AN INTEGRATED MODEL FOR URBAN NETWORK DYNAMIC O-D ESTIMATION

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Abstract: In this paper, we propose an integrated approach for dynamic O-D in urban networks. With the initial estimated O-D set, we can compute the link-incident matrix with any acceptable dynamic traffic assignment model and generate a revised distribution of network O-D set. To improve the estimation accuracy and also account for the impact of urban signals, we present an intersection O-D estimation model that can produce an additional set of system observation constraints based on either existing or estimated intersection turning fractions. The results of simulation experiments indicate that our proposed method is quite promising.

Key Words: dynamic O-D estimation, dynamic traffic assignment, an integrated model

1. INTRODUCTION

As the estimation of time-varying O-D distributions at different aggregation levels provides of time-varying O-D distributions at different aggregation levels provides a direct and cost-economic way for understanding urban traffic flow patterns, it has considerable number of methods for O-D estimation has been reported in the literature. Depending on whether a dynamic traffic assignment model (DTA) is needed or not, one may classify all such studies into the following two categories : assignment-based and non-assignment-based methods.

1.1 Assignment-based Approaches

All methods in this category are based on a common assumption that a reliable descriptive dynamic model for network traffic assignment is available for generating the link flow usage patterns. With such a critical assumption, the interrelations between its dynamic O-D distributions and resulting link flows can be described with the following equation:

$$Z_l(k) = \sum_m \sum_r \theta_l^m(k) B_r(k-m) \tag{1}$$

where:

$B_r(k)$: flows between O-D pair r during time interval k;

$Z_l(k)$: flows at a counting station on link λ during time interval k;

$\theta_{rl}^m(k)$: the fraction of O-D flow $B_r(k-m)$ contributing to link flows $Z_l(k)$.

For all assignment-based approaches, Eq.(1) serves as their core system model for use in parameter estimation.

Along this research line, Willumsen (1984) has first extended the static entropy concept to multiple time intervals, and thus transformed the underdetermined static relations to over-determined dynamic formulations. With a similar assignment logic but not the maximum entropy distribution, Cascetta and Nguyen (1988) later proposed a family of statistical approaches for contending with inconsistencies in link traffic counts, including the generalized least squares estimator, Bayesian inference estimator, and the maximum likelihood estimator. More recently, Cascetta et al.(1993) extended those statistical estimators to two dynamic estimators (i.e. simultaneous and sequential estimators) for approximating the time-varying network O-D patterns.

To circumvent extensive data needs, some researchers have developed revised modeling procedures. For instance, Okutani (1987) formulated a Kalman-filter model, based on the assumption that the time-varying O-D flows follow an autoregressive relation. Ashok and Ben-Akiva (1993) have replaced the state variables of time-varying O-D flows in the Okutani's work with their deviations from available historical O-D flow data.
Note that dynamic models developed along this direction appear to be promising in contending with the complex time-dependent network O-D issues, if an accurate descriptive assignment model for network flow distributions does exist and a time-series set of previous

time-varying network O-Ds is available. However, the development of an accurate descriptive DTA and the acquisition of reliable prior O-Ds remain to be on-going challenging research at the current stage.

1.2 Non-assignment-based Approaches

With respect to the non-assignment-based methods, their key features lie in the direct estimation of O-D parameters from time –series measurements of network input-output and link flows. To date, most existing studies in this category discussed the application of such O-D estimation methods for only a single intersection or a small freeway segment.

To illustrate the core concept of such approaches, consider a network of N nodes where any node can be either an origin, a destination, or both. With the available input/output flows, one can formulate the interrelations between the dynamic O-D patterns and the resulting node flows as follows:

$$y_j(k) = \sum_{m=0}^{M} \sum_{i=1}^{I} \rho_{ij}^{m}(k) b_{ij}(k-m) q_i(k-m) \qquad j = 1,\ldots,J \qquad (2)$$

where:

$y_j(k)$: the number of vehicle trips arriving at destination node j during interval k;

$b_{ij}(k)$: the proportion of demand $q_i(k)$ heading toward destination node j during interval k;

$q_i(k)$: the number of vehicle trips generated from origin node i during interval k;

$\rho_{ij}^{m}(k)$: the fraction O-D flows $q_i(k-m) b_{ij}(k-m)$ trips, arriving at destination node j during interval k;

Cremer and Keller (1981) shall be credited for their first application of the above model in identifying turning flows from traffic counts at complex intersections. Under the assumption of having a constant link travel time, the same logic was applied later by Cremer and Keller (1984; 1987) in a small freeway segment. Further developments along the same line were pursued later by Nihan and Davis (1987; 1987), and Nihan and Hamed (1992).

