A DYNAMIC O-D ESTIMATION MODEL FOR URBAN NETWORKS.

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Abstract : This paper presents an effective model for analyzing dynamic urban network O-D distributions. The proposed model incorporates signal effects on the computation of travel time variability and thus is capable of providing realistic estimation of time-varying O-D distributions in urban signalized networks. To accommodate the variation of traffic sensor density and distribution in various networks, this paper has discussed the flexibility of constructing intersection-based cordonlines under the available surveillance system. With the additional constraints constructed from observed cordonline and intersection flows, the proposed method substantially increases the observability of a dynamic O-D system, and yields significantly improved results.

1. INTRODUCTION

As the estimation 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 is needed or not, one may classify all such studies into assignment-based and non-assignment-based methods.

Methods in frist category are based on the assumption that a reliable descriptive dynamic model for network flow assignment is available for generating the link flow usage pattern. To circumvent the need of extensive data, some researchers have developed revised modelling procedures.

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, without applying dynamic traffic assignment matrices and any prior O-D information. To date, most literatures in this category discussed the O-D estimation only for a single intersection or a small freeway segment. Dynamic O-D estimation for an urban network has not yet been addressed.

The core concept of such dynamic O-D estimation models was originally proposed by Cremer and Keller(1981) and Cremer(1983) for identifying turning flows from traffic counts at complex intersections. To improve the system observability for a network in which each O-D pair may distribute along several routes, Chang and Wu(1996) have further revised their model to include constraints established from dynamic screenline flows. As each urban network may exist numerous independent screenlines, one can establish sufficient constraints for O-D parameters and thus obtain a reliable estimate for time-varying O-D patterns.

The purpose of this study is to extend the work by Chang and Wu(1996) to signalized networks. The proposed model has the following distinct features:

- Utilization of dynamic constraints established from the cordonline flows to increase the system observability without additional surveillance systems.
- No need to rely on any prior O-D information and a dynamic assignment model.
- Incorporation of the signal effects on travel time variability.
- Computationally efficient for potential applications in large-scale networks.

2. MODEL FORMULATION WITH THE CORDONLINE FLOWS

Consider a network of N nodes, where any node can be either an origin, a destination, or both. The interrelations between its dynamic O-D patterns and resulting link flows can best be described with the following equation.

$$y_j(k)=\sum_{m=0}^{M}\sum_{i=1}^{I}\rho_{ij}^{m}(k)x_i(k-m)=y_j(k)=\sum_{m=0}^{M}\sum_{i=1}^{I}\rho_{ij}^{m}b_{ij}(k-m)q_i(k-m) \qquad (1)$$

$$j=1,2,\ldots,J$$

Eqn(1) is subjected to two natural constrains:

$$\sum_{j=1}^{J} b_{ij}(k)=1 \qquad i=1,2,\ \ldots,\ I$$

$$b_{ij}(k)\geq 0 \qquad i=1,2,\ \ldots,\ I;\ j=1,2,\ \ldots,\ J$$

where :

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

$x_{ij}(k)$: O-D vehicle trips from origin node i to destination node j during time interval k;

$b_{ij}(k)$: the proportion of demand q(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 of x_{ij}(k-m) trips arriving at destination node j during interval k;

I : the number of origin nodes;

J : the number of destination nodes;

M: the maximum number of time lags

Both $\rho_{ij}^{m}(k)$ and are unknown parameters to be estimated. Such a dynamic interrelation represents the fact that vehicles arriving at the same destination during the same time interval may come from either the same origin but different departure times, or different origins and different starting intervals due to the discrepancy in their selections of route and travel speed.

Assuming that a basic surveillance system for traffic counts is available in a network, the directly obtainable information for dynamic O-D estimation this includes:

- The time-varying input flows arriving at each network entry or trip generation node $\{q_i(k)\}$;
- The time-varying flows arriving at each network exit or destination node $\{y_i(k)\}$; and
- The time-varying link flow rate and intersection vehicle arrival as well as departure rates.

