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ESTIMATION OF PATH FLOWS AND MODIFICATION OF O-D FLOWS BASED ON PROBE VEHICLE INFORMATION AND TRAFFIC COUNTS

Yukimasa MATSUMOTO
Associate Professor
Department of Civil Engineering
Meijo University
1-501, Shiogamaguchi, Tenpaku-ku,
Nagoya, 468-8502 Japan
Tel: +81-52-832-1151,
Fax: +81-52-832-1178,
E-mail: matumoto@civil.meijo-u.ac.jp

Yosuke HORIBA
Graduate Student
Department of Civil Engineering
Meijo University
1-501, Shiogamaguchi, Tenpaku-ku,
Nagoya, 468-8502 Japan
Tel: +81-52-832-1151,
Fax: +81-52-832-1178,
E-mail: m0437012@ccmailg.meijo-u.ac.jp

Motohiro FUJITA
Associate Professor
Graduate School of Engineering
Nagoya Institute of Technology
Gokiso-cho, Showa-ku, Nagoya,
466-8555 Japan
Tel: +81-52-735-5492
Fax: +81-52-735-5492
E-mail: fujita@doboku2.ace.nitech.ac.jp

Hiroshi MATSUI
Professor
Department of Civil Engineering
Meijo University
1-501, Shiogamaguchi, Tenpaku-ku,
Nagoya, 468-8502 Japan
Tel: +81-52-832-1151,
Fax: +81-52-832-1178,
E-mail: hmatsui@ccmfs.meijo-u.ac.jp

Abstract: A model for estimating path flows and modifying O-D flows simultaneously is proposed, in which probe vehicle information and traffic counts are used. The probe vehicle information is accumulated to obtain prior information on path proportions. The link traffic counts are used as sectional volume information of links. The proposed model is constructed as a two stage model. The first stage model is estimation model of path flows and the second stage model is modification model of O-D flows. The proposed model was applied to the Sioux Falls network. As a result, the accuracy of estimated path flows changed in proportion with a ratio of probe vehicles. Moreover, it was clarified that the proposed two stage model had enough ability to estimate path flows and to modify O-D flows accurately even when prior O-D flows had inconsistency with the current traffic conditions.

Key Words: path flow, O-D flow, probe vehicle

1. INTRODUCTION

Path flows are essential sources for traffic operation such as a vehicle navigation system and provision of travel time information, as well as for transportation planning. It is, moreover, the most critical task for traffic operators and transportation planners to obtain path flows on practical work so that precisely estimated path flows are highly required in order to tackle traffic problems such as traffic congestion, traffic accidents and so forth.

In situations where a large number of vehicle detectors are located widely on road networks, estimation of network flows from traffic counts has attracted attention of researchers. It is also indispensable for traffic operation to grasp O-D (Origin-Destination) flows as well as path flows. So far, various methods for estimating O-D flows from traffic counts have been proposed. Cascetta and Ngyuyen (1988) comprehensively reviewed these estimation methods.

Many of these methods can be suitable for estimation of O-D flows only when estimated O-D flows are similar to prior O-D flows. Bell (1991) has shown the Generalized Least Squares (GLS) approach with inequality constraints for estimation of O-D matrices from traffic counts and Yang *et al*. (1992) have examined an equilibrium based O-D matrix estimation problem. These models concentrated the estimation of O-D flows rather than path flows so that path choice behavior of drivers has to be presumed to follow the user equilibrium principle or a constant path choice proportion given in advance.

In terms of path flows, Bell *et al*. (1997) proposed a path flow estimator in which a path choice proportion was determined by the stochastic user equilibrium principle. Matsumoto *et al*. (1999) also proposed a recursive estimation model of path flows for the use of on-line traffic control. Nie *et al*. (2005) has developed equilibrium based trip matrix estimation combined with a decoupled path flow estimator. However, these models cannot reflect actual path choice behavior of drivers.

Probe vehicle information seems to be practical for collecting data on actual path choice behavior of drivers as well as for real-time traffic operation, incident detection and route guidance application. In Japan, some experiments, in which probe vehicles run on a road network, have recently been conducted so that the probe vehicle information will soon be available widely and used easily in order to estimate traffic conditions even for practical work. Since this probe vehicle information also directly reflects the actual path choice behavior of drivers on a road network, the estimates of path flows with the probe vehicle information are able to reflect the actual traffic conditions.