To contend with the embedded travel time variability, Bell (1991) has presented an extended linear model that employs Robertson's (1969) platoon dispersion relation in representing the dynamic interactions between link entry and existing flows. To accommodate with various possible travel patterns, Bell (1991) has also proposed an enhanced version of his model that allows, in principle, for incorporation of any type of travel time distributions. Such a flexible modeling concept was reported to be effective for a small network or freeway segment on which travel times for any O-D pair are shorter than two observation time intervals.

Note that using only the information from node flows as constraints, Eq. (2) is certainly underdetermined. For most urban networks, the number of unknown O-D parameters. Is often much larger than the available system constraints. Thus, it is unlikely to obtain an accurate estimate using only the constraints from node flows. To contend with such limitations, one needs to employ either some plausible assumptions or to creatively identify some additional constraints based on observable system properties. A commonly-used method in the existing literature is to assume the availability of a prior set O-Ds for use as a reference target.

More recently, Kim and Chon (1999) have further extended the screenline concept to signalized networks, and developed a two-stage estimation method for the dynamic network O-D distributions. The core concept of such a model includes:

- Applications of cordonlines based on the available detectors to decompose the entire network into several subnetworks;
- Computation of the time-varying intersection turning fractions and the O-D distributions for each subnetwork encircled by each cordonline;
- Establish an additional set of constraints between the observed cordonline flows and those O-D pairs either originated from or destined to each encircled subnetwork;
- Perform O-D estimation for the entire network with the basic constraints in Eq. (2) along with the cordonline-based constraines.

The results of simulation experiments have indicated the effectiveness of such a two-state estimation method for urban networks.

Despite the promise of our proposed two-stage, non-assignment-based method for applications in signalized networks, the research team fully recognizes that many transportation researchers have continuously devoted considerable efforts on developing dynamic assignment models. It is likely that some reasonably reliable DTA model for location-specific applications may be available in the future. To take full advantage of such developments and to make our proposed method sufficiently effective in using all available information, we have further developed an integrated method for dynamic network O-D estimation.

The results from a two-stage estimation model will provide a set of preliminary dynamic O-Ds for the available DTA model to compute the assignment matrix. Such a matrix functions to bridge the relations between the O-D distributions and the resulting link flows. The constraints from link flows and DTA are used subsequently to improve the O-D estimation.

One key feature of the proposed approach is to employ the intersection turning flow data along with the path flow information from a DTA model to increase the observability of a given network system. In this paper, the turning flows are used not only for the subnetwork O-D estimation in a two-stage computational process, but also used to provide an additional set of constraints in identifying path flows from a DTA model. The application of such turning flow information has significantly improved the estimation accuracy.

2. A CORDONLINE MODEL FOR NETWORK O-D ESTIMATION

With decomposition one can first estimate the dynamic O-Ds for each subnetwork and subsequently construct the relations between the network O-Ds and each set of cordonline flows. For an urban network, a cordonline is defined as a hypothetical closed curve that intersects with a set of link stations, and divides the network into two parts: inside and outside each encircled subnetwork. The set of detector or counting stations on both the cordonline network links provide the time-varying flow information for estimation.

To facilitate the model presentation, we have defined the following variables, and compress the notation, l, for a given cordonline in all subsequent formulations:

