wctr'04
4-8 july 2004 / istanbul-turkey

DYNAMIC ESTIMATION OF ROAD NETWORK FLOW USING OBSERVED TRAFFIC DATA

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Abstract

A better understanding of the dynamic flow of road traffic is required to provide more efficient and optimal operations, and management of road transport systems. This study proposes a dynamic estimation model of path-specific origin/destination traffic flow using dynamic traffic observations from detectors. This model is based on the least squares method. The origin-path-specific link traffic volumes and trip generation volumes are estimated sequentially. Because of the robust structure of the model, which permits missing data and observation errors, it can be applied not only to expressway networks with restricted entrances/exits but also to general surface road networks, where it is very hard to observe the trip generation volume. In this study, the proposed model was applied to simple hypothetical networks, where we could control the availability and accuracy of observations, and also to a real world network, to check its validity for practical use. Analyses conducted both on the hypothetical and real world networks confirmed the efficiency and practicability of the proposed model.

Keywords: Dynamic path flow estimation; Least square method; Sequential estimation; Practical application
Topic Area: C3 Traffic Control

1 Introduction

Traffic accidents and congestion are no longer a problem only on our roads; they bring with them social and economic problems that require attention. To tackle these problems, many traffic measures have been implemented using intelligent transport systems (ITS) based on mutual cooperation between machinery and communication technology. However, the dynamic change of traffic network flows must be explored and suitable traffic operations and management measures must be implemented to improve the efficiency of these technologies. Therefore, a reliable estimation method for dynamic origin and destination (OD) traffic flows or path traffic flows would be indispensable.

Many OD matrices estimation models have been developed, but most adopt strict or unrealistic assumptions that make them difficult to apply to a real world network. This study attempts to construct a model to estimate road network flow using simple practical calculations. A dynamic combined least squares with trip generations as the dependent variables (DCLS-TGV) model was constructed based on a dynamic combined least squares with non-negative constraints (DCLS-NNC) model that was previously proposed by the authors (Kurauchi *et al.*, 2000). The previous model required various types of inputs, such as traffic generation flows and link velocities that were sometimes difficult to obtain for a real world network. The DCLS-TGV model was developed to relax the data acquisition requirements. With this modification, we expect that the model will be applicable to a general surface road network.

Generally, OD matrices are estimated or surveyed to explore current traffic flow characteristics. These matrices are used mainly as inputs for policy evaluations. Considering that we implement so many dynamic traffic control measures, such as information provision or route guidance, one should recognize that the estimates of traffic flow patterns observed during one day constitute merely the flow pattern conditioned by the traffic flow and dynamic traffic measures of that particular day. Therefore, repeated observations of traffic flow patterns are required to obtain the expected or average traffic pattern. A mail-back questionnaire survey is no longer adequate; dynamic traffic flow observations must be utilized for this purpose. The DCLS-TGV model is also suitable from this point of view because of its simple algorithm and applicability for online estimation. Moreover, because the DCLS-TGV model estimates the path flow directly, without assuming any predetermined path use ratio, it can also be used as an evaluation tool for dynamic traffic measures. By comparing the change in the network flow before and after the implementation of traffic measures, we can analyze the qualitative change of traffic flow.

A literature review of the existing dynamic network flow estimation models is presented in the following section to define the problem. Following this, a mathematical formulation of the DCLS-TGV is described, together with its characteristics. The proposed model adopts the method of least squares, and estimates the trip generation volume for each origin, together with the origin-path-specific link traffic volume. The model was formulated as a quadratic program with linear equality and inequality constraints. An active set method was adopted to obtain an optimal solution. The model was applied to simple hypothetical networks, where we can control the availability and accuracy of observations, and then to a real world network, to check its validity for practical use. We will discuss the efficiency and practicability of the model using these results.

2 Review of dynamic origin destination matrices estimation models

Dynamic traffic measures, such as information provision or dynamic congestion charging, have been implemented around the world. The dynamic OD traffic volume and its pattern constitute indispensable input data for these measures. Hence the study of estimating dynamic OD matrices has attracted many transport researchers and professionals. Most estimates of dynamic OD matrices are based on extensions of existing static estimation methods, which introduce so-called dynamic network loading problems into the static models. In this section, we describe several existing models and discuss the remaining problems that must be considered.

The representative estimation techniques for OD traffic volume are based on either the entropy maximization method or the least squares (LS) method. Willumsen (1984), Nguyen *et al*. (1988), and Oneyama and Kuwahara (1997) extended the entropy maximizing method to a dynamic case; Cascetta *et al*. (1993) and Cremer and Keller (1987) proposed similar extensions to the LS method. The entropy maximizing method has been formulated to maximize the joint probability for the produced OD traffic volume, such that the link traffic volume meets the observed volume and the OD production probability is predetermined. For entropy maximization-based estimation techniques, the calculation algorithm must solve a non-linear set of equations; this requires iterations and is computationally demanding.

Oneyama and Kuwahara (1997) proposed a dynamic OD matrices estimation model by constructing a three-dimensional network. Links connected the origin node at the current time to destination nodes at the (current time + link travel time). Although the model required a huge amount of computational memory, because the number of links was multiplied by the number of time intervals, any static estimation technique could be applied to their extended network. In their work, an extended entropy maximization estimator was adopted. The model assumed a logit-type path choice ratio to calculate the link use ratio. One of the limitations of the model was that the link travel time had to be a unit of the length of the time interval.

There are typically two LS-based estimators: one uses observations of link traffic volumes only (the link LS model), and the other uses prior information about OD patterns, together with link traffic volumes (combined least squares method or CLS model). OD traffic volumes will be underestimated using the LS model if the volume of unknown OD traffic is greater than the observed volume of link traffic, which is what usually happens in the real world. Cremer and Keller (1987) relaxed this defect by assuming that several observations of the volume of traffic entering the link would have the same OD patterns. The CLS model guarantees a unique solution set by utilizing prior information for the OD volumes. Generally, if the non-negative constraints on unknown variables are ignored, the algorithm for typical LS estimators must solve a set of linear equations only. However, if there are large errors in the observed link traffic volumes or significant changes in the real OD patterns, as compared to expected patterns, the estimated OD traffic volumes can be negative.

Cascetta *et al*. (1993) proposed a model that minimized the sum of the differences between the observed and estimated link traffic volumes, and the differences between the present and prior information of OD flow. This model adopted the ordinal least squares (OLS) method and considered the correlation of the observed link traffic volumes. To determine the effects of the OD traffic volume on specific links, the link use ratios were calculated by assuming a logit-type route choice structure using the algorithm proposed by Dial (1971).

