&R assignment needs a dynamic O/D matrix with preferred departure times under uncongested conditions. We will call this matrix the uncongested O-D matrix (uOD). This paper proposes a method to estimate the uncongested Origin-Destination (uOD) demand matrix that reflects preferred rather than realised departure times. In order to carry out this estimation, the Dynamic User-Optimal Departure time and Route choice (DUO-D&R) problem are formulated and solved. The schedule delay function and the departure choice model are assumed to be known. The possible advantage of the DUO-D&R assignment over DUO assignment is demonstrated through numerical experiments that correspond to scenarios in which infrastructure is expanded and travel demand is subject to uniform growth.
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INTRODUCTION

It is well known that increased congestion levels not only lead to increased dispersion of O-D-demand over multiple routes, but also to shifts in departure time. On an aggregate level this leads to the widely observed peak-spreading phenomenon. Departure time choice may be modelled simultaneously with route choice, using a utility maximisation framework. In such an approach, each traveller has a preferred departure- and arrival time. A traveller may deviate from these times at the cost of a certain disutility. This type of assignment is called the Dynamic User Optimum Departure time and Route choice (DUO-D&R) assignment.

Where the DUO assignment needs a dynamic Origin-Destination (O-D) matrix with fixed departure times, the DUO-D&R assignment needs a dynamic O/D matrix with preferred departure times under uncongested conditions, and a function that specifies the so-called schedule delay costs. The schedule delay cost measures the disutility of a traveller who departs or arrives at a time other than the preferred arrival or departure time. We will focus on departure time schedule delay, and we will call the matrix of the demand stratified by preferred departure time period the uncongested O-D matrix (uOD).

As opposed to research that is concerned with estimating time dependent O-D demand for networks (see e.g. Willumsen (1984), Bell et al. 1996) or freeway corridors (see e.g. Cremer and Keller (1981), Van der Zijpp and Hamerslag (1994)), this paper is concerned with the estimation of the uncongested Origin-Destination (uOD) demand. The uOD demand reflects the preferred rather then realised departure times. In order to carry out this estimation, the Dynamic User-Optimal Departure time and Route choice (DUO-D&R) problem is formulated and solved. The schedule delay function and the departure-time choice model are assumed to be known.

Our hypothesis is that dynamic traffic assignment based on the use of the uOD matrix provides a better basis for predicting how traffic flows will respond to changes in the level of service. This hypothesis will be tested by two numerical experiments. A DUO-D&R is calculated on a known uOD matrix, and the resulting flows are stored. Next, travel demand is estimated in two ways: First a dynamic uOD matrix is estimated such that it will reproduce the flows if it is assigned using the DUO-D&R assignment. Second a dynamic O-D matrix is estimated such that it will reproduce the flows if it is assigned using a DUO assignment.

In the first experiment the network is changed to reflect future changes, and the resulting flows are again calculated using the DUO-D&R assignment and stored for future reference. Two sets of estimates of these flows are then made by assigning the estimated uOD matrix with the DUO-D&R assignment module, and by assigning the estimated dynamic O-D matrix with the DUO assignment module. In the second experiment the network remains unchanged but the travel demand is uniformly increased with 20%. The final step is to compare both sets of estimated flows with the reference flows and test the hypothesis.

This paper builds on existing literature in various ways. Firstly it extends the Dynamic User Optimal assignment problem proposed in Chen (1999) and Ran and Boyce (1996) with departure time choice (see Arnott et al. (1990) for a discussion). The resulting problem is that of finding a user equilibrium on a Space Time Expanded Network (STEN), which can be solved with the Frank Wolfe algorithm, see e.g. Sheffi (1985). Subsequently the equilibrium based O-D estimation problem is formulated. This problem is in fact similar to the equilibrium based O-D estimation problem originally proposed by Nguyen (1977) and recently investigated by Yang et al. (1992, 1994). The solution
algorithm that is used is of the constrained Generalised Least Squares type, see e.g. Cascetta and Nguyen (1988) and Bell (1991).