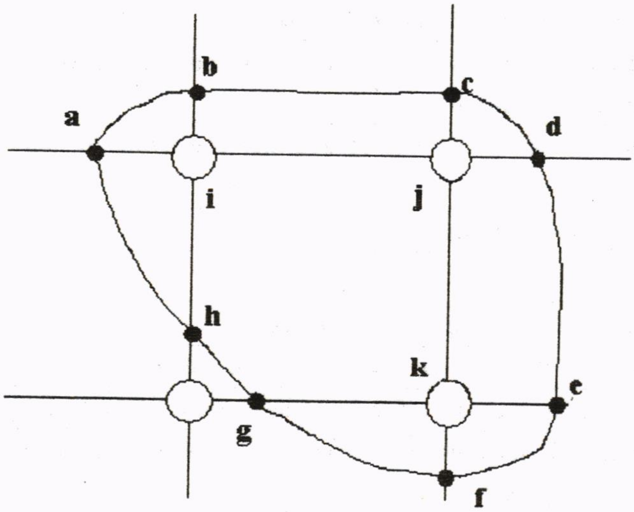

Figure 1. Cordonline Concept

Table 1. Notations

Variables	Definitions
O_0	the set of origin nodes not in the subnetwork encircled by a cordonline;
O_I	the set of origin nodes in the subnetwork encircled by a cordonline;
D_0	the set of destination nodes not in the subnetwork encircled by a cordonline;
D_I	the set of destination nodes in the subnetwork encircled by a cordonline;
$V^+(k)$	the total cordonline flows moving into the encircled subnetwork during time k;
$V^-(k)$	the total cordonline flows moving out of the encircled subnetwork during time k;
$V_1^+(k)$	part of $V_1^-(k)$ coming from O_o and destined to D_I.
$V_2^+(k)$	part of $V^+(k)$ coming from O_o which have crossed the cordonline and destined to D_0;
$V_1^-(k)$	part of $V^-(k)$ coming from O_I and destined to D_0;
$V_2^-(k)$	part of $V^-(k)$ coming from Oo which have crossed the cordonline and destined to D0;
$\rho_{ilj}^m(k)$	the fraction of $V_1^-(k)$ trips which arrive at cordonline l during interval k;
$\alpha(k)$	fraction of $V_1^-(k)$ which will have experienced the second crossing over the same cordonline during time interval k.
$\beta(k)$	fraction of $V_1^-(k)$ which will arrive at a cordonline encircling node j during time interval k.
S_1	A subnetwork encircled by one cordonline;
S_2	the set link detector stations, viewed as nodes and used to constitute a hypothetical cordonline;
S	the network encircled by a cordonline, consisting of nodes in both S_1 and S_2
$P(r)$	the set of paths connecting O-D pair r
l	link index
d	indes intersection turning movement types
$A_r^p(k)$	the fraction of flows between O-D pair r using path $p,p \in P(r)$
$\delta(p.l)$	dummy variable. It equals 1 if path p contains link l. otherwise, it equals 0
$\delta^*(p.d)$	dummy variable. It equals 1 if path p contains turning movement d. otherwise, it equals 0
$Z_l(k)$	flows at a counting station on link l during interval k
$T_d(k)$	tatal flows for turning movement d during interval k
$p_{rl}^m(k)$	the fraction of path flows, $B_r(k-m)A_r^p(k-m)$, contributing to link flow

	$Z_l(k)$
$p_{rd}^{*m}(k)$	the fraction of path flows, $B_r(k-m)A_r^p(k-m)$, contributing to turning flow $T_d(k)$
$B_r^0(k)$	O-D flows for pair r estimated with non-assignment approaches
$B(k-m)$	a vector of previously estimated O-D flows for all pairs during previous interval $(k-m)$

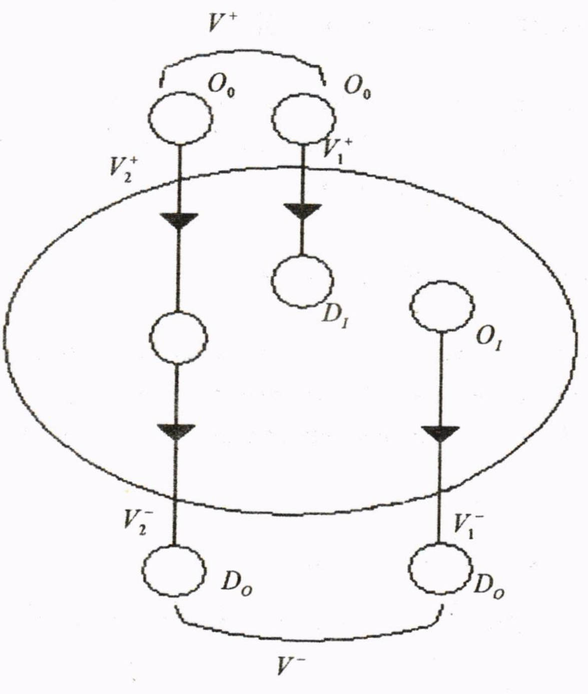

Figure 2. Cordonline flow

With the above definitions, the observable flows, $V^+(k)$ and $V^-(k)$, for cordinline l are the sums of the following two components:

$$V^+(k) = V_1^+(k) + V_2^+(k) \quad (3)$$
$$V^-(k) = V_1^-(k) + V_2^-(k) \quad (4)$$