In this paper, a model for estimating path flows and modifying O-D flows simultaneously is proposed, in which the probe vehicle information and traffic counts are used. The probe vehicle information is accumulated to calculate prior information on the actual path choice behavior of drivers, and traffic counts are used as volume information on links of a network. The proposed model is, therefore, able to estimate the path flows which reflect the actual path choice behavior of drivers and traffic conditions.

The feature of the proposed model is to estimate path flows and modify O-D flows simultaneously. Hence, the proposed model is suitable for the conditions where observed link traffic counts and prior O-D flows are inconsistent. Another feature is that the proposed model regards the calculated path proportions from the probe vehicle information and the observed link traffic counts as probabilistic variables. Therefore, the path proportions and traffic counts are allowed to have some errors such as measurement errors or errors arisen by the time lag between observation dates of the data. This means that this proposed model is capable of estimating path flows even when there is inconsistency among O-D flows, actual path choice behavior of drivers and link traffic counts. Furthermore, the proposed model is applicable to the situation where traffic conditions change because the O-D flows can be modified in the proposed model.

The proposed estimation and modification model is constructed as a two-stage problem. The first stage problem is to estimate path flows based on prior O-D flows, in which probabilities of simultaneous occurrence on path flows and link flows are coincidentally maximized. In the first stage, the prior O-D flows, the path proportions and the link traffic counts are regarded as reliable values for estimating accurate path flows. However, these observations are also treated as probabilistic variables so that the proposed model can estimate path flows even when these observation values are inconsistent.

The second stage problem is to modify O-D flows based on errors of link flows between observations and estimations calculated with the estimated path flows. This is based on the concept that the current link traffic counts and the current probe vehicle information are easily available even in real world while it is impossible to obtain the current O-D flows without efforts. Hence, the errors of link traffic counts between observations and estimations are arisen by the inconsistent O-D flows so that the prior O-D flows should be modified by the model.

2. MODEL FORMULATION FOR ESTIMATING PATH FLOWS AND MODIFYING O-D FLOWS

2.1 Model for estimating path flows (First stage)

A model for estimating path flows using probe vehicle information and traffic counts is constructed as a mathematical programming, in which a probability of simultaneous occurrence on path flows is maximized. In this model, prior probabilities of each path flow are calculated from accumulation of data on probe vehicles running a road network. This model doesn't need any assumptions on path choice behavior of drivers such as the user equilibrium principle or the stochastic user equilibrium principle. Consequently, the estimates of path flows are able to directly reflect the actual path choice behavior of drivers as long as a high ratio of the probe vehicle is obtained.

First, the following notations are introduced:

q_{ij} : the O-D flow from origin i to destination j,
h_{ijk} : the path flow on path k between origin i and destination j,
p_{ijk} : the path proportion, i.e. the proportion of the path flow on path k to the O-D flow q_{ij},
V : the total link flow on the network,
v_l : the link flow on link l,
γ_l : the link proportion on link l, i.e. the proportion of the link flow on link l to the total link flow V.

The above variables are interconnected by the following fundamental relations:

$$q_{ij} = \sum_k h_{ijk} , \tag{1}$$

$$V = \sum_l v_l , \tag{2}$$

$$p_{ijk} = \frac{h_{ijk}}{q_{ij}} , \tag{3}$$

$$\gamma_l = \frac{v_l}{V} . \tag{4}$$

When the O-D flows are given, the probability of simultaneous occurrence on path flows is expressed as follow:

$$\max \quad \prod_i \prod_j \frac{\hat{q}_{ij}!}{\prod_k h_{ijk}!} \prod_k (\hat{p}_{ijk})^{h_{ijk}} . \tag{5}$$

The sign of ^ denotes that the variable with this sign is observed or obtained in advance. In

eqn (5), the prior path proportion is also assumed to be obtained from the probe vehicle information. Therefore, the prior path proportion inherently includes an error in inverse proportion to the ratio of probe vehicles to all vehicles running on the network.