All of the papers cited above utilized Dial's algorithm; *i.e*., the link use ratio was predetermined. However, there are two problems with this approach. Dial's algorithm assumes that the travel time information for each link is perfect, but this assumption may be unrealistic if the network is large and complex. Also, there are few available results for Dial's parameter that describe the dispersion tendency of the path use ratio. Thus the assumption may not be valid, especially when estimating dynamic traffic flows with short time intervals.

3 Formulation of a dynamic network flow estimation model

3.1 DCLS-NNC model

3.1.1 Formulation

The DCLS-NNC model proposed by Kurauchi *et al*. (2000) adopted the dynamic combined least squares method, which is based on the static CLS model (Iida *et al*., 1986). This model considered origin-path-specific link traffic volume as unknown variables. Origin-path-specific link traffic volume, y_{iaps}, is defined as the traffic volume on branch p that uses link a generated at origin i during time interval s. The suffix p represents the branch number; the definition of a branch will be explained later. On a linear network, we have only one branch. Figure 1 shows the concept of unknown variables.

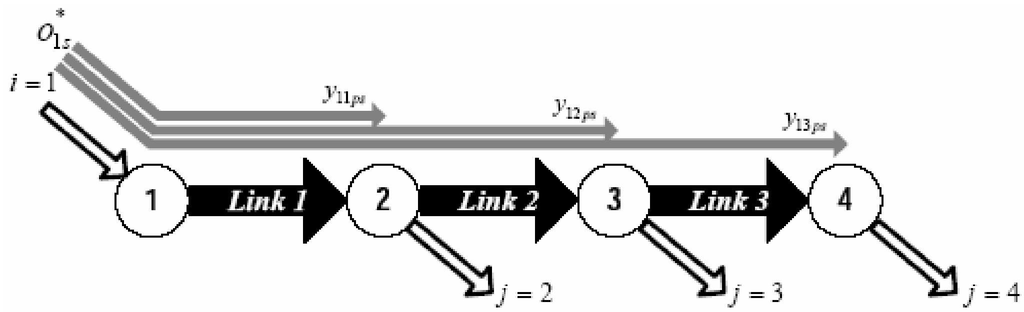


Figure 1. Concept of Origin-Path-Specific Link Traffic Volume

According to Figure 1, y_{11ps} indicates the traffic volume that uses link 1 generated at origin 1 during time interval s. The OD traffic volume can be easily calculated using these origin-path-specific link traffic volumes. For example, the traffic volume generated at origin 1 destined to 2, x_{12ps}, is calculated as follows:

$$x_{12\,ps} = y_{11\,ps} - y_{12\,ps} \tag{1}$$

Based on the concept of this unknown variable, the DCLS-NNC model is formulated as follows:

min

$$\sum_{a \in A_{ot}} \left\{ \begin{aligned} & \left(\sum_{p=1}^{P_{ia}} \sum_{i \in I} \sum_{s=1}^{t} (\delta_{iaps} \cdot q_{iapst} \cdot y_{iaps} + (1-\delta_{iaps}) \cdot q_{iapst} \cdot \hat{y}_{iaps}) - v^*_{at} \right)^2 \\ & + \sum_{i \in I} \sum_{s=1}^{t} \sum_{p=1}^{P_{ia}} (y_{iaps} - O^*_{is} \cdot g_{iaps})^2 \end{aligned} \right\} \tag{2}$$

subject to

$$\sum_{a \in A^i_{out}} y_{iaps} = O^*_{is} \qquad \text{for all } i \in I, s(1 \le s \le t) \tag{3}$$

$$\sum_{a \in A_{ot}} \sum_{p}^{P_{ia}} \sum_{i \in I} \sum_{s=1}^{t} (k^1_{m_1, iaps} y_{iaps}) - z_{m_1} \le 0 \quad \text{for all } m_1 (1 \le m_1 \le M_{1t}) \tag{4}$$

$$\sum_{a \in A_{ot}} \sum_{p}^{P_{ia}} \sum_{i \in I} \sum_{s=1}^{t} (k^2_{m_2, iaps} y_{iaps}) = 0 \qquad \text{for all } m_2 (1 \le m_2 \le M_{2t}) \tag{5}$$

$$y_{iaps} \ge 0 \qquad \text{for all } i \in I,\ a \in A,\ p(1 \le p \le P_{ia}),\ s = \{s \mid 1 \le s \le t\} \tag{6}$$

where

A_{ot}	: set of links on which link traffic volume is observed during time interval t,
P_{ia}	: the number of branches generated at origin i on link a according to *branch enumeration*,
I	: set of origins,
y_{iaps}	: traffic volume on the pth branch that uses link a generated at origin i during time interval s (origin-path-specific link traffic volume),
q_{iapst}	: proportion of the traffic that is generated at origin i during time interval s and on link a during time interval t, corresponding to pth branch (dynamic link use ratio),
v^*_{at}	: observed link traffic volume on link a during time interval t,
g_{iaps}	: prior probability of y_{iaps},
O^*_{is}	: observed traffic volumes generated at origin i during time interval s,
A^i_{out}	: set of links leading out of origin i,

m_1 : set of nodes with traffic concentration,

m_2 : set of nodes without traffic concentration,

$k^1_{m_1,iaps}$: binary variable that is 1 if it corresponds to y_{iaps} and the link a is leading out of a node that belongs to m_1; and 0 otherwise,

$k^2_{m_2,iaps}$: binary variable that is 1 if it corresponds to y_{iaps} and the link a is leading out of a node that belongs to m_2; -1 if it corresponds to y_{iaps} and the link a is leading into a node that belongs to m_2; and 0 otherwise,

z_{m_1} : estimates of the origin-path-specific link traffic volume, y_{iaps}, corresponding to node m_1,

M_{1t} : the number of inequality constraints (except non-negative constraints of unknown variables) during time interval t,

M_{2t} : the number of equality constraints during time interval t,

t : index for the current time interval.

The first term of the objective function represents the differences between the observed and estimated link traffic volumes. The second term represents the differences between the estimated traffic volume and observed trip generation volume compared to its prior probability. All of the constraints describe traffic conservation rules. The first constraint provides that the traffic volume generated from an origin is equal to the sum of the link traffic volume flowing out from that origin. The second constraint ensures that the traffic volume that traverses a concentration centroid node must be less than the traffic volume that arrives at that node if the node is a destination for any OD pair. The third constraint guarantees that the traversing traffic volume is equal to the arriving traffic volume if the node is not a destination for any OD pair.