Clearly, each observable set of flows, regardless of the differences in location(e.g., entry, exit, or link), constitutes a set of dynamic constraints for Eqn(1). Hence, one can perform an estimation of the dynamic network O-D patterns with a sufficient number of such constraints. Unfortunately, using only the information from link and node flows as constraints, Eqn(1) is certainly underdetermined, and its resulting solution may not be unique and stable. To increase such a system observability and stability, without incurring additional costs for surveillance, Chang and Wu(1995) have proposed the use of the dynamic screenline concept to increase the model constraints. Along the same direction, in this study, We have introduced the cordonline concept, a special type of screenline, to further capture the dynamic interactions between the network flows and their O-D patterns.

2.1 Cordonline Formulations for Signalized Networks

A cordonline is defined as a hypothetical closed curve that intersects with a set of links, and divides the network into two parts: inside and outside the encircled subnetworks. For convenience of presentation, the cordonlines are so selected as to satisfy the following assumptions: trips originating from the encircled subnetwork and destined to the outside subnetwork will have only one crossing over the cordonline, and no trip will cross the same cordonline more than twice. Each cordonline thus contains two sets of dynamic flow information(i.e., from inside to outside of the encircled subnetwork and from the opposite direction) for developments of constraints for Eqn (1).

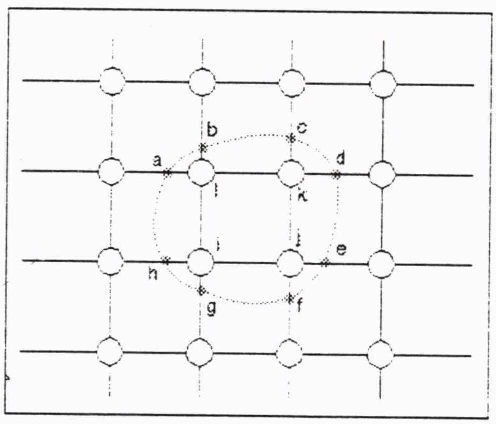

Figure 1. A graphical illustration of a cordonline

To facilitate the presentation, the notation for all variables involved in constructing such constraints is defined below. To compress the notation, ℓ for a given cordonline is eliminated in the following illustration, and the remaining variables are defined below:

O_o : the set of origin nodes not within the cordonline;

O_i : the set of origin nodes within the cordonline;

D_0 : the set of destination nodes not within the cordonline;

D_1 : the set of destination nodes within the cordonline;

k : time interval index;

$V^{+}(k)$: the total cordenline flows moving into the encircled subnetwork during time k (see figure 2);

$V^{-}(k)$: the total cordonline flows moving out of the encircled subnetwork during time k;

$V_1^{+}(k)$: part of $V^{+}(k)$ coming from O_o and destined to D_1 (see Figure 2);

$V_2^{+}(k)$: part of $V^{+}(k)$ coming from O_o which have crossed the cordonline and destined to D_0 (see Figure 2);

$V_1^{-}(k)$: part of $V^{-}(k)$ coming from O_1 and destined to D_0 (see Figure 2);

$V_2^{-}(k)$: part of $V^{-}(k)$ coming from O_o which have crossed the cordonline and destined to D_0 (see Figure 2);

$\rho_{i\ell j}^{m}(k)$: the fraction of $X_{ij}(k-m)$ trips which arrive at cordinlin ℓ during interval k;

$\alpha(k)$: fraction of $V_2^{+}(k)$ which will have experienced the second crossing over the same cordonline during time interval k.

$\beta(k)$: fraction of $q_i(k)$ which will arrive at a cordinline encircling node j during time interval k.

S_1 : a subnetwork encircled by the cirdonline;

S_2 : the set of link detector stations, viewed as nodes and used to constitute a hypothetical cordinlie;