$V_1^+(k)$ and $V_2^+(k)$ can further be expressed as:

$$V_1^+(k)=\sum_{i\in O_0}\sum_{j\in D_I}\sum_{m=0}^{M}\rho_{ilj}^m(k)b_{ij}(k-m)q_i(k-m) \tag{5}$$

$$V_2^+(k)=\sum_{i\in O_I}\sum_{j\in D_0}\sum_{m=0}^{M}\rho_{ilj}^m(k)b_{ij}(k-m)q_i(k-m) \tag{6}$$

As all flows in $V_2^-(k)$ are form flow $V_2^+(k-m)$ with a time lag m. Thus, the interrelation between $V_2^-(k)$ and $V_2^+(k)$ can be expressed as follows:

$$V_2^-(k)=f\left|V_2^+(k),V_2^+(k-1),\ldots,V_2^+(k-M)\right| \tag{7}$$

where f is a function. If the cordonline covers a relatively small subnetwork, most trips in $V_2^-(k)$ shall come from $V^-(k)$ and $V_2^+(k-1)$. Thus, the above equation can be simplified as

$$V_2^-(k)=\alpha(k)V_2^+(k)+[1-\alpha(k-1)]V_2^+(k-1) \tag{8}$$

where $\alpha(k)$ is the fraction of $V_2^+(k)$ having the second crossing over the cordonline during time interval k. Based on Eqs. (5), (6) and (8), one can construct the following relations between each set of cordonline flows and O-D flows:

$$\begin{aligned}&\alpha(k)V^+(k)+[1-\alpha(k-1)]V^+(k-1)-V^-(k)\\&=\sum_{i\in O_0}\sum_{j\in D_I}\sum_{m=0}^{M}\left[\alpha(k)\rho_{ilj}^m(k)+[1-\alpha(k-1)]\rho_{ilj}^{m-1}(k-1)\right]q_i(k-m)\,b_{ij}(k-m)\\&-\sum_{i\in O_I}\sum_{j\in D_0}\sum_{m=0}^{M}\rho_{ilj}^m(k)q_i(k-m)b_{ij}(k-m)\end{aligned} \tag{9}$$

If the fraction parameters $\{\alpha(k)\}$ and $\{\rho_{ilj}^m(k)\}$ are known, one can directly use Eq.(9) along with Eq.(2) to estimate OD parameters.

Note that one may assume the set of parameters $\{\alpha(k)\}$ to remain constant over the peak period [e.g. $\alpha(k)$=1] and perform the estimation with the above derived constraints. However, parameters $\alpha(k)$ in some scenarios may be time-varying and thus need to be computed. The computation of $\alpha(k)$ is not straightforward, as it needs the unobservable flows $\{V_2^+(k)\}$ and $\{V_2^-(k)\}$. To solve this issue, one can compute flows $\{V_2^+(k)\}$ and $\{V_2^-(k)\}$ from the intersection turning factions and estimated O-Ds for the small subnetwork encircled by the cordonline (see Chang and Tao, 1996). The time-varying O-Ds for each subnetwork will provide the direct information for computing the parameters $\alpha(k)$.

2.1 Integration of Constraints Form Link And Intersection Turning Flows Given A Reliable DTA Model

Note that although our proposed two-stage method circumvents the need of prior O-Ds and a DTA model, it remains ground on a commonly-used assumption, such as the O-Ds follow an autoregression or random walk process, that may not be in consistency with actual O-D patterns.

Hence, if a reliable DTA is available, one can further increase the observability of network flow patterns by integrating both constraints from the link and intersection turning flows, and use those to update the set of O-Ds estimated from the non-assignment based approach.