3.1.2 Branch Enumeration

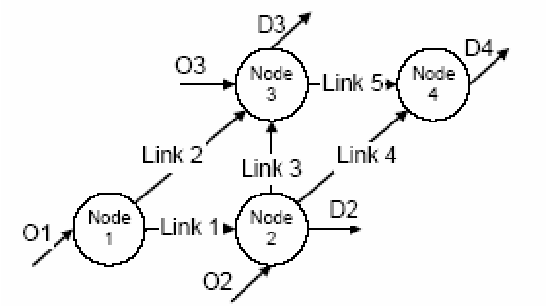


Figure 2. Example of a Multi-path Network

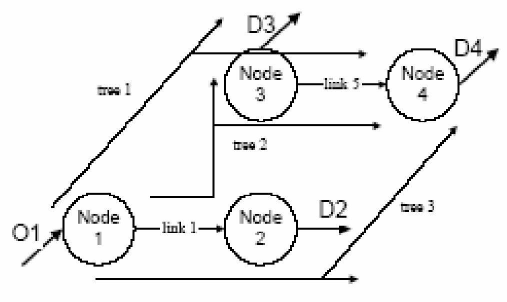


Figure 3. Tree Composition

The branch enumeration is explained by the network illustrated in Figure 2, in which the origin-link traffic volume that entered at origin O1 is considered. The possible destinations of the traffic generated at O1 are D2, D3, and D4. The number of possible paths to each destination is one (link 1) for D2, two (link 2 and links 1-3) for D3, and three (links 1-4, links 2-5, and links 1-3-5) for D4. These six paths can be integrated into the tree diagram shown in Figure 3.

By integrating the paths into tree diagrams, each branch becomes similar to a linear network. We then find branches that share a common link with other trees. In Figure 3, trees 2 and 3 share link 1, and trees 1 and 2 share link 5. The next step is to determine whether the previous links used to reach the shared links from the origin are the same. From origin O1 to link 1, trees 2 and 3 are the same; on the other hand, trees 1 and 2 have different routes from the origin to link 5. Additional origin-specific link traffic volumes are prepared for the links that are shared between several trees, where the previous links for each tree are different. In the case of Figure 3, link 5 meets this condition. Finally, links 1-4 need only one origin-specific link variable, but link 5 needs two variables. In the calculations, the path enumeration is executed first, and then the dynamic link use ratio is calculated for each path. Additional origin-specific link traffic volumes are added if there are different values for the dynamic link use ratios on the same link. Even though this method appears complicated, preparing the unknown origin-specific link traffic volumes is quite easy if the possible paths are enumerated.

This procedure provides a very useful characteristic. From the travel time for each link, we can easily calculate how much a vehicle from an origin running on one specific path may affect one link. Therefore y_{iaps} can be regarded as the origin-path-specific link traffic volume, and the path traffic volume can be calculated without making any assumptions for the path use ratio.

3.1.3 Input Variables

The DCLS-NNC model requires two coefficients: the dynamic link use ratio and prior probability.

The *dynamic link use ratio*, q_{iapst}, is defined as the proportion of the traffic generated at origin i during time interval s and on link a during time interval t, corresponding to the p^{th} branch. The link use ratio can be calculated dynamically from the moving locus of cars for a specific path on a time-space diagram. Here, we make the following two assumptions to simplify the calculations:

(A.1) vehicles that enter a link are uniformly distributed for a period of one time interval, which is short enough that the vehicles do not traverse the entire link,
(A.2) vehicles are running with an observed average velocity at each link, and this velocity is maintained for a period of one time interval.

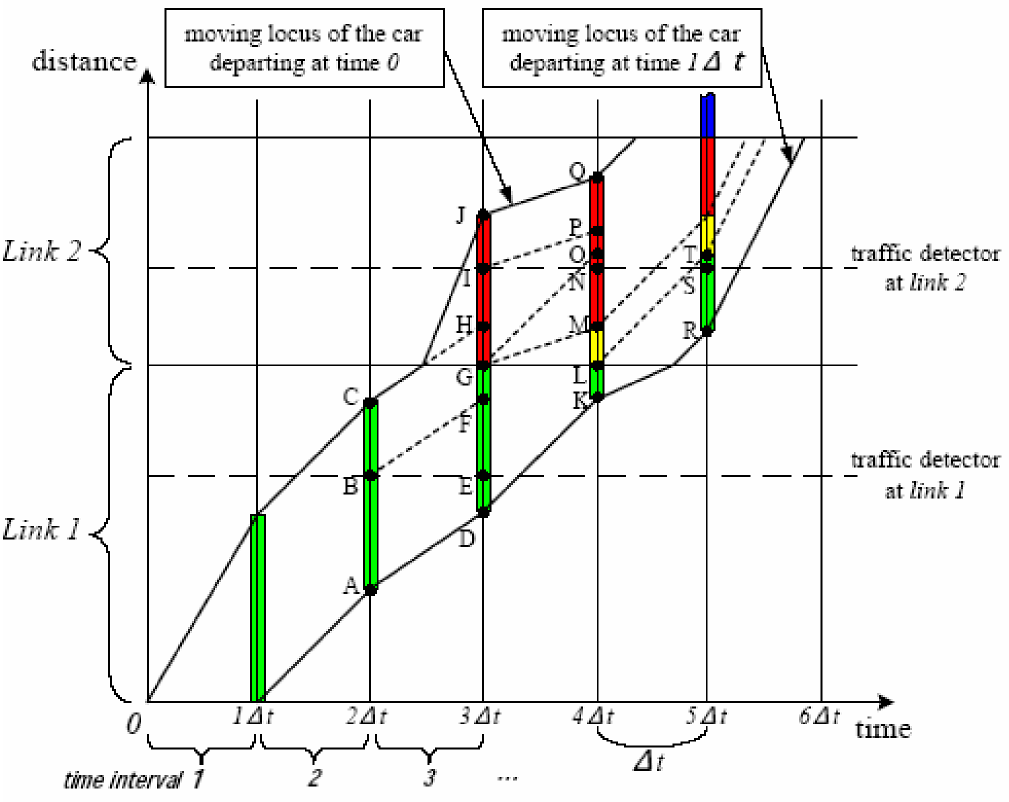


Figure 4. Moving Locus of Cars

Figure 4 illustrates a time-space diagram for a moving locus of cars based on the above assumptions. To explore the methodology, let us consider the traffic that was generated during the first time interval. During time interval 3, all of these cars are assumed to run with the velocity that was observed at point B. This can be expressed as follows:

$$\overline{BF} \,//\, \overline{CH} \,//\, \overline{AD} \tag{13}$$

where // represents a parallel relationship in the graph.