HYPOTHESIS AND EXPERIMENTAL SETUP

The hypothesis we wish to test is that a predictive method which involves estimating and assigning uncongested O-D demand would result in more accurate forecasts of traffic flows on network variants than a method that is based on estimating and assigning true O-D demand. To test this hypothesis numerical experiments were carried out for which the experimental set-up shown in Figure 1 was used.

The experiments consist of the following steps:

- Define the network for the base situation (1). This definition includes the layout of the network, the capacity and speed-flow relationships of each link. The network definition also includes the schedule delay costs: these are the disutilities that are incurred by travellers if they do not depart during their preferred departure time interval.
• Define the true uncongested dynamic travel demand (2). This is the travel demand that results if everybody departs in his or her preferred departure time interval. The uncongested travel demand is represent by a dynamic O-D matrix $T_{ijt}$.

• Define a network variant ((3): the future state of the network). This involves modifying the base network, for example by increasing the capacity of a bottleneck.

• Compute the "true" network flows for the base situation (4a) and the future state (4b) using dynamic traffic assignment with both route choice and departure time choice (DUO-D&R). If applicable, apply a growth factor to the O-D demand for the future state.

• Estimate the uncongested O-D demand using the DUO-D&R based method. This will result in an ODT (8a) matrix that, if assigned using the DUO-D&R method, reproduces the Network flows and the static O-D matrix for the current state.

• Estimate the ODT demand using the DUO based method, resulting in an ODT matrix (8b) which, if assigned using the DUO method, reproduces the Network flows and Aggregate O-D demand for the current state.

• Assign the uncongested O-D demand to the future network, using the DUO-D&R method (9a), and assign the ODT demand to the future network, using the DUO method (9b), giving traffic flow forecasts (10a) and (10b). If applicable, apply the growth factor first.

• Evaluate the performance of the DUO-D&R and that of the DUO method by comparing the forecasts with the "true" network flows.

THE DUO-D&R ASSIGNMENT PROBLEM

In this section we will note the role of Space-Time Extended Networks (STEN's) in linking dynamic traffic assignment and dynamic matrix estimation with their static counterparts. We will also state the DUO and DUO-D&R assignment problems, and highlight their close relationship.

STEN networks

A Space-Time Extended Network (STEN) explicitly represents time by having a complete layer of all nodes of the physical network per time period. The travel time on STEN links corresponds to the time difference between the time periods of the start-and end node of the link. An example of a STEN is given in Figure 2. Shown on top is the original (two-link) network, with origin r and destination s, and one intermediate node.

The STEN is built by replicating the physical network as many times as there are time periods, and replacing each link of the resulting network (shown as dotted lines) by a STEN link (shown as sloping solid lines). Traffic entering a link's a-node arrives at its b-node at time $t + \tau$, with $t$ the time of entry, and $\tau$ the link travel time. If $t$ and $t + \tau$ are in the same time period, the link does not cross a period boundary (corresponding to a horizontal link in Figure 2); if $t$ and $t + \tau$ are not in the same period, the STEN link connects nodes that belong to different time periods (shown as sloping links in Figure 2).

To link a dynamic O/D/t matrix $T_{ijt}$ with the STEN, we can add a virtual destination, and virtual links connecting it to the STEN, as shown in Figure 2. Note the absence of links between the physical origin $r$ and the time-dependent origins $r(1), \ldots, r(4)$. This highlights the fact that the matrix $T_{ijt}$ specifies the departure times. Traffic using virtual links incurs no link costs, but on all other links, traffic incurs link costs that can be related to travel time, tolls, petrol cost, or any weighted sum of these.
Modelling departure time choice as route choice in the STEN

In Figure 2 it is assumed that the dynamic O/D/t matrix $T_{ijt}$ specifies a fixed travel demand that is not influenced by the level of service in the network. We will now distinguish between preferred departure time and realised departure time. Travellers may deviate from their preferred departure time at the cost of so called schedule delay costs.

These schedule delay costs can be accounted for by extending the STEN with artificial nodes that represent the ‘desired’ departure time, and connecting these nodes with the STEN using links that represent the schedule delay costs, see Figure 3.