S : a cordinline-associated network, consisting of nodes in S_1 and S_2

With the above definitions, the observable flows, $V^{+}(k)$ and $V^{-}(k)$, for cordinline l are the sums of the following two components(see Figure 2):

$$V^{+}(k)=V_1^{+}(k)+V_2^{+}(k) \tag{2}$$

$$V^{-}(k)=V_1^{-}(k)+V_2^{-}(k) \tag{3}$$

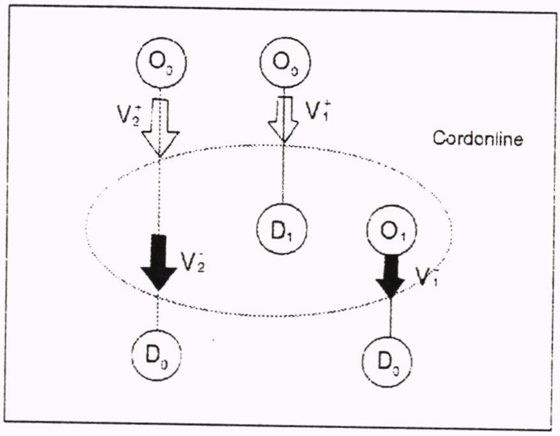

Figure 2. A graphical illustration of a cordonline flows

$V^+(k)$ and $V^-(k)$ can further be expressed as:

$$V_2^-(k) = \sum_{i\in O_0}\sum_{j\in D_1}\sum_{m=0}^{M}\rho_{ij}^{m}(k)\,x_{ij}(k-m)$$

$$= \sum_{i\in O_0}\sum_{j\in D_1}\sum_{m=0}^{M}\rho_{ij}^{m}(k)\,b_{ij}(k-m)\,q_i(k-m) \qquad (4)$$

$$V_1^-(k) = \sum_{i\in O_1}\sum_{j\in D_0}\sum_{m=0}^{M}\rho_{ij}^{m}(k)\,x_{ij}(k-m)$$

$$= \sum_{i\in O_1}\sum_{j\in D_0}\sum_{m=0}^{M}\rho_{ij}^{m}(k)\,b_{ij}(k-m)\,q_i(k-m) \qquad (5)$$

As all flows in are from flow $V_2^-(k-m)$ with a time lag m(see Figure 2). Thus, the interrelation and can be expressed as follows:

$$V_2^-(k) = f\left[V_2^-(k), V_2^-(k-1), \ldots, V_2^-(k-M)\right] \qquad (6)$$

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

$$V_2^-(k) = \alpha(k)V_2^-(k) + \left[1-\alpha(k-1)\right]V_2^-(k-1) \qquad (7)$$

where $\alpha(k)$ is the fraction of $V_2^-(k)$ having the second crossing over the cordonline during time interval k. Based on Eqns (4), (5) and (7), ws can construct the following relations between cordonline flows and OD patterns:

$$\alpha(k)V^{-}(k)+[1-\alpha(k-1)]V^{-}(k-1)-V^{-}(k)=$$
$$\sum_{i\varepsilon O_{3}}\sum_{j\varepsilon D_{1}}\sum_{m=0}^{M-1}\left[\alpha(k)\rho_{i\ell j}^{m}(k)+[1-\alpha(k-1)]\rho_{i\ell j}^{m}(k-1)\right]q_{i}(k-m)b_{ij}(k-m)$$
$$-\sum_{i\varepsilon O_{1}}\sum_{j\varepsilon D_{2}}\sum_{m=0}^{M-1}\rho_{i\ell j}^{m}(k)\,q_{i}(k-m)\,b_{ij}(k-m) \tag{8}$$

where:

$$\rho_{i\ell j}^{-1}(k)=0;\ \rho_{i\ell j}^{M+1}(k)=0$$

If the fraction parameters $\{\alpha(k)\}$ and $\{\rho_{i\ell j}^{m}(k)\}$ are known, Eqn (8) can be used to estimate OD parameters along with Eqn(1).

Note that with a relatively long time interval, most trips in $V_{2}^{+}(k)$ may have their second crossings over the same cordonline during the same time interval k, and $\{\alpha(k)\}$ can thus be approximated to one. Consequently, Eqn(8) can be simplified as:

$$V^{+}(k)-V^{-}(k)=\sum_{i\varepsilon O_{0}}\sum_{j\varepsilon D_{1}}\sum_{m=0}^{M}\rho_{i\ell j}^{m}(k)q_{i}(k-m)b_{ij}(k-m)-\sum_{i\varepsilon O_{I}}\sum_{j\varepsilon D_{0}}\sum_{m=0}^{M+1}\rho_{i\ell j}^{m}(k)q_{i}(k-m)D_{ij}(k-m) \tag{9}$$