Because at time interval 4, the velocity on link 2 is larger than that on link 1, a proportion of the vehicles ($\overline{GH}/\overline{HD}$) disperse to $\overline{GJ}$. Therefore, the vehicles that departed during time interval 1 are divided into two groups. Also, at the end of time interval 3, the following relationship must hold:

$$\overline{DK} \,//\, \overline{GN} \tag{14}$$

$$\overline{IP} \,//\, \overline{JQ} \,//\, \overline{GM} \tag{15}$$

According the above, the ratio of traffic generated at origin i during time interval 1 and observed at link 1 during time interval 2, q_{i1p12}, can be expressed as follows:

$$q_{i1p12} = \frac{\overline{BC}}{\overline{AC}} \tag{16}$$

The link use ratio for link 1 during time interval 3, q_{i1p13}, is the ratio of traffic that traverses below the traffic detector for link 1 at time interval 3,

$$q_{i1p13} = \frac{\overline{AB}}{\overline{AC}} \cdot \frac{\overline{EF}}{\overline{DF}} \tag{17}$$

Similarly, the link use ratio for link 2 at the same time interval, q_{i2p13}, is

$$q_{i2p13} = \frac{\overline{BC}}{\overline{AC}} \cdot \frac{\overline{GH}}{\overline{FH}} \cdot \frac{\overline{IJ}}{\overline{GJ}} \tag{18}$$

All of the required dynamic link use ratios can be calculated using this method. The *prior probability*, g_{iaps}, refers to the origin-path-specific traffic volume, as compared to the trip generation variables. The prior probability is calculated simply from estimates made for the former time interval. The latest n estimates are calculated as follows:

$$g_{iaps} = \frac{\sum_{k=S_{t-1}-(n-1)}^{S_{t-1}} \frac{\hat{y}_{iapk}}{\hat{O}_{ik}}}{n} \tag{19}$$

where $S_{t\text{-}1}$ is the most current time interval during which $\hat{y}_{iaps}$ and $\hat{O}_{is}$ are estimated.

3.1.4 Characteristics and problems of the DCLS-NNC model

The DCLS-NNC model employs a sequential estimation technique so that it can be used online. Another advantage of the DCLS-NNC model is that there is no need to predetermine the link use ratio. This characteristic enables us to explore changes in the path traffic volumes. The results of the origin-path-specific link traffic volume estimates are useful for practical applications.

According to the first constraint, however, the observed trip generation volume must be equal to the sum of the estimated origin-path-specific link traffic volume leading out of the origin. Because of this strict condition, the model can only be used in a network, such as an urban expressway network, where the trip generation is easily observed. In addition, this model requires the link traffic volume, link travel time, and trip generation volume as inputs. These restrictions prevent the model from being applied to networks without trip generation observations, such as general surface road networks. The model limitations should be relaxed so that it can be applied to practical situations.

3.2 DCLS-TGV model

3.2.1 Formulation

The DCLS-TGV model is an improved version of the DCLS-NNC model. Observation errors are permitted for the trip generation because the constraints have been relaxed. The DCLS-TGV model estimates not only the origin-path-specific link traffic volume, y_{iaps}, using the same concept as the DCLS-NNC model, but also the trip generations, O_{is}. It can be formulated as follows:

min

$$\sum_{a \in A_{ot}} \left\{ \begin{array}{l} [\sum_{p=1}^{P_{ia}} \sum_{i \in I} \sum_{s=1}^{t} (\delta_{iaps} \cdot q_{iapst} \cdot y_{iaps} + (1-\delta_{iaps}) \cdot q_{iapst} \cdot \hat{y}_{iaps}) - v_{at}^{*}]^2 \\ \qquad + \sum_{p=1}^{P_{ia}} \sum_{i \in I} \sum_{s=1}^{t} \delta_{iaps} \cdot (y_{iaps} - O_{is} g_{iaps})^2 \end{array} \right\} \quad (7)$$

$$+ \sum_{i \in I^*} \sum_{s=1}^{t} (O_{is} - O_{is}^{*})^2$$

subject to

$$\sum_{a \in A_{out}^{i}} y_{iaps} = O_{is} \quad \text{for all } i \in I, s(1 \le s \le t) \quad (8)$$

$$\sum_{a \in A_{in}^{n}} y_{iaps} = \sum_{a \in A_{out}^{n}} y_{iaps} \quad \text{for all } i \in I, n \in \{N - N^{off}\}, p(1 \le p \le P_{ia}), s = \{s \mid 1 \le s \le t\} \quad (9)$$

$$\sum_{a \in A_{in}^{n}} y_{iaps} \ge \sum_{a \in A_{out}^{n}} y_{iaps} \quad \text{for all } i \in I, n \in N^{off}, p(1 \le p \le P_{ia}), s = \{s \mid 1 \le s \le t\} \quad (10)$$

$$y_{iaps} \ge 0 \quad \text{for all } i \in I, a \in A, p(1 \le p \le P_{ia}), s = \{s \mid 1 \le s \le t\} \quad (11)$$

$$O_{is} \ge 0 \quad \text{for all } i \in I, s = \{s \mid 1 \le s \le t\} \quad (12)$$

where

δ_{iaps} : binary variable that is 0 if y_{iaps} is estimated from the time interval t; and 1 otherwise,

O_{is} : traffic volumes generated at origin i during time interval s,

I^* : set of origins over which a trip generation is observed,

N : set of nodes,

N^{off} : set of nodes with traffic concentration,

A^{n}_{in} : set of links leading into node n,

A^{n}_{out} : set of links leading out of node n,

$\hat{y}_{iaps}$: estimates of y_{iaps}.

3.2.2 Characteristics of the DCLS-TGV model

The DCLS-TGV model has all of the advantages of the DCLS-NNC model. It does not require a path use ratio in advance, and it can perform a multi-path online estimation using any time interval. The model can estimate the path-specific traffic volume, and it can explore the change in the quality of the network traffic volume, such as path choice probability. In addition, because trip generations are treated as unknown variables, the proposed model can be applied to surface road networks where it is difficult to observe the traffic volume. The observed trip generation traffic can be either utilized or neglected, depending on its accuracy.