There is a fundamental relationship on link flows, in which the link flow calculated with the estimated path flows may be equal to an observed link traffic count $\hat{v}_l$. Hence, the following relationship should be established.

$$\hat{v}_l = \sum_i \sum_j \sum_k \delta_{ijk}^l h_{ijk} \ , \tag{6}$$

where δ_{ijk}^l is equal to 1 if link l is on path k connecting origin i and destination j, and 0 otherwise. This static relationship only holds when traffic conditions are regarded as a steady state so that the time difference between generation of trips and observation at links is negligible. In order to introduce this static relationship to the model, a time period has to be long enough. Although time period depends on the size of a network, a day (24 hours) seems to be suitable for general conditions.

Zuylen and Willumusen (1980) and Willumsen (1984) have addressed the same problem and formulated an entropy maximizing model and an information minimizing model for estimating O-D matrices. However, in the real world, the observed link traffic counts must include measurement errors, and vary because of a day to day change of traffic conditions. The inconsistency arisen form the given path proportions and the link traffic counts may lead the path flow estimation problem with eqns (5) and (6) to an infeasible problem. Thus, link traffic counts should be regarded as probabilistic variables rather than deterministic values so that the probability of simultaneous occurrence on link flows should be also introduced to the proposed model. The probability of simultaneous occurrence on link flows is also formulated as follow:

$$\frac{\hat{V}!}{\prod_l v_l!} \prod_l (\hat{\gamma}_l)^{v_l} \ . \tag{7}$$

In eqn (7), $\hat{V}$ and $\hat{\gamma}_l$ are calculated by eqns (2) and (4) respectively with the observed link traffic count $\hat{v}_l$. By introducing eqn (7) to the estimation model, link flows are allowed to vary according to changes of traffic conditions and also estimated simultaneously when the path flows are estimated.

Finally, the estimation model of path flows is formulated as the following mathematical programming to maximize the probability of simultaneous occurrence on path flows and link flows with some equality constraints.

$$\max \quad \left[\prod_i \prod_j \frac{\hat{q}_{ij}!}{\prod_k h_{ijk}!} \prod_k (\hat{p}_{ijk})^{h_{ijk}} \right]^{\alpha} \left[\frac{\hat{V}!}{\prod_l v_l!} \prod_l (\hat{\gamma}_l)^{v_l} \right]^{\beta}, \tag{8}$$

$$\text{subject to} \quad \hat{q}_{ij} = \sum_k h_{ijk},$$

$$\hat{V} = \sum_l v_l,$$

$$v_l = \sum_i \sum_j \sum_k \delta_{ijk}^l h_{ijk},$$

where α and β are parameters to weight each probability of simultaneous occurrence. The path proportion is obtained from probe vehicle information and the link proportion is calculated by the observed link traffic counts as the following:

$$\hat{\gamma}_l = \frac{\hat{v}_l}{\sum_l \hat{v}_l}. \tag{9}$$

Oneyama *et al*. (1997) also formulated an estimation model for time dependent O-D matrices from traffic counts based on the same concept of this model. The accuracy of the estimated O-D flows by this model depends on the prior O-D flows. If the current condition doesn't change from the condition when the prior O-D flows were observed, the model seems to estimate path flows accurately. However, in general, it is difficult to obtain appropriate prior O-D flows in real world. Therefore, in this paper, the prior O-D flows are modified according to the current traffic conditions. The model for modifying prior O-D flows is explained as the following chapter.

2.2 Model for modifying prior O-D flows (Second stage)

In general, prior O-D flows have differences from the current O-D flows, which are actually unknown and tried to estimate, because traffic conditions change. It is easier to observe the current link flows and probe vehicles than to obtain appropriate prior O-D flows. Therefore, the model to modify the prior O-D flows is formulated here.

The prior O-D flows are modified based on the differences between link traffic counts and estimated link flows because link traffic counts and path proportions are more accurate than the prior O-D flows. Kitaoka *et al*. (2002), Kato *et al*. (2003) and Murakami *et al*. (2004) proposed a modification method of O-D flows respectively by a simulation model, in which errors of link flows are minimized. However, these methods don't use the path proportions which describe relationship between link flows and O-D flows and seem to be effective to obtain an optimal solution. In the proposed model, the modification model of the prior O-D flows is constructed, in which the errors of link flows are minimized using the path proportions calculated from the probe vehicle information. This model is more efficient to minimize the link errors because the relationship between O-D flows and link flows is grasped with the path choice proportions.