Note that one may assume the set of parameters $\{\alpha(k)\}$ to remain constant over the peak period 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 straight forward as it needs the unobservable flows $\{V_{2}^{+}(k)\}$ and $\{V_{2}^{-}(k)\}$. To solve this issue, We propose a two-stage estimation process. At the first stage, one can estimate flows $\{V_{2}^{-}(k)\}$ and $\{V_{2}^{-}(k)\}$ with our proposed O-D estimation method on a small dubnetwork encircled by the cordinline, and compute the parameters $\{\alpha(k)\}$. The estimated results from the first stage will then be used in the second stage along with Eqn(8) for estimation of the entire network O-D pattern.

More specifically, with the cordinline introduced in the example network (see Figure 1), the subnetwork encircled by the cordonline consists of two sets of nodes: intersections within the cordonline and the link detector stations on the cordinline. Those flow counting stations are viewed as entry or (and) exit nodes of the subnetwork. Let S_1 and S_2 represent these two sets of nodes, respectively. One may select a subnetwork which contains only a small number of S_1 nodes. The O-D estimation for such a small network S and its sensitivity is available elsewhere(Chang and Tao, 1996).

Let $q_i(k)$ and $y_j(k)$ denote the node entry flows and exit flows, respectively, for subnetwork S, and $x_{ij}(k)$ represent the O-D flows from node i to node j estimated from subnetwork S. Thus, $V^+(k)$. $V_1^+(k)$ and $V_2^+(k)$ can be computed as

$$V^-(k)=\sum_{i\varepsilon S_2} q_i(k)=\sum_{i\varepsilon S_2}\sum_{i\varepsilon S} x_{ij}(k)$$

$$V_1^-(k)=\sum_{i\varepsilon S_2}\sum_{j\varepsilon S_1} x_{ij}(k)$$

$$V_2^+(k)=\sum_{i\varepsilon S_2}\sum_{j\varepsilon S_2} x_{ij}(k) \tag{10}$$

Likewise, $V^-(k)$. $V_1^-(k)$ and $V_2^-(k)$ can be obtained with the following expressions:

$$V^-(k)=\sum_{j\in S_2} y_j(k)=\sum_{j\varepsilon S}\sum_{j\varepsilon S_2}\sum_{m=0}^{l} x_{ij}(k-m)\rho_{ij}^{m}(k)$$

$$V_1^-(k)=\sum_{i\varepsilon S_1}\sum_{i\varepsilon S_2}\sum_{m=0}^{l} x_{ij}(k-m)\rho_{ij}^{m}(k)$$

$$V_2^-(k)=\sum_{i\varepsilon S}\sum_{i\varepsilon S_2}\sum_{m=0}^{l} x_{ij}(k-m)\rho_{ij}^{m}(k) \tag{11}$$

2.2 Formulations for Node-specific Cordonlines

Now consider a special type of cordonline which encircles only one destination node. In such a case, the model can be reformulated more compactly, and the estimation will be more efficient.

For a cordonline enciciing only one destination node, denoted as j, flows

$\{V_1^-(k)\}$ can be expressed as

$$V_i^-(k) = \beta(k)\, q_j(k) + (1-\beta(k))\, q_j(k-1) \tag{12}$$

where $\beta(k)$ is the fraction of $q_j(k)$ which arrive at the cordonline during time k. The procedures for computation of $\{\beta(k)\}$ are similar to those for estimating $\{q(k)\}$. Let

$$Z_j(k) = \alpha(k)V^-(k) + [1-\alpha(k-1)]V^-(k-1) - V^-(k) + \beta(k)q_j(k) + [1-\beta(k-1)]q_j(k-1) \tag{13}$$

then, Eqn(8) can be rewritten as

$$Z_j(k) = \sum_{i=1}^{I}\sum_{m=0}^{M-1}\left[\alpha(k)\rho_{ij}^m(k) + [1-\alpha(k-1)]\rho_{ij}^{m-1}(k-1)\right] q_i(k-m)\, b_{ij}(k-m) \tag{14}$$