3.3 Solution algorithms

The model uses a least squares estimator with linear equality and inequality constraints, which guarantees global optimal solutions. The active set method (Gill *et al.*, 1989) is applied to obtain an optimal solution. If the active constraints are known in advance, the problem can be treated as a non-constrained quadratic programming problem. The first part of the algorithm forecasts the set of active constraints (*i.e.*, variables with zeros), and the unconstrained optimization problem is solved using the other variables and Newton's method. If the solution set is optimal, all of the variables must satisfy the Kuhn-Tucker constraints. The variables within the active set that do not satisfy the Kuhn-Tucker conditions are removed from the active set, and the variables outside the active set that satisfy the conditions are inserted into the active set. The unconstrained optimization problem is then solved using the updated active set of variables. This iteration procedure continues until all of the variables satisfy the Kuhn-Tucker conditions.

4 Application to hypothetical networks

In this section, the DCLS-TGV model is applied to hypothetical networks to determine its accuracy and performance. These hypothetical networks consist of a linear network with a single path between OD pairs, and a multi-path network with several paths between OD pairs.

4.1 Linear network

4.1.1 Data

This network consisted of three links and four nodes with two origins and three destinations (Figure 5). The lengths of links were 10, 15, and 5 km, respectively, and the time interval between observations was set to 5 minutes. First, hypothetical OD traffic volumes were created from random numbers. These were regarded as true traffic volumes. The link travel time was assumed to be a function of the link traffic volume. Assumption (A.2) was strictly satisfied here. The true values of the link traffic volumes were then calculated using the link travel time function, assumption (A.2), and OD traffic volumes. The dynamic link use ratios, q_{iapst}, and prior probabilities, g_{iaps}, were calculated using these data. Origin and link traffic volumes that included some observation errors were also prepared to explore the effect of these errors on the accuracy of the model estimates. Observed traffic volumes with errors were created by adding a normal random error with a mean of zero and a variance of ε % to the true traffic volume. Four values were used for ε: 3, 5, 10, and 15.

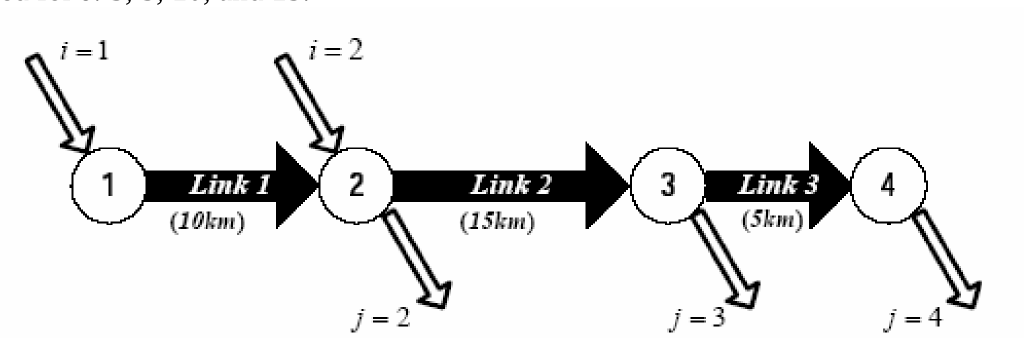


Figure 5. Hypothetical Linear Network

4.1.2 Estimation results

We first estimated the OD traffic volume using accurate values of the link traffic volume, without any observation errors, to determine the maximum performance of the DCLS-TGV model. Most of the estimated OD traffic volumes corresponded to the true OD traffic volumes. Figure 6 shows the results for one of the longest OD pairs, OD(1,4). The proposed model estimated the OD traffic volumes very accurately.

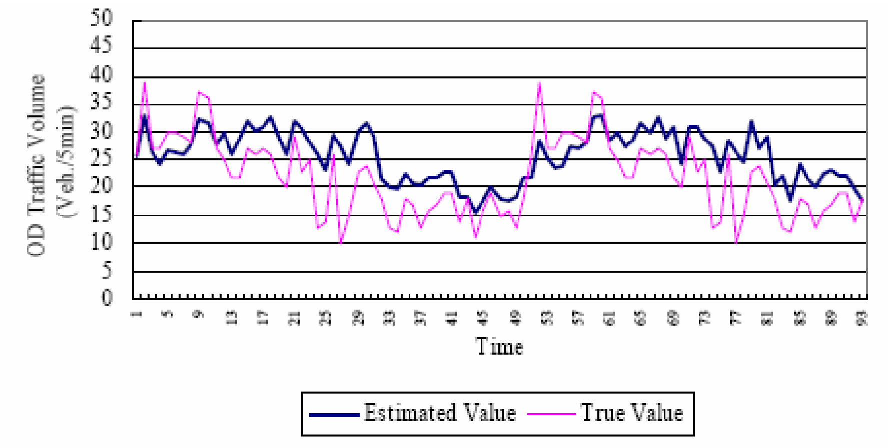


Figure 6. Transition of the Estimates of the OD Traffic Volume (1,4)

The OD traffic volumes with observation errors were estimated with both the DCLS-TGV and DCLS-NNC models. The results are compared in Figure 7. A root mean square normalized (RMSN) value was used to compare the accuracy of the estimates. From Figure 7, the DCLS-NNC model was slightly more accurate than the DCLS-TGV model when the variance of the observation error was either 0 or 3%. This is because the DCLS-NNC model does not assume an observation error for the trip generation; this assumption is suitable for observations with small errors. However, the DCLS-TGV model gave more accurate estimates as the variance of the observation error increased. Thus we can conclude that the observation errors generally reduced the accuracy of the estimates, but the effect was smaller in the DCLS-TGV model, as compared to the previous DCLS-NNC model.