The estimated link flows are calculated with the estimated path flows by the following:

$$v_l = \sum_i \sum_j \sum_k \delta_{ijk}^l h_{ijk}. \tag{10}$$

These estimated path flows are obtained by the first stage model. The errors between the observed link traffic counts and the estimated link flows are divided into each O-D pair, φ_{ij}^l,

as the following:

$$\varphi_{ij}^{l} = (\hat{v}_l - v_l) \times \frac{\sum_k \delta_{ijk}^{l} \hat{p}_{ijk}}{\sum_i \sum_j \sum_k \delta_{ijk}^{l} \hat{p}_{ijk}} . \tag{11}$$

Using this portion of the link errors, the modified volume of the prior O-D flow, Δq_{ij} , is calculated as the following:

$$\Delta q_{ij} = \sum_l \left(\varphi_{ij}^{l} \times \frac{\sum_k \delta_{ijk}^{l} \hat{p}_{ijk}}{\sum_k \sum_l \delta_{ijk}^{l} \hat{p}_{ijk}} \right) . \tag{12}$$

The prior O-D flow is modified by using this Δq_{ij} .

$$q'_{ij} = q_{ij} + \Delta q_{ij} . \tag{13}$$

The O-D flow and the link flow are updated by the modified O-D flow q'_{ij} as the follows:

$$q_{ij} = q'_{ij} , \tag{14}$$

$$v_l = \sum_i \sum_j \sum_k \delta_{ijk}^{l} q'_{ij} \hat{p}_{ijk} . \tag{15}$$

3. SOLUTION FOR ESTIMATING PATH FLOWS AND MODIFYING O-D FLOWS

3.1 Solution for Two Stage Problem

The problem described in the previous chapter can be expressed by a two stage problem with the path flow estimation problem and the O-D flow modification problem. In this problem, the first stage problem is composed of strictly convex functions with respect to h_{ijk} and v_l under given prior O-D flows. However, the convexity of the second stage model depends on the number or the place of link observations. This two stage problem is not necessarily convex and may have multiple local minima. In this study, a heuristic solution approach where the first stage problem and the second stage problem are solved iteratively is constructed for practical use and for convenience. This approach solves each problem separately. When the two stage problem is not convex, it is required to give proper initial values to the algorithm.

3.2 Solution for Path Flow Estimation Model

Since the objective function of the path flow estimation model is difficult to be solved directly, logarithmic form of the objective function is taken. By using Stirling's approximation for log X! and introducing Lagrangean multipliers for the equality constraints, the problem becomes

$$\begin{aligned} L = & \sum_i \sum_j (q_{ij} \ln q_{ij} - q_{ij}) - \sum_i \sum_j \sum_k (h_{ijk} \ln h_{ijk} - h_{ijk}) + \sum_i \sum_j \sum_k h_{ijk} \ln \hat{p}_{ijk} \\ & + \hat{V} \ln \hat{V} - \hat{V} - \sum_l (v_l \ln v_l - v_l) + \sum_l v_l \ln \hat{\gamma}_l + \sum_i \sum_j \mu_{ij} (\sum_k h_{ijk} - q_{ij}) \\ & + \sum_l \lambda_l (\sum_i \sum_j \sum_k \delta_{ijk}^{l} h_{ijk} - v_l) + \upsilon (\sum_l v_l - \hat{V}), \end{aligned} \tag{16}$$

where L is the objective function of the problem for estimating path flows, λ_l, μ_{ij} and υ are the Lagrangean multipliers for equality constraints. The parameters to weight each probability of

simultaneous occurrence are set to be 1.0 in this paper.

Since solving the above Lagrangean problem explicitly requires much computer resources, an iterative algorithm to solve the problem is constructed. From the necessary and sufficient condition for an optimum of the Lagrangean problem, the following equations are yielded.