We propose to use the departure time matrix $T_{ijt}^0$ that would result if all travellers would experience only free-flow travel times $\tau_{ij}$ on the entire network, and to model their actual departure times as a re-routing within the STEN from their preferred departure time to their actual departure time. In Figure 3 an extra set of virtual origin nodes ($r'(1)$, $r'(2)$, $r'(3)$, $r'(4)$) has been added to the network. These nodes correspond to preferred departure time of travellers from origin $r$. We assume that travellers select their preferred departure time through some mechanism unknown to us. Given their preferred departure time travellers will reschedule their departure to an actual departure time under the influence of e.g. congestion.

The links between $r'(t)$ and $r(t)$ denote the actual departure times given the preferred departure time. In this way a time-dependent schedule delay cost can be modelled for all traffic that enters the network from origin $r$, according to its preferred and actual departure time.
Figure 3: Augmented STEN with schedule delay costs that depend on the preferred departure time

By extending the STEN in this way, the DUO-D&R problem is reformulated as a DUO problem with respect to the augmented STEN.

Dynamic Traffic Assignment and STEN’s

In previous sections it was illustrated that an augmented STEN can be used to simultaneously model route- and departure time choice. The importance of STEN’s is that they can be used to obtain a discrete-time approximation of DTA (see [Chen (2000)]). The STEN may be thought of as a graph $G$, the structure of which is determined by the link travel times $t$.

If spillback effects are ignored, DUO-D&R assignment can be viewed as a static UO assignment on a STEN whose link travel times are consistent with the delay that is caused by the assigned flow. However, the difficulty is that the STEN itself is determined by the link travel times and therefore a change in travel times results in a different STEN, so that the STEN itself becomes one of the unknowns.

If the STEN $G$ is fixed, the link flows $q$ and link travel times $t$ are uniquely implied and can be computed by performing a UO assignment of the travel demand $T$ to this STEN using a Frank-Wolfe iterative scheme. During this computation it is important to keep track of the assignment map $A$, that describes the relation ship between the dynamic O-D demand and the link flows, because this matrix will be needed during the O-D estimation step.

The link travel times again imply the structure of the STEN. Hence $G=G(t)$. A solution of the DUO-D&R assignment problem is found if a STEN $G$ is found that is consistent with its user optimal link flows.

In search for such a solution we use the iterative procedure introduced by [Chen] consisting of an inner loop that solves a UO assignment problem and an outer loop in which the STEN is updated:

initialise
$t = \text{free flow travel time}$
$[A, t^*] = \text{UO}(G(t), T)$

while $G(t) \neq G(t^*)$
$\alpha = \min\{\alpha \mid G((1-\alpha)t + \alpha t^*) \approx G(t)\}$
$t = (1-\alpha)t + \alpha t^*$
$[A, t^*] = \text{UO}(G(t), T)$

The vector of link travel times $t$ is initialised with free flow travel times. Subsequently a UO assignment is performed on the STEN $G(t)$ implied by these free flow travel times. The relevant outputs of this UO assignment step are an auxiliary vector of link travel times ($t^*$) and the assignment
map \( A \). As long as the STEN implied by the auxiliary vector \( (Gt^*) \) differs from the STEN that was used in the latest UO assignment \( (Gt) \), the travel time vector \( t \) is changed to a convex combination of \( t \) and \( t^* \), and the UO assignment is repeated.

A novelty relative to Chen is the determination of the stepsize \( \alpha \). Instead of defining \( \alpha \) as a decreasing function of the iteration number, we choose the minimum value of \( \alpha \) that implies a change in the STEN. This is a shortcut relative to the original iterative scheme. This shortcut is intended to prevent the procedure from recomputing UO assignments for the same STEN over and over again.

**ESTIMATING THE DYNAMIC UNCONGESTED TRAVEL DEMAND MATRIX**

In the previous sections a method was described to assign travel demand to a network taking into account user optimal route and departure time choice. This process is based on a number of behavioural assumptions and knowledge of the time dependent uncongested O-D demand and outputs estimates of link flows, travel delays, and combined route-departure time proportions.

In this section we describe a method that reverses this process, hence taking observed link flows and link travel-times as its input and estimating uncongested time dependent travel demand. As an additional input a target matrix is used. Basically this problem does not deviate from the static problem of finding an O-D matrix that reproduces traffic counts when route flows are in user equilibrium, see Nguyen (1977) and Yang, et al., (1994).