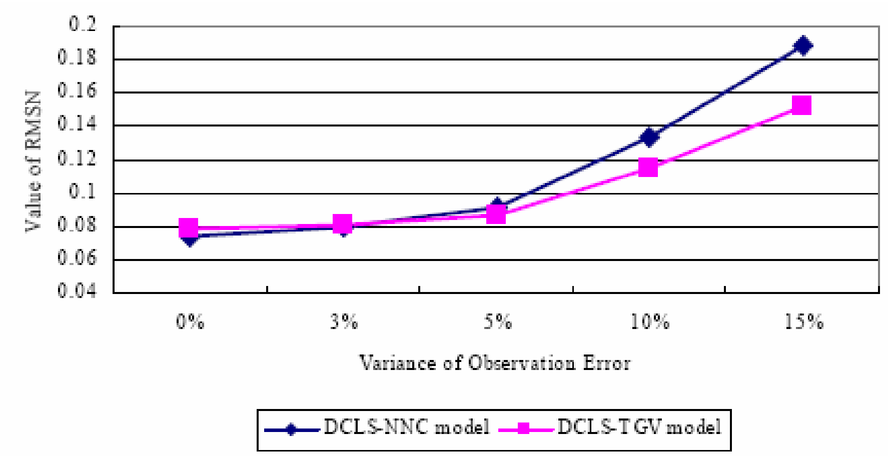


Figure 7. Estimation Accuracy of the Models using Data with Observation Errors

The most striking difference between the DCLS-TGV and DCLS-NNC models is that the volume of trip generations can be used either as known or unknown variables. This implies that the model can be applied to situations where we cannot observe trip generations, or where the observation errors are huge and the data are unreliable. Figure 8 compares the results obtained when the observed trip generation volumes with observation errors are either used or discarded. In this example, the observed link traffic volumes were assumed to not have any errors, so that the results illustrated only the effects of the observation errors on the traffic generation volumes. The estimation results show that the trip generation observations should be ignored when the data observation error is greater than 7%.

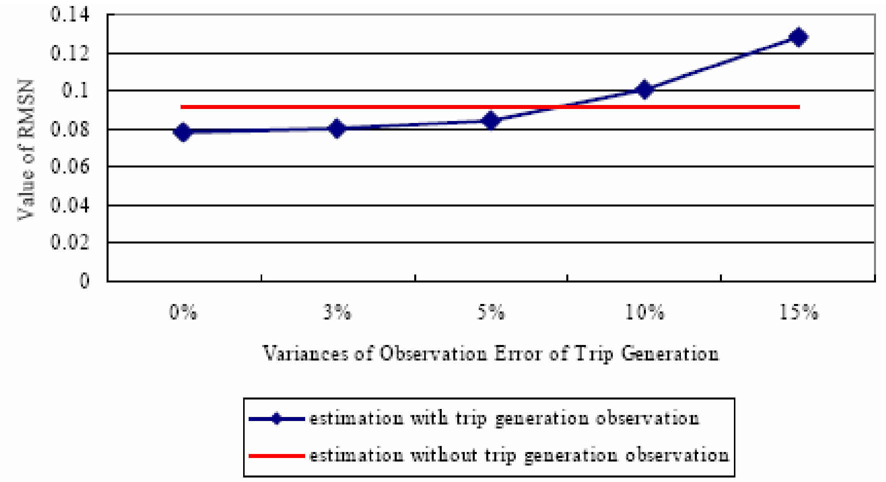


Figure 8. Estimation Results with and without Trip Generation Observations

4.2 Multi-path network

4.2.1 Data

The DCLS-TGV model was also applied to the hypothetical multi-path network shown in Figure 9. This network had 6 OD pairs and 10 paths. The data required for the estimates were obtained from the simulation model proposed by Uno *et al*. (2001). In this simulation model, the link lengths were set to 3, 6, 2, 6, and 3 km, respectively. Because the DCLS-TGV utilizes observed (or estimated) velocities to calculate the dynamic link use ratio, the estimation results were influenced by the locations of the traffic counters. To evaluate these effects, the link traffic volumes and velocities were collected at the head, middle, or tail of each link. To consider the dynamic changes of traffic flow according to the traffic conditions, we assumed that 50 percent of the drivers used travel time information to change their path.

4.2.2 Estimation results

The RMSN values in the multi-path network were higher than those obtained for the previous case, but overall the DCLS-TGV model estimates were generally accurate. The observed traffic volumes and velocities differed, according to locations of the traffic counters. To relate this effect to the accuracy of the estimates, the RMSN values for data obtained using three different observation locations are shown in Figure 10. The results indicated that the locations of traffic counters had a big influence on the estimation results, and that the model worked the best when the traffic counter data was located in the middle of each link.

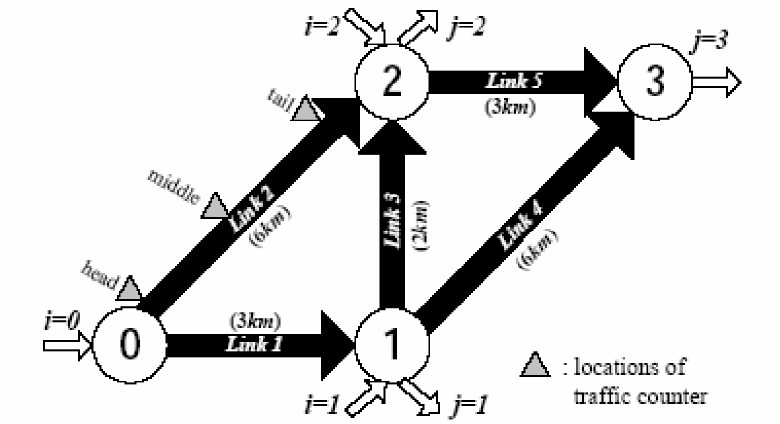


Figure 9. Hypothetical Multi-Path Network

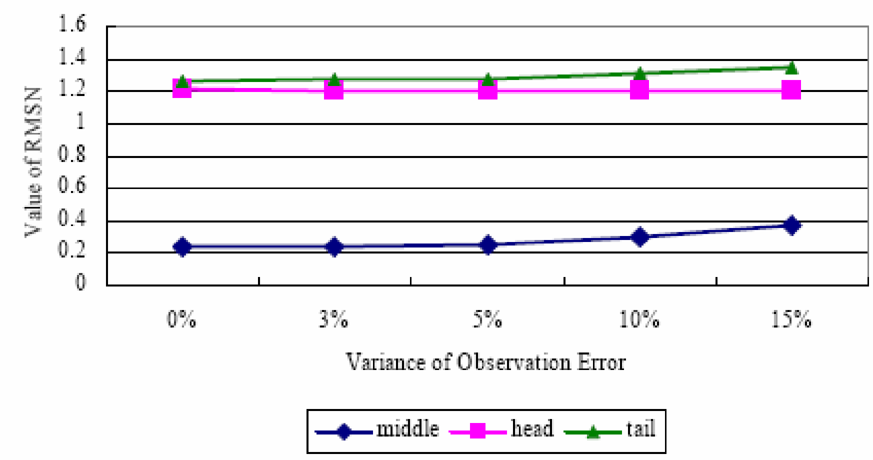


Figure 10. Effect of the Traffic Counter Location on the Estimation Accuracy

According to recent developments in traffic data collection techniques, probe car data should also be considered because the accuracy of these data may be greater than the accuracy of roadside observations. The previous paragraph indicated that the accuracy of the model estimates varied according to the location of the traffic counters. Therefore, velocity data obtained from probe cars were also used to calculate the dynamic link use ratio. Here, six cases were considered, with 100%, 50%, 25%, 12.5%, 6.25% and 3.125% probe cars on the network. The velocity for each link was calculated from the probe car data. The estimation results for each case are compared to each other in Figure 11.