To facilitate the presentation of model formulation, we first define the following variables:

Assuming that the estimated O-Ds, $\{B_r^0(k)\}$, have been obtained with our proposed non-assignment model, one can assign $\{B_r^0(k)\}$ with an available DTA model to compute the route-choice matrices $\{A_r^p(k)\}$, parameters $\{p_{rl}^m(k)\}$ and $\{p_{rd}^{*m}(k)\}$. The route-choice fractions are used to bridge the O-D flows with their resulting link and turning flows.

With all such information, one can construct the following set of constraints based of the flow counts $\{Z_l(k)\}$ on link l:

$$Z_l(k) = \sum_m \sum_r \sum_p B_r(k-m) A_r^p(k-m) \delta(p,l) p_{rl}^m(k) \tag{10}$$

Note that Eq. (10) is identical to Eq. (1) but with different notation, and it is the core equation of all assignment-based O-D estimation models. To take full advantage of available information, we propose, in addition to Eq. (10), to construct the following set of new constraints from intersection turning flow data:

$$T_d(k) = \sum_m \sum_r \sum_p B_r(k-m) A_r^p(k-m) \delta^*(p,d) p_{rd}^{*m}(k) \tag{11}$$

To compress the notation, we redefine the following vectors:

$$Z(k) = (Z_1(k), \ldots, Z_l(k), \ldots)^T$$

$$T(k) = (T_1(k),\ldots,T_d(k),\ldots)^T$$

$$B(k) = (B_1(k),\ldots,B_r(k),\ldots)^T$$

$$c_{rl}^{m}(k) = \sum_{p\in P(r)} A_r^p(k-m)\delta(p,l)p_{rl}^{m}(k)$$

$$c_{rl}^{*m}(k) = \sum_{p\in P(r)} A_r^p(k-m)\delta^*(p,d)p_{rl}^{*m}(k)$$

$$C^m(k) = \begin{pmatrix} c_{11}^m(k),\cdots,c_{11}^m(k),\cdots, \\ \vdots \qquad\qquad \vdots \\ c_{11}^m(k),\cdots,c_{11}^m(k),\cdots, \\ \vdots \qquad\qquad \vdots \end{pmatrix}$$

$$C^{*m}(k) = \begin{pmatrix} c_{11}^{*m}(k),\cdots,c_{rl}^{*m}(k),\cdots, \\ \vdots \qquad\qquad \vdots \\ c_{11}^{*m}(k),\cdots,c_{11}^{*m}(k),\cdots, \\ \vdots \qquad\qquad \vdots \end{pmatrix}$$

Then, Eqs. (10) and (11) be restated in a more compact form as :

$$Z(k) = \sum_{m=0}^{M} C^m(k)B(k-m) \tag{12}$$

$$T(k) = \sum_{m=0}^{M} C^{*m}(k)B(k-m) \tag{13}$$

where M is the number of lag intervals.

Eqs. (12) and (13) are the two sets of assignment-based constraints which serve as the measurement equations for model estimation.. For instance, one can restate Eqs. (12) and (13) into the following forms:

$$Z(k) - \sum_{m=1}^{M} C^m(k)B(k-m) = C^0(k)B(k) + \varepsilon(k) \tag{14}$$

$$T(k)-\sum_{m=1}^{M}C^{*m}(k)B(k-m)=C^{0}(k)B(k)+\gamma(k) \tag{15}$$

where $\varepsilon(k)$ and $\gamma(k)$ are two error terms. The left-side terms of Eqs. (14) and (15) can be computed with measurable flows (e.g. $\{Z(k)\}$ and $\{T(k)\}$) and previously estimated O-Ds (e.g. $B(k-m), m=1,\ldots,M$). The vector $B(k)$ in the right terms is the system parameter that needs to be estimated.

To improve the estimation accuracy, one can also employ the estimated O-Ds from the previously discussed two-stage approach to set up the following additional constraints:

$$B^{0}(k)=B(k)+\eta(k) \tag{16}$$

where $\eta(k)$ is a vector of error terms associated with the estimated O-Ds $\{B^{0}(k)\}$. Eq. (16) serve as a measurement equation along with Eqs. (14) and (15) for model estimation.

Similar to those studies in the literature, we apply the Kalman-filtering approach on system Eqs.(14-16) to derive the O-D matrix. To do so, one needs to assume that the time-varying O-Ds follow an autoregression process as follows:

$$B(k)=\alpha_{1}B(k-1)+\alpha_{2}(k-2)+\cdots+\alpha_{p}B(k-p)+\mu(k) \tag{17}$$

where $\mu(k)$ is a vector of error terms and p is a prespecified constant.