$$h_{ijk} = \hat{p}_{ijk} e^{\sum_l \lambda_l \delta_{ijk}} e^{\mu_{ij}} \tag{17}$$

$$v_l = \hat{\gamma}_l e^{\upsilon - \lambda_l} \tag{18}$$

$$\lambda_l = \frac{1}{2} \ln \frac{\hat{\gamma}_l e^{\upsilon}}{\sum_i \sum_j \sum_k \delta^l_{ijk} \hat{p}_{ijk} e^{\sum_{n \neq l} \lambda_n \delta^n_{ijk}} e^{\mu_{ij}}} \tag{19}$$

$$\mu_{ij} = \ln \frac{q_{ij}}{\sum_k \hat{p}_{ijk} e^{\sum_l \lambda_l \delta^l_{ijk}}} \tag{20}$$

$$\upsilon = \ln \frac{\hat{V}}{\sum_l \hat{\gamma}_l e^{-\lambda_l}} \tag{21}$$

3.2 Iterative Algorithm for Two Stage Problem

The algorithm of the model for estimating path flows and modifying prior O-D flows simultaneously from probe vehicle information and traffic counts is as follow:

Step0: Initialize λ_l, μ_{ij} and υ, and set n_1=1 and m=1,
Step1: Update λ_l
Step2: Update μ_{ij} and υ using updated λ_l,
Step3: If a convergence criterion of the first stage problem is met, go to Step5; otherwise go to next step,
Step4: Set n_1=n_1+1 and go to Step1,
Step5: Compute Δq_{ij} and update q_{ij}, and set n_2=1,
Step6: Update v_l,
Step7: If a convergence criterion of the second stage problem is met, go to Step9; otherwise go to next step,
Step8: Set n_2=n_2+1 and go to Step5,
Step9: If a convergence criterion of the two stage problem is met, then stop; otherwise go to next step,
Step10: Set m=m+1 and go to Step1.

This algorithm is composed of two parts. The first part from Step0 to Step4 is estimating path flows iteratively using the observations of link proportions, path proportions and given prior O-D flows until a certain convergence criterion is met. The second part from Step 5 to Step8 is modifying prior O-D flows using the observations of link proportions and calculated path flows by the first part. The two stage problem can be solved iteratively by the constructed algorithm which doesn't need higher computer resources and also is suited for the practical use.

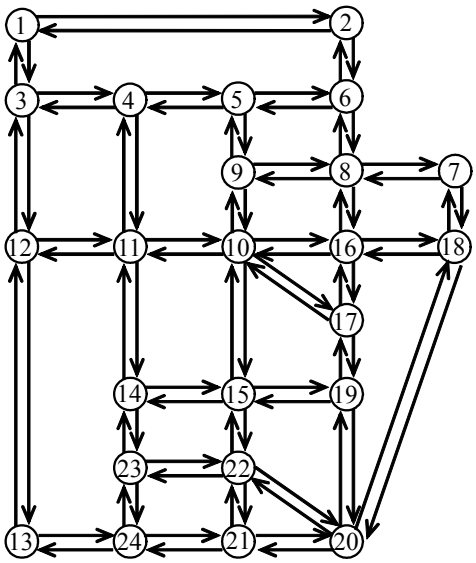

Figure 1 Sioux Falls Network

4. EXAMPLES

4.1 Data Generation

The proposed estimation model is applied to the Sioux Falls network as shown in Figure 1. This network consists of 24 nodes and 76 links. There are 552 O-D pairs in this network. The number of paths on each O-D pair is different each other. The O-D flows were set from 570 to 41939 veh. and the BPR function was used for a link cost function.

In order to produce observed flows of this network, O-D flows were generated first and then assigned on the network by user equilibrium assignment. Although the user equilibrium assignment was used in this example, it is not necessary for estimating path flows by the proposed model that drivers follow the equilibrium principle. The other assignment methods can be also used for producing observed flows. In real world, link traffic counts and probe vehicles, which follow some kind of path choice principle and yield these counts consistently, are available to estimate path flows by the proposed model.

As a result, link flows were obtained for all links and link proportions were also calculated from the assigned link flows. In this example, it is assumed that all link flows are observed and all generated link flows are used for path flow estimation. Path flows were also calculated with a constraint of the assigned link flows. For generating the situation where a certain ratio of probe vehicles was included in the vehicles running on the network, a certain ratio of vehicles was randomly sampled. The ratio of the probe vehicles was made change from 1% to 100%. These sampled vehicles were regarded as the probe vehicles and path proportions were also calculated from this probe vehicle information. Ten times of random samplings were conducted for each ratio of probe vehicles.