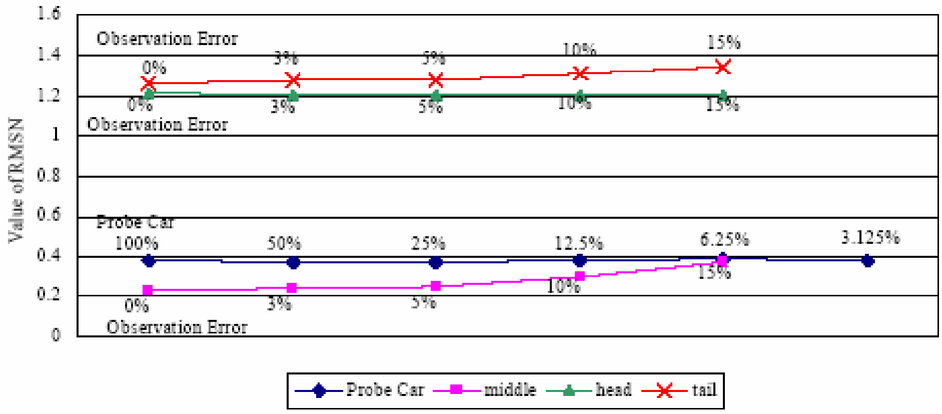


Figure 11. Estimation Results for Probe Car and Traffic Counter Data

Figure 11 shows that the estimates obtained using observed data, with the traffic counter located in the middle of each link, are better than the estimates made using probe car data. However, if we use probe car data, the effect of the traffic counter location can be avoided, producing stable estimates.

5 Application to a real world network

The DCLS-TGV model was applied to a portion of the Hanshin Expressway network, and the resulting estimates were compared to a questionnaire survey conducted for the 20th Survey of Origin and Destination in 1994. The section between the Tsukimiyama on-ramp and the Mukogawa off-ramp on the Kobe Route of the Hanshin Expressway, shown in Figure 12, was selected as the research area. The Hanshin Expressway is an access-restricted elevated roadway, with traffic detectors located between ramps. The length of the entire research area was about 27.5 km, and it contained 10 on-ramps and 9 off-ramps.

The OD traffic volume estimation was performed using the link traffic volume and link velocity from the traffic detectors. The 20th Survey of Origin and Destination was performed over a 24-hour period between Tuesday, 1st November, 1994, 7:00 A.M. and Wednesday, 2nd November, 1994, 7:00 A.M. The results of this survey were aggregated and multiplied to obtain unbiased OD traffic volumes between the on- and off-ramps. The observed link and on-ramp traffic volumes and the observed link velocities were also collected on the same day to estimate the dynamic OD traffic volume. The surveyed OD traffic volume was only an estimate; we do not know the true traffic volume. However, if the proposed model obtains results that are similar to the surveyed OD traffic volume, our level of confidence in the model estimates will improve.

For simplicity, the results of the OD traffic volume estimates were aggregated into the blocks shown in Figure 12. There are five origin-blocks between A and E, and five destination-blocks between B and F. The relationship between the estimated and surveyed OD traffic volumes is shown in Figure 13.

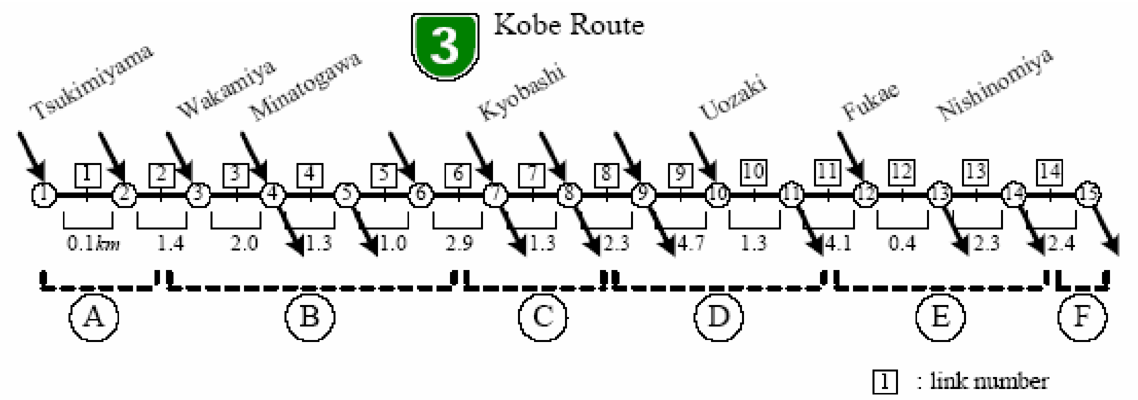
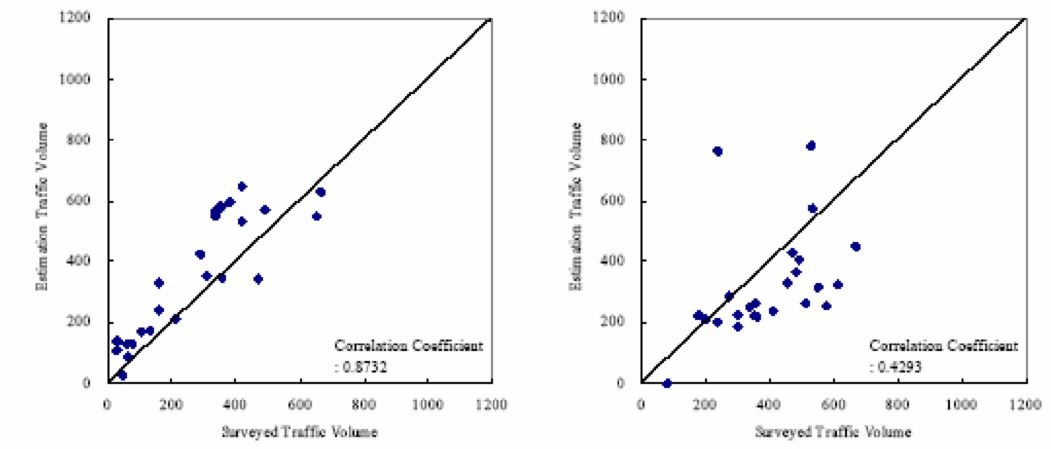


Figure 12. Research Area



(a) OD(A,B) **(b) OD(A,F)**

Figure 13. Relationship between the Estimated and Surveyed OD Traffic Volumes

Link OD(A,B), shown in Figure 13(a), is the shortest OD pair section, and link OD(A,F), shown in Figure 13(b), is the longest OD pair section in the research area. Link OD(A,B) was more accurately estimated, and the value of the correlation coefficient, 0.8732, suggests a high correlation between the estimated and surveyed values. In contrast, the surveyed OD traffic volumes on link OD(A,F) were generally larger than the estimated values, and the correlation coefficient was low. All correlation coefficient values between the blocks are shown in Table 1.

