MULTI-VEHICLE OD TRIP MATRIX ESTIMATION FROM TRAFFIC COUNTS

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Abstract: The previous OD matrix estimations from link traffic counts use only one vehicle type, despite it is possible to obtain link flows easily by individual vehicle types. Therefore those methods use a deteriorated information and decrease the performance of OD matrix estimator. We suggest a multi-vehicle OD matrix estimation method from traffic counts using genetic algorithm(GAMUC). Numerical examples show that the performance of GAMUC is better than that of the previous methods for the error of target OD matrix and of link counts. And the previous OD matrix estimation methods may produce wrong OD matrix structures, which are different from that of true OD matrix.

KeyWords: OD matrix estimation, Genetic Algorithm, Multi-vehicle traffic assignment, Bilevel OD matrix estimation

1. INTRODUCTION

Most OD matrix estimation methods from link traffic counts use the previous OD matrix survey data and current link traffic counts data. But the OD matrix survey data have sampling errors and time variation errors. In general it is possible to obtain whole link traffic counts data on roads and the link traffic counts data are accepted more useful than OD matrix ones in that they have current information of the network. In addition to, link flows become more important because estimated OD matrix is affected by the error of link traffic counts than that of target OD matrix in the criteria of OD matrix estimation. Therefore we should reduce the error of traffic counts as possible.

However, conventional OD matrix estimations from link traffic counts use only one vehicle-type, despite it is possible to obtain link flows easily by individual vehicle types. This implies that the flows of multiple-vehicles are converted into one vehicle type by the factor of passenger car equivalency(PCE). Therefore those methods may use deteriorated information and may decrease the performance of OD matrix estimator. In