4.2 Estimation Result of Path Flows

First, in order to analyze the properties of the path flow estimation model in the first stage problem, the estimation model is only applied to the realistic conditions, where some errors

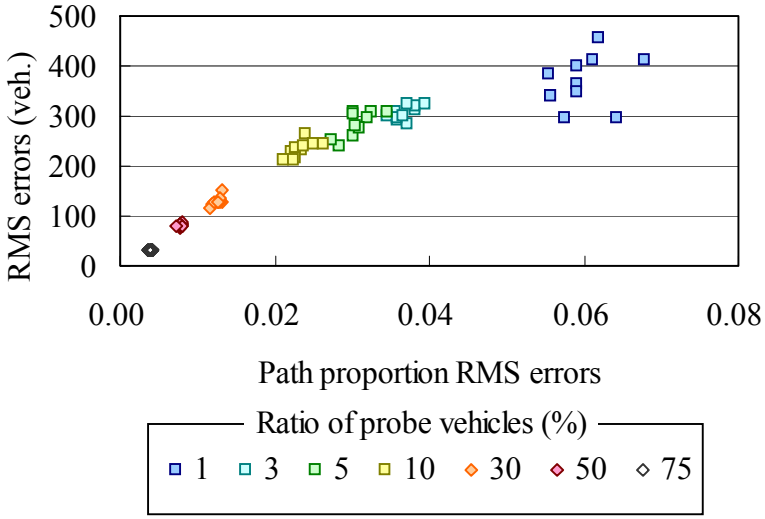

Figure 2 Relationship between RMS Errors of Path Flows and Path Proportions

are included to observations of the link flows and the probe vehicles.

(1) Influence of probe vehicle ratio on estimation result

The influence of the calculated path proportions form the probe vehicle information on the accuracy of path flow estimation is analyzed because probe vehicles do not necessarily generate the accurate path proportions. Figure 2 shows the relationship between RMS errors of the calculated path proportions and RMS errors of the estimated path flows. The RMS errors of the estimated path flows decrease according to the reduction of the RMS errors of the calculated path proportions.

In term of the ratio of probe vehicles, the RMS errors of the path proportions depend on the ratio. The higher the ratio is, the more accurate the path proportion becomes. Hence, the path flows are estimated accurately with a high ratio of probe vehicles.

(2) Influence of observed data errors on estimation result

When the proposed model is applied to a real world, the observed link flows and the prior O-D flows, which are input data to the model, must include some errors. Figure 3 shows the estimation results of path flows when the observations have some errors. When the link flows and the O-D flows have more than 10 percent errors, the accuracy of the estimated path flows is sharply decreasing. Even when the ratio of probe vehicles is 100%, namely, the true path proportions are given to the proposed model, the estimated path flows have still some errors because of inconsistency between the O-D flows and the link flows. The proposed model has an ability to estimate path flows even when the observations are inconsistent. The influences of input data errors become larger as the ratio of probe vehicles is higher. It is clarified that the influence of the O-D flow errors on the estimation result of path flows is larger than that of the link flow errors.

The figure 3 also shows the estimation result when 10 links are lacking for the observation, in which 66 links are randomly selected and regarded as the observed links. It is clarified that accuracy of the estimated path flows have small influence of the lacking of the observed links. It means that the proposed model can be applied even when all links are not observed