Table 1. Correlation Coefficients between the Estimated and Surveyed OD Traffic Volumes

OD pair	AB	AC	AD	AE	AF	BD	BE
Correlation Coefficient	0.8732	0.812	0.7789	0.5694	0.4293	0.7794	0.7686
OD pair	BF	CE	CF	DE	DF	EF	
Correlation Coefficient	0.4898	0.6615	0.7754	0.7409	0.8321	0.9273	

According to Table 1, the OD pairs that span long distances, such as OD(A,F) and OD(B,F), have low correlation values. The rest of the OD pairs had high correlations between the estimated and observed data. There are several possible reasons for this result. First, the surveyed OD traffic volumes were estimated from a mail-back survey, and thus do not always express the traffic flow accurately. The effect of time lag is another reason. In this study, the prior probability was calculated from the latest estimated results over a 30-minute interval. Thus, if the travel time between one OD pair was 30 minutes, estimates during an interval of up to 60 minutes before were used for the prior probability calculations. As the distance between the OD pair increased, the values used for calculating the prior probability could differ from the actual values. To reduce the effects of this problem, the prior probability could also be calculated from data obtained on prior days, during the same time interval.

Although some modifications to the model are still required in order to obtain more accurate estimates, especially for long distance OD pairs, the results of this study generally support the efficiency and practicability of the proposed model.

6 Summary and further studies

In this paper, we proposed a dynamic OD estimation DCLS-TGV model that can estimate dynamic path-specific origin/destination traffic volumes and that does not require predetermined path choice ratios. Due to the robust structure of the model, it permits rather large observation errors. The model can also be applied to networks where the trip generation volumes are unknown, because both the path-specific origin/destination traffic flows and trip generations are used as unknown variables.

The characteristics and performance of the model were verified using two hypothetical network case studies. The results demonstrated that the DCLS-TGV model provided more accurate estimates than the previous DCLS-NNC model, with increasing observation errors of the traffic volume data. Since the model also estimated trip generation volumes, the observed trip generation data could be ignored if the observation errors were large. The estimation accuracy changed according to the locations of the traffic counters, and the data suggested that the most accurate results were obtained when the traffic counters were located in the middle of each link. The estimation results utilizing velocity data from probe cars supported the accuracy and efficiency of the model when using data obtained from traffic counters located in the middle of the links.

For the purpose of confirming the practicality of the proposed model, it was applied to a part of the Hanshin Expressway network. The results were compared with those obtained from an origin and destination questionnaire survey. Although the estimation accuracy worsened as the OD distance became longer, the estimation results were generally acceptable.

The series of DCLS models proposed by the authors utilize variable data as much as possible. In this study, the traffic flow was estimated using probe car data. More case studies utilizing probe car data are required, including calculations of the prior probability of origin-path-specific link traffic volume based on this data. The model was applied to an urban expressway network in this study, but applications to more complex networks, such as a general surface road network, should also be considered. In addition, further improvements to the DCLS-TGV model are also possible. For example, the model consists of linear equality and inequality constraints. The inequality constraints can be replaced by equality constraints, thereby simplifying the model formulation.

Acknowledgments

We are indebted to the Hanshin Expressway Public Corporation for providing the traffic data. The hypothetical traffic data for the multi-path network were created by the simulator developed by Dr. Nobuhiro Uno (Kyoto University) and Mr. Yoshisada Hamada (West Japan Railway Company). We would like to thank them for their support.

References

Cascetta, E., Inaudi, D., and Marquis, G., 1993. Dynamic Estimators of Origin-Destination Matrices Using Traffic Counts, Transportation Science, 27(4) 363-373.

Cremer, M. and Keller, H., 1987. A New Class of Dynamic Methods for the Identification of Origin-Destination Flows, Transportation. Res. –B, 21B, pp. 117-132.

Dial, R. B. 1971. A Probabilistic Multipath Traffic Assignment Algorithm Which Obviates Path Enumeration, Transportation Research 5, 83-111.

Gill, P. E., Murray, W., Saunders, M.A., and Wright, M.H., 1989. Sequential quadratic programming methods. In, Optimization (Nemhauser, G.L, Rinnooy Kan, A.H.G, Todd, M.J. Eds.) North-Holland, pp. 186-208.

Hanshin Expressway Public Corporation, 1994. The 20th Origin-Destination Survey on Hanshin Expressway.

Iida, Y. and Takayama, J., 1986. Comparative Study of Model Formulations on OD Matrix Estimation from Observed Link Flows, Proceedings of 4th World Conference on Transportation Research, 2, 1570-1581.

Kurauchi, F., Iida, Y., and Aizawa, T., 2000. An Evaluation of Effect of Travel Time Information from Real-Time Origin-Destination Matrices Estimation Model, Proceedings of the 7th Conference on Intelligent Transport Systems, CD-ROM.

Kurauchi, F., Iida, Y., Aizawa, T., and Li, L., 1999. A Method for Estimation Dynamic Origin-Destination Matrices from Traffic Counts on Urban Expressways, Transportation and Traffic Theory (Abbreviated Presentation Sessions), pp. 205-230.

Oneyama, H. and Kuwahara, M., 1997. Estimation of Time Department OD Matrices from Traffic Counts, Traffic Engineering, 32 (2) 5-16 (in Japanese).

Uno, N., Iida, Y., and Hamada, Y., 2001. A Meso Traffic Simulation Model to Evaluate Control Strategy for Urban Expressway, Proceedings of the 9th World Conference on Transport Research, CD-ROM.

Willumsen, L. G., 1984. Estimating Time-Dependent Trip Matrices from Traffic Counts, Ninth International Symposium on Transportation and Traffic Theory, VNU Science Press, pp. 397-411.