To compress the notation, let

$$B_j(k) = (b_{1j}(k),\ b_{2j}(k),\ \ldots,\ b_{Ij}(k))^T$$

$$Q_j^m(k) = \begin{pmatrix} [\alpha(k)\rho_{1j}^m(k) + (1-\alpha(k-1))\rho_{1j}^{m-1}(k-1)]q_1(k-m) \\ \cdots \\ [\alpha(k)\rho_{Ij}^m(k) + (1-\alpha(k-1))\rho_{Ij}^{m-1}(k-1)]q_I(k-m) \end{pmatrix} \tag{15}$$

Thus, Eqn(14) can be expressed compactly as

$$Z_j(k) = \sum_{m=0}^{M-1} B_j^T(k-m)\, Q_j^m(k) \tag{16}$$

Note that Eqn(16), for the relation between O-D parameter $\{b_{ij}(k)\}$ and cordonline flows, provides a set of effective constraints for use in the O-D estimation. As each set of constraints from Eqn(16), based on specially-designed cordonlines with each encircling only one destination node, involves relatively few unknown parameters, it will certainly contribute significantly to the improvement of estimation accuracy.

3. AN ILLUSTRATIVE EXAMPLE

This section presents some numerical results with the proposed models. As none of the existing traffic simulation models is capable of tracking individual vehicle routes at the microscopic level, We have to employ a time-consuming way of tracking vehicles by placing detectors extensively in the entire network and simulate the system with TRAF-METSIM(FHWA, 1992).The experiment consists of three scenarios. The results of scenario-1, based only on entry and exit flows, are with the method in the literature. In scenario-2, two cordinlines, each surrounding only one destination node, are introduced. Dynamic flow information in those two cordonlines is used along with the entry and exit flows for estimation. In scenario-3, two additional cordonlines, each encircling two destination nodes are selected to evaluate their compound effects on the dynamic O-D estimation.

3.1 Example Network Design

The example network, shown in Figure 3, has two entry links, denoted as $\ell_{1.3}$, $\ell_{1.4}$ and four exit links, denoted as $\ell_{5.7}$, $\ell_{5.9}$ $\ell_{6.8}$, $\ell_{6.10}$. For convenience of computation, those trips exiting from links, $\ell_{5.9}$, $\ell_{6.10}$ are assumed to destine to nodes 5, 6 respectively. Thus, the network has two origin nodes and four destination nodes. There are two entry streams, q_1, q_2 at nodes 1, 2 and four exit streams, y_5, y_6, y_7, y_8 at nodes 5, 6, 7, 8. Since each entry stream can reach any exit node, there exists up to the folliwing 8 O-D parametes:

$$b_{1.5},\ b_{1.6},\ b_{1.7},\ b_{1.8}$$
$$b_{2.5},\ b_{2.6},\ b_{2.7},\ b_{2.8}$$

Note that to realistically represent the urban network condition, nodes 5, 6, 7, 8 are designed to be pretimed signalized intersections.

3.2 Data Set Generation

As NETSIM only takes entry volumes and turning movement fractions at intersections rather than O-D flows for its input, up to 10 sets of different entry volumes $\{V_1(k), V_2(k)\}$ and turning fractions have been specified, where k=1, 1, ..., 10 represents the time interval index. Each time interval is 2 minute. The entry volumes, $\{V_1(k), V_2(k)\}$ were generated randomly and shown in Table 1. The actual O-D splits for each time interval were identified with loop detectors, and shown in Table 2. As a large portion of O-D trips need more than one time interval to reach their destination nodes, the actual O-D splits for the last time interval is unobtainable.

3.3 Experimental Design

All data involved in each of the following three scenarios are summarized below:

Scenario-1:

- Entry flows from nodes 1, 2;
- Exit flows from nodes 5, 6, 7, 8

Scenario-2:

- Entry flows from nodes 1, 2;
- Exit flows from nodes 5, 6, 7, 8
- Cordonline flows from two node-specific cordonlines ℓ_1, ℓ_2 (see Figure 4).

Scenario-3:

- Entry flows from nodes 1, 2;
- Exit flows from nodes 5, 6, 7, 8
- Cordonline flows from four cordonlines ℓ_1, ℓ_2 ℓ_3, ℓ_4 (see Figure 5).