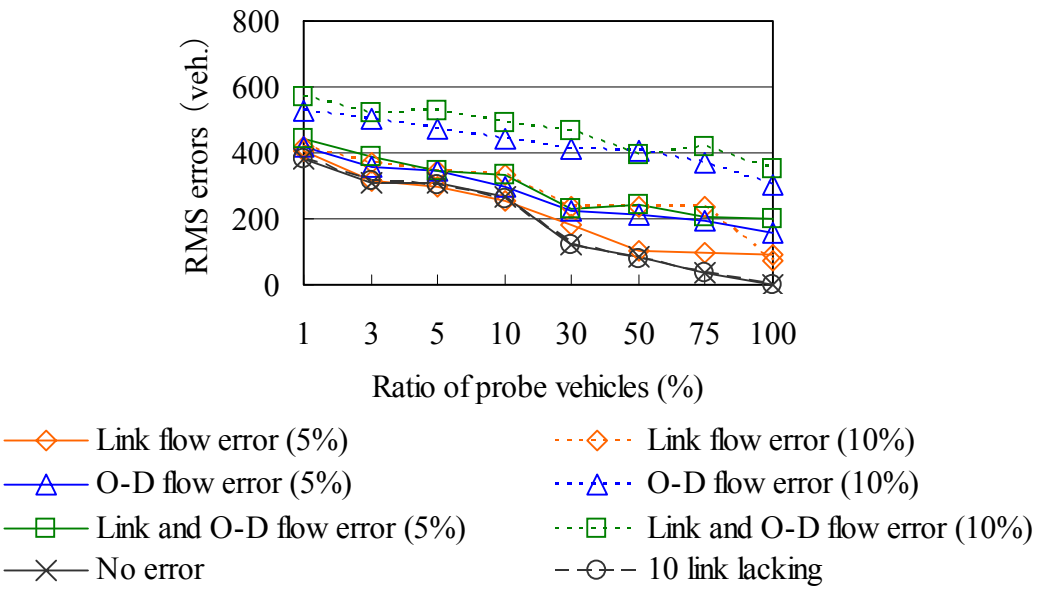

Figure 3 Estimation Results of Path Flows

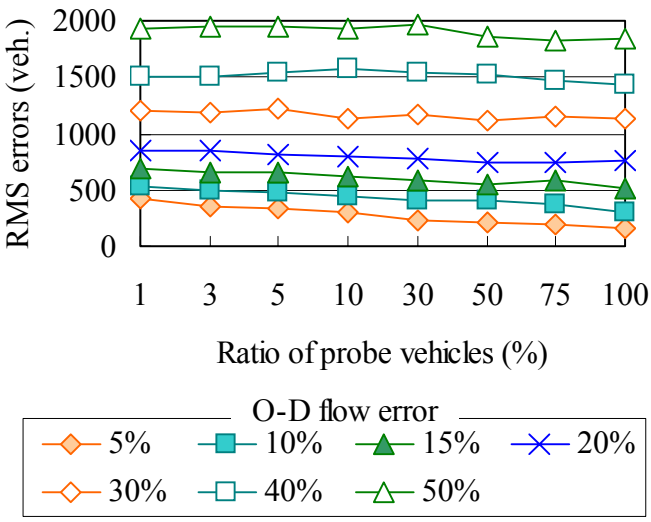

Figure 4 Relationship between RMS error of path flows and O-D error

on the network.

(3) Influence of O-D flow differences on estimation result

The link flows and the probe vehicles under current conditions can be easily observed even in a real world so that these observations seem to be reliable. Conversely, in general, because the O-D flows from roadside interview surveys or person trip surveys are used for input data as the prior O-D flows, it may have the low confidence if there is the time lag between the survey date and the current estimation date. Therefore, the proposed model is applied to the situation where the current O-D flows have a change from the prior O-D flows.

Figure 4 shows relationship between RMS error of the estimated path flows and the ratio of probe vehicles when the prior O-D flows have differences form the unknown current O-D flows. Regardless of the ratio of probe vehicles, the larger the differences of the O-D flows

Table 1 Estimation Result with O-D flow differences (75% probe vehicle)

	O-D flow change	20%	30%	40%	50%
First stage model	RMS error (veh.)	756.64	1213.88	1566.37	1922.86
	Correlation coefficient	0.97	0.95	0.91	0.91
Two stage model	RMS error (veh.)	644.37	990.16	1319.78	1668.35
	Correlation coefficient	0.98	0.97	0.94	0.94

are, the larger the RMS errors of path flows become. It means that the prior O-D flows should be modified when the O-D flows are inconsistent with the current conditions.

4.3 Estimation Result of Simultaneously Estimating Path Flows and Modifying O-D flows

So far, it is clarified that differences between the current unknown O-D flows and the prior O-D flows have a large influence on the accuracy of estimated path flows. It is required to modify the O-D flows simultaneously when path flows are estimated. Therefore, the proposed two stage model for simultaneously estimating path flows and modifying O-D flows is applied to the situation where the current O-D flows change largely from the prior O-D flows.