Applying the Kalman-filtering procedures on those measurement and state transmission equations [i.e. Eqs. (14)-(17)], one can easily obtain the following recursive solution for O-D parameters $\{B(k)\}$:

$$\begin{aligned}B(k)=B(k-1)&+G_{1}[Z(k)-\sum_{m=1}^{M}C^{m}(k)B(k-m)-C^{0}(k)\widetilde{B}(k)]\\&+G_{2}[T(k)-\sum_{m=1}^{M}C^{*m}(k)B(k-m)-C^{*0}(k)\widetilde{B}(k)v]\\&+G_{3}[B^{0}(k)-\widetilde{B}(k)]\end{aligned} \tag{18}$$

where $\widetilde{B}(k)$ is the predicted O-Ds with state transmission equation that is computed as:

$$\widetilde{B}(k)=\alpha_{1}B(k-1)+\alpha_{2}(k-2)+\cdots+\alpha_{p}B(k-p) \tag{19}$$

and $G=(G_1,G_2,G_3)$ is the gain matrix which can be computed as:

$$(G_1,G_2,G_3)=U(k)\begin{pmatrix} c \\ C^{*0}(k) \\ I \end{pmatrix}^T \left[\begin{pmatrix} C^0(k) \\ C^{*0}(k) \\ I \end{pmatrix} U(k) \begin{pmatrix} C^0(k) \\ C^{*0}(k) \\ I \end{pmatrix}^T + \begin{pmatrix} V_\varepsilon(k) & 0 & 0 \\ 0 & V_\gamma(k) & 0 \\ 0 & 0 & V_\eta(k) \end{pmatrix}\right]^{-1} \quad (20)$$

I in Eq. (20) is the identical matrix. $U(k)$ is the covariance matrix of $\mu(k)$, and $V_\varepsilon(k)$, $V_\gamma(k)$, $V_\eta(k)$ are covariance matrices of $\varepsilon(k)$, $\gamma(k)$ and $\eta(k)$, respectively.

Note that the set of O-Ds computed with Eq. (20) may not satisfy the conservation constraint, that is, $\sum_j b_{ij}(k)=1$. One can, however, apply the normalization technique proposed by Nihan and Davis (1987) to resolve such inconsistencies.

In practice, if the intersection turning flow information is not available, one can collect the turning flow data at selected sites with any surveillance system, or apply the existing approach based on the entry/exit flows at each intersection approach and signal settings. Since intersection turning flows provide the direct constraints to both link and path flows, the applications of such information as constraints can substantially improve the estimation accuracy.

2.2 Algorithm

A step-by-step description of the estimation algorithm for the proposed integrated model is presented below :

- Step 0 : Perform the two-stage O-D estimation and compute O-D flows $\{B_r^0(k)\}$ estimated with non-assignment approaches;
- Step 1 : Assign the estimated O-D $\{B_r^0(k)\}$ flows with the available DTA model, and compute the assignment matrix $A_r^p(k)$;
- Step 2 : Construct constraints shown as Eq. [(14)-(16)] and establish additional constraints if sampled or partial O-Ds are available;
- Step 3 : Compute the coefficient matrix $C^m(k)$, $C^{*m}(k)$ in Eq. (14) and (15);
- Step 4 : Compute the gain matrix G with Eq. (20) ;
- Step 5 : Predict $\{B_r^0(k)\}$ with state transmission Eq. (19)

Step 6 : Compute the O-D estimate with Eq. (18)

3. AN ILLUSTRATIVE EXAMPLE

3.1 Example Network Design

- origin nodes ; 1, 2
- destination nodes ; 5, 6, 7, 8
- 8 O-D parameters ; $b_{1,5}$, $b_{1,6}$, $b_{1,7}$, $b_{1,8}$, $b_{2,5}$, $b_{2,6}$, $b_{2,7}$, $b_{2,8}$
- intermediate nodes ; 3, 4
- pretimed signalized intersections ; 3, 4, 5, 6
- two entry streams g_1, g_2 at nodes 1, 2
- four exit streams y_5, y_6, y_7, y_8 at nodes 5, 6, 7, 8
- 35 sets of different entry volumes and turning fractions, where k=1,2,· · · ,35
- each time interval ; 10 min.
- The information of turning flows, route-choice splits and actual O-D data were identified from the simulation output data.
- Simulation tool : NETSIM.