The objective is to estimate a matrix \( T \) in such a way that, if assigned using the DUO-D&R method, it reproduces the observed link flows, and at the same time is as close as possible to the target matrix \( T^0 \). Hence the objective is to minimise the following function:

\[
J(T) = \sum_{ap} \left( \sum_{ijq} A_{apijq}(T)T_{ijq} - Q_{ap} \right)^2 + \lambda \sum_{ijq} \left( T_{ijq} - T_{ijq}^0 \right)^2
\]

with:

- \( T \) the unknown uncongested time dependent travel demand matrix, with elements \( T_{ijq} \) denoting the demand from origin \( i \) to destination \( j \) in period \( q \).
- \( T^0 \) the target matrix
- \( Q \) the matrix of observed flows, with elements \( Q_{ap} \) denoting the observed flows entering link \( a \) during period \( p \).
- \( A(T) \) the assignment map that results from assigning matrix \( T \), using the DUO-D&R assignment procedure. The elements \( A_{apijq} \) of \( A \) represent the proportion of travel demand \( T_{ijq} \) that contributes to the flow entering link \( a \) during period \( q \).
- \( \lambda \) weight parameter. A small value is chosen for this parameter, to make sure that the emphasis in the objective function is on reproducing the traffic counts.

Note that in this expression the assignment map depends on the unknown O-D matrix. If the assignment map is kept constant the objective function \( J \) has a unique minimum which can be found by solving a quadratic programming problem. However, the assignment map depends on the O-D demand and can only be determined by performing a DUO-D&R assignment. Hence, an iterative procedure is proposed to minimise \( J \):
Initialise

\[ n=1, \quad \hat{T}^n = T^0, \quad \beta = 1 \]

Repeat

\[
T^* = \arg \min_{T, T \geq 0} \frac{1}{2} \sum_{ijp} \left( \sum_{ap} A_{ijp}(\hat{T}^n)^{T_{ijp}} - d_{ap} \right)^2 + \beta \sum_{ijp} (T_{ijp} - T^0_{ijp})^2
\]

while \( J((1-\hat{\alpha})\hat{T}^n + \hat{\alpha}T^*) \geq J(\hat{T}^n) \)

\[
\hat{\alpha} = \frac{\hat{\alpha}}{2}
\]

\[
\hat{T}^{n+1} = (1-\hat{\alpha})\hat{T}^n + \hat{\alpha}T^*
\]

\[
\hat{\alpha} = \frac{\hat{\alpha}}{2}
\]

Until \( n = N_{\text{max}} \)

The procedure starts with the initial solution \( T^0 \). Subsequently an auxiliary solution \( T^* \) is determined by minimising the objective function while keeping the assignment map constant. The vector \( T^* - \hat{T}^n \) can be considered as a feasible descent direction of the minimisation problem (1) in the point \( T = \hat{T}^n \). The next task is to find a stepsize \( \beta \) that insures that \( J((1-\hat{\alpha})\hat{T}^n + \hat{\alpha}T^*) < J(\hat{T}^n) \). Once such a stepsize is found, a new auxiliary solution is computed.

Note that the most time consuming task in this procedure is the evaluation of the assignment map \( A \), because this requires a DUO-D&R assignment. Solving the minimisation problem (1) while keeping the assignment map fixed is relatively inexpensive. Therefore the search for a stepsize \( \beta \) is stopped at the moment that a value is found that implies a decreased objective function.

**NUMERICAL EXPERIMENTS AND RESULTS**

The hypothesis is that the impact of new infrastructure and traffic growth can be predicted in a more realistic way by assigning an uncongested dynamic O-D demand using the DUO-D&R method. Two experiments are performed to check this hypothesis and to demonstrate the DUO-D&R assignment procedure and the O-D estimation module associated with it.