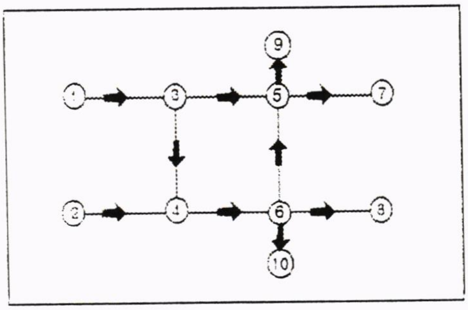

Figure 3. A graphical illustration of the example network

Table 1. The Time-Series of Entry Volumes Generated Randomly for NETSIM Simulation

K	1	2	3	4	5	6	7	8	9	10
$v_1(k)$	900	905	911	907	901	899	896	902	909	913
$v_2(k)$	703	712	722	709	718	707	704	726	728	701

Table 2. The Actual O-D Splits for Each Time Interval

K	$b_{1,5}$	$b_{1,6}$	$b_{1,7}$	$b_{1,8}$
1	0.241	0.253	0.265	0.242
2	0.290	0.221	0.285	0.204
3	0.241	0.229	0.252	0.278
4	0.259	0.255	0.270	0.216
5	0.321	0.261	0.261	0.157
6	0.252	0.252	0.252	0.244
7	0.267	0.279	0.232	0.222
8	0.268	0.195	0.305	0.233
9	0.279	0.279	0.232	0.211

Table 2. (Continue)

K	$b_{2,5}$	$b_{2,6}$	$b_{2,7}$	$b_{2,8}$
1	0.202	0.261	0.306	0.231
2	0.238	0.253	0.242	0.267
3	0.253	0.224	0.255	0.268
4	0.327	0.195	0.254	0.224
5	0.242	0.169	0.362	0.227
6	0.328	0.268	0.181	0.223
7	0.261	0.246	0.247	0.246
8	0.268	0.165	0.328	0.239
9	0.328	0.134	0.315	0.223

In scenario-2, cordonlines ℓ_1, ℓ_2 are node-based and are used to capture the node specific information, such as trip time variances from origin nodes to the destination nodes 5, 6. Hence, it is expected that the estimated O-D splits for trips destined to nodes 5, 6 be more accurate when these two cordonlines are introduced. In Scenario-3, all estimated O-D splits are expected to be improved with those four specially-designed cordinlines.

As the focus of this paper is on the modelling concept rather than the effectiveness of various estimation algorithms, We simple apply the Kalman-filtering approach in all three scenarios. To reduce the computation work, the state equation is assumed to follow an autoregression process:

$$b_{ij}(k) = rb_{ij}(k-1) + \ldots + r^m b_{ij}(k-m) + w(k)$$

where w(k) is an input vector of random white noise terms with zero means and known covariances. The parameters m and r are chosen to be 2 and 0.4 respectively, based on the results of exploratory analyses.

Note that to estimate the dynamic O-D matrices for urban networks, one needs to specify a set of unknown parameters, $\rho_{ij}^{m}(k)$ and $\rho_{i\ell j}^{m}(k)$ to capture the travel time variability. To focus this study on the impacts of screenline information on O-D estimation, We take the travel time information as given, and compute all those parameters $\rho_{ij}^{m}(k)$ and $\rho_{i\ell j}^{m}(k)$ with the trip times identified from a surveillance system in simulation. In reality, the distribution of O-D trip times may be estimated with the link travel time information, depending the available surveillance system.

In this example, the initial variances of all $b_{ij}(k)$ are set to be 0.001, and the initial values of $b_{ij}(k)$ are set as follows:

$b_{1,5} = 0.30$	$b_{1,6} = 0.20$	$b_{1,7} = 0.30$	$b_{1,8} = 0.20$
$b_{2,5} = 0.25$	$b_{2,6} = 0.10$	$b_{2,7} = 0.35$	$b_{2,8} = 0.20$

In scenario two and three, the dynamic O-D estimation as discussed in Section 2 needs the values of flows $V_2^{-}(k)$ and $V_2^{-}(k)$ for each cordonline. In this example, We compute flows $V_2^{-}(k)$ and $V_2^{-}(k)$ for each cordonlines with existing methods for turning fraction estimation.