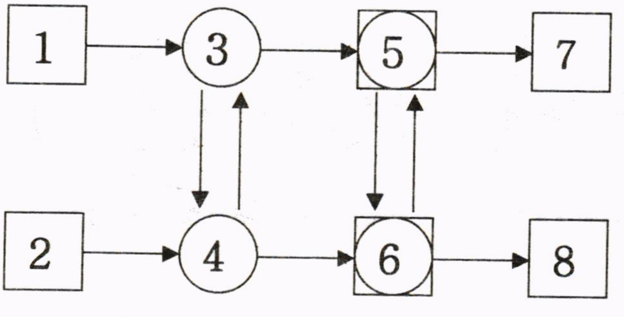

Figure 3. A Graphical Illustration of The Example Network

3.2 Experimental Design

- Scenario-1

- Entry flows from nodes 1, 2
- Exit flows from nodes 5, 6, 7, 8
- Non-assignment based approach based on entry and exit flow.

• Scenario-2
- Entry flows from nodes 1, 2
- Exit flows from nodes 5, 6, 7, 8
- Cordonline flows from two cordonlines l_1, l_2
- Non-assignment based approach with a cordonline model

• Scenario-3
- Entry flows from nodes 1, 2
- Exit flows from nodes 5, 6, 7, 8
- Cordonline flows from two cordonlines l_1, l_2
- Flows from all links
- Route-choice splits from each O-D pair and its feasible paths
- Turning flows at intersection 3, 4, 5, 6
- Integrated estimation method with intersection turning flow data

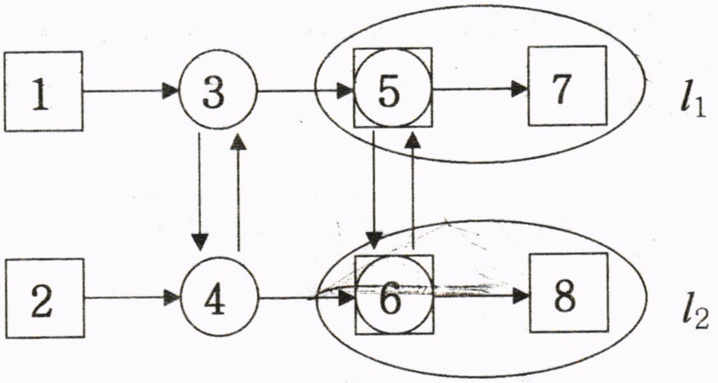

Figure 4. Two cordonlines introduced in Scenario-2,3

In this example, we compute flows $V_2^+(k)$ and $V_2^-(k)$ for each cordonlines from the simulated turning fraction data.

Using the rooted-mean-squared (RMS) errors as the evaluation criterion ; the comparison results between those scenarios are reported in Table 2. It clearly indicated that if a reliable DTA is available, the proposed combined approach can provide an effective and accurate of dynamic network O-Ds

Table 2. Comparison of RMS among Different Scenarios

	Scenario-1	Scenario-2	Scenario-3
$b_{1,5}$	0.0459	0.0373	0.0219
$b_{1,6}$	0.0318	0.0292	0.0157
$b_{1,7}$	0.0283	0.0284	0.0106
$b_{1,8}$	0.0341	0.0195	0.0163
$b_{2,5}$	0.0406	0.0242	0.0156
$b_{2,6}$	0.0276	0.0203	0.0091
$b_{2,7}$	0.0384	0.0272	0.0122
$b_{2,8}$	0.0338	0.0179	0.0078
overall	0.0351	0.0201	0.0137

4. CONCLUSIONS

This paper presents an effective method for dynamic O-D distributions in urban networks. The proposed method not only has the strengths of both categories of dynamic O-D estimation models in the literature, but also is capable of taking advantage of intersection turning fraction data.

The construction of an additional set of constraints with available or estimated intersection turning flows has substantially improved the estimation results. It thus is not only a core of our proposed combined estimation method, but also an improvement to those studied relying on a DTA model for exploring the dynamic O-D issue.

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