Table 1 shows the estimation results by the first stage model for estimating path flows, and the two stage model for simultaneously estimating path flows and modifying O-D flows, in which there are 75 % of probe vehicles. The RMS errors and the correlation coefficients between the true path flows and the estimated path flows are shown in this table. For all cases with different O-D flow changes, the accuracy of the estimated path flows is improved. Therefore, the RMS errors become smaller and the correlation coefficients become larger by modifying the prior O-D flows, even when the prior O-D flows have larger differences form the current O-D flows. When the O-D flow change is 30% and the probe vehicle ratio is 50% for example, the RMS error before the modification is 1157.50 and one after the modification is 1050.82. This accuracy improvement is smaller than the case with 75% of probe vehicles. Other cases yield the same tendency of the improvement. It means that, for the case with lower ratio of probe vehicles, the accuracy improvement becomes smaller.

Figure 5 shows an example relationship between the estimations and the observations of path flows under the situation where the ratio of probe vehicle is 75 % and the prior O-D flows have 30 percents of the differences. The estimation results by the two stage model are more accurate than those by the path flow estimation model, namely, the first stage model. Especially, a large part of the O-D flow estimations are more improved by the two stage model.

5. CONCLUSION

A model for estimating path flows and modifying O-D flows simultaneously was proposed, in which the probe vehicle information and traffic counts were used. The probe vehicle

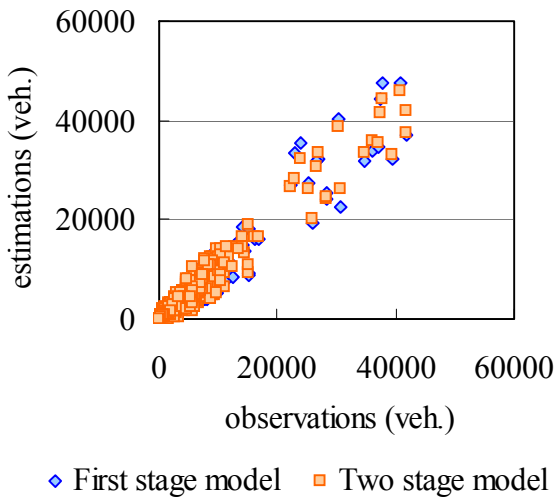

Figure 5 Relationship between Estimations and Observations of Path Flows

information is accumulated to calculate prior information on actual path choice behavior of drivers, and traffic counts are used as sectional volume information on links of a network. The proposed model is constructed based on the concept of maximizing the probabilities of simultaneous occurrence on path flows and link flows so that the model is suitable for the conditions when the observed link traffic counts and the prior O-D flows are inconsistent. In this model, the path choice proportions and traffic counts are allowed to have some errors such as measurement errors and errors arisen by the time lag between observation dates of the data. Moreover, the proposed model is applicable to the situation where traffic conditions change because the O-D flows are simultaneously modified in the proposed model.

The proposed estimation model is constructed as a two-stage problem. The first stage problem is to estimate path flows based on the prior O-D flows. The second stage problem is to modify O-D flows based on errors of link flows between observations and estimations calculated with the estimated path flows. This is based on the concept that the latest link traffic counts and the latest probe vehicle information are easily available even in real world while it is difficult to obtain the latest O-D flows. For solution of this two stage problem, the iterative algorithm was constructed in consideration of practical use and convenience.

The proposed model was applied to the Sioux Falls network with various ratios of probe vehicles and various error levels of link traffic counts. As a result of this application, the accuracy of the estimated path flows was changed in inverse proportion to the ratio of the probe vehicles obtained. However, it is clarified that the proposed model had enough precision of the estimated path flows even when the prior information calculated by the probe vehicles included some errors. Furthermore, the proposed two stage model is applied to the situation where the current O-D flows change largely from the prior O-D flows. As a result, it was clarified that the two stage model had enough capability to estimate path flows and to modify O-D flows even when the prior O-D flows have inconsistency with the current traffic conditions.

In this paper, the iterative algorithm for the proposed two stage algorithm was constructed and applied to the Sioux Falls network. As a result, the proposed model yielded valid estimation results. However, this algorithm does not always yield the unique solution. The uniqueness of

the two stage problem depends on the form of network or the place of the observation. Therefore, the condition for the uniqueness of the problem should be certified and an efficient algorithm should be developed for further research. Moreover, although the Sioux Falls network is real network, the larger real networks will be used to verify the applicability of the proposed model. Furthermore, since almost all links were assumed to be observed in this paper, influence of lack of may link observations on path flow estimations should be clarified for further research.

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