Using rooted-mean-squared(RMS) errors as a criterion. the comparison results between scenarios one and two. and between one and three. are reported in Tables 3 and 4. As expected. with two one-node cordinlines has yielded a better estimation results than scenario-1 on any O-D pair. Scenario-3 that employes additional four cordonlines has achieved the best estimation results. Compared to scenario-1. the improvement on some O-D pairs has been up to 16%. Overall. it has achieved an average of 9.4% improvements over scenario-1. Hence. the contribution of such cordonlines in capturing the dynamics of the time-varying O-D distribution is certainly invaluable.

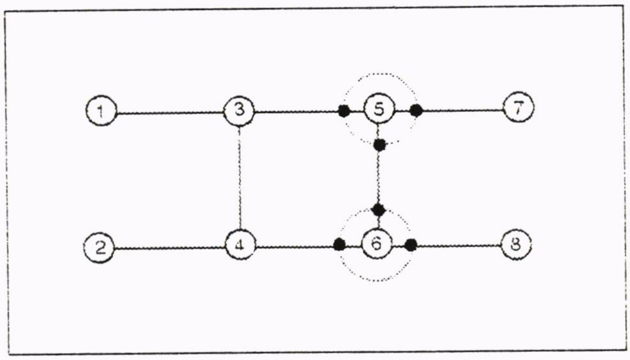

Figure 4. Two cordonlines introduced in scenario-2

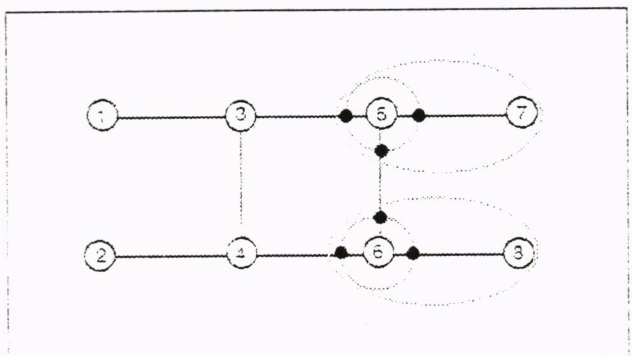

Figure 5. Four cordonlines introduced in scenario -3

4. CONCLUSIONS

This paper has presented an effective model for estimation of dynamic O-D distributions in urban networks. The proposed methodology offers the flexibility to construct various system constraints from observed cordonline and intersection flows, and allows traffic operations to take full advantage of the available surveillance system. As the formulations take into account the effects of signal delay on the dynamic O-D distribution, it has the potential to be applied in urban networks.

Due to the lack of available simulation models to track individual network vehicles at the microscopic level in the current transportation field. We are not able to conduct comprehensive evaluation of a proposed model with various urban networks of realistic size. However, both the mathematical formulations and the results of example analysis have shown the promising properties of a proposed method.

The authors fully recognize that much remains to be done to have a reliable dynamic O-D system for efficient use in practice. Grounded on this step of advance We will further pursue the research on some critical aspects, such as the development of an efficient decomposition algorithms for real time applications, and the estimation of time-varying trip time under a network of sparsely deployed surveillance systems.

Table 3. Comparison of RMS between Scenario-1 and Scenario-2

	Scenario-1	Scenario-2	Imptovement
b1.5	0.0306	0.0295	3.7%
b1.6	0.0348	0.0301	15.6%
b2.5	0.0411	0.0397	3.5%
b2.6	0.0407	0.0372	9.4%

Table 4. Comparison of RMS between Scenario-1 and Scenario-3

	Scenario-1	Scenario-3	Imptovement
b1.5	0.0306	0.0288	6.3%
b1.6	0.0348	0.0300	16.0%
b1.7	0.0351	0.0303	15.8%
b1.8	0.0402	0.0389	3.3%
b2.5	0.0411	0.0378	8.7%
b2.6	0.0407	0.0381	6.8%
b2.7	0.0384	0.0335	14.6%
b2.8	0.0422	0.0406	3.9%
overall	0.0379	0.0348	9.7%

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