Both experiments use the network shown in Figure 4. This network consists 13 nodes and 26 directed links. Nodes 9, 11 and 12 are selected as origins while nodes 4, 6 and 13 are selected as destinations. Links A and B are designated as bottleneck links, with a capacity of 2000 vehicles per hour. All other links are assumed to have infinite capacity.
The experiments follow the set-up outlined in Figure 1 and consist of evaluating a base and an future situation. Both experiments share the same base situation. For experiment 1 the future state corresponds to a scenario in which the capacity of bottleneck link A is expanded to 3000 vehicles per hour. Experiment 2 corresponds to the scenario that travel demand grows uniformly with 20%.

Time is divided in half hour slots, and the travel demand for all 9 O-D pairs for the periods 7:30-8:00, 8:00-8:30 and 8:30-9:00 is 500 vehicles and zero for all other periods. This implies that during the peak there is a demand for 9000 crossing movements over links A and B, while the joint capacity of these links is only 4000.

The travel delay on the links is approximated with the BPR function:

\[ t_u(q_u) = t^0_u \left( 1 + \alpha \left( \frac{q_u}{q^{cap}} \right)^\delta \right) \]

\( \alpha = 1, \quad \delta = 4 \)  

(2)

The schedule delay costs are derived by multiplying the difference between travellers’ preferred departure time with travellers’ realised departure time with a factor 1/3.

Figure 5 shows the results of the DUO-D&R assignment for the base situation and scenarios 1 and 2. The black bars represent the total ‘uncongested’ demand for bottleneck crossing movements for the base situation and scenario 1. The light grey bars represent the actual total flow on link A and B for the base situation. Due to insufficient capacity during the peak, travellers divert to earlier and later departure times. The white bars represent the flows for scenario 1. It is clearly visible that due to the extra capacity on link A traffic is more concentrated around the peak. Finally, the dark grey bars represent the total flow on link A and B for scenario 2. It can clearly be seen that the 20% uniform growth of travel demand leads to increased flows during all periods. But relative growth is highest during the shoulders of the peak.
Figure 5: Total flow over bottleneck links A and B.

The next step is to estimate the uncongested O-D demand using the method described in the previous section, and then assigning it again for scenario 1 and 2.

The target O-D matrix (see Figure 1) that is needed in this step was obtained as follows: The uncongested matrix that was used to generate the flows is aggregated over all periods, resulting in a static matrix. This static matrix is de-aggregated again using an average time profile that is obtained by adding up the flow on all network links. The target matrix hence incorporates the peak spreading that is present in the network flows in the base situation.

As a reference also a matrix is estimated that reproduces the observed flows if assigned using the DUO method. Note that the DUO based dynamic O-D estimation is a special case of the DUO-D&R based method: Schedule delay costs are set to infinity which disables departure time choice so that all travellers are forced to depart in their preferred period.

Figure 6 shows the estimated flows, plotted against the observed flows for both the DUO-D&R method and the DUO method. The flows estimated with the DUO-D&R method reproduce the true flows much more reliable than the flows that are estimated and assigned using the DUO method. The Root Mean Squared Error (RMSE) for the link flow estimates for the DUO-D&R method is 99 while the RMSE for the DUO method considerably higher at 216.

Figure 7 plots the estimated flows against the observed flows for the uniform growth scenario (scenario 2). In this case the flows estimated and assigned with the DUO-D&R method reproduce the observed flows very accurate. The RMSE is only 29. The results obtained with the DUO method (RMSE = 303) do not at all capture the changes in network flow that are caused by the uniform growth of demand. This is also illustrated in Figure 8. This figure shows the total flow over the bottlenecks A and B as a function of time. The flows estimated and assigned with DUO-D&R method capture the changes in departure time that occur as a result of increased demand during the peak much better then the flows that are estimated and assigned with the DUO method.
Figure 6: Estimated versus observed flows (increased capacity of bottleneck A). •: link flows estimated and assigned using the DUO-D&R method. x: link flows estimated and assigned using the DUO method.

Figure 7: Estimated versus observed flows for scenario 2 (uniform growth of travel demand). •: link flows estimated and assigned using the DUO-D&R method. x: link flows estimated and assigned using the DUO method.
DISCUSSION

This paper presents a method for Dynamic User Optimal traffic assignment taking into account Departure time and Route choice (DUO-D&R). This is done by solving a traditional User Optimal (UO) assignment problem for an augmented Space Time Expanded Network (STEN). Subsequently a dynamic O-D matrix is estimated that, if assigned using the DUO-D&R method, reproduces a given set of traffic counts. Our numerical experiments lead to a number of observations that extend to related areas of research, like Dynamic User Optimal (DUO) assignment and the equilibrium-based origin-destination matrix estimation problem.

The first observation concerns link travel time functions and related numerical convergence issues. In our experiments the BPR link travel time function has been used. This function only depends on link inflow and defines a separable cost structure. The resulting problem can be solved with relative ease. To increase realism, other cost structures may be considered, for example cost functions that do not only depend on link inflow but also on link occupancy and link inflow in earlier periods, see e.g. [Chen, 1999]. However, this will add considerably to the complexity of the problem.

Our expectation is that in the present application it would be sufficient for the Dynamic Network Loading to use the so-called bottleneck model for all its links. In a bottleneck model link impedance is constant, but link flow is constrained to the capacity of a link. The bottleneck model can be emulated by the choice of a large value for the $\beta$ parameter in the BPR function (1). The effect of this on the assignment is that link flows will only exceed capacity with very small margins, while the presence of alternative underutilized departure time-route combinations will determine the equilibrium route travel time.

The Frank-Wolfe algorithm that is used in the present approach has been found incapable of dealing with the numerical implications of the choice of large values for the parameter $\beta$. This is because in assignments where peak spreading occurs, the equilibrium solution involves heavy congestion during the peak period. If $\beta$ is large, very small changes in link flow lead to large changes in travel time. In this case the Frank-Wolfe method that has been used converges very slow. During the first few iterations the procedure detects all routes but after that it basically exchanges small quantities of flows between these. Convergence is only reached at the cost of an extremely high number of iterations.

In this case another solution procedure would probably be more effective. One approach that could be investigated in the future is to alternate iterations that scan for new paths with optimization steps that solve a nonlinear minimization problem with all the path-flows as the unknowns. This procedure requires storing all paths that are in use but is guaranteed to terminate at the moment all paths have been found.
A second observation concerns the convergence of the DUO assignment procedure outlined in this paper. This procedure consists of an inner loop and an outer loop. In the inner loop, link flows and travel times are computed by performing an UO assignment based on a STEN that is defined in the outer loop. In the outer loop a moving average is calculated of these link travel-times, which is used to build an (augmented) STEN in each iteration of the outer loop. Each STEN defined in the outer loop implies a set of User Optimal link flows and travel times which again uniquely identify a STEN. The procedure converges if a matching STEN and set of travel times is found.

However, our experiments have shown that given a certain choice of parameters the situation may occur that the iterative procedure that is used to find such a fixed point gets stuck a cycle of STEN’s: the UO solution that is associated with STEN A implies STEN B and vice versa. This problem arises as an effect of the time discretisation and applies to all Variational Inequality based DNL methods. Possibly the problem can be avoided by choosing a suitable time step. However the authors are not aware of any formal proof of this.

The final observation concerns the uniqueness of the minimization problem (1). In order to prove this solution to be unique it would be sufficient to prove that (1) is a convex function. Although Yang (1994) proves a similar static minimization problem to be convex, proving the convexity of the present problem might turn out to be a challenging task. Our experiments showed that, regardless of the value of $\lambda$, the objective function $J$ dropped steeply during the first few iterations and then asymptotically converged to a positive value despite the existence of a solution that implies a much lower objective value. This indicates the existence of a local minimum or a saddle point.

CONCLUSIONS

As congestion not only results in the dispersion of O-D demand over multiple routes, but also in peak-spreading, use of dynamic traffic assignment (DTA) models as a means to predict the impact of new infrastructure should take account of departure time choice in addition to route choice. This paper shows that Augmented STEN’s are an effective way to model simultaneous departure time and route choice, and that the inverse problem, estimating uncongested O-D demand, can be formulated as a minimization problem which can then be successfully solved. Assigning the uncongested O-D demand with the DUO-D&R method allows the prediction of peak spreading effects. Experiments that compare this method with DUO based O-D estimation and assignment, clearly show the potential increase of accuracy of link flow predictions that can be reached with this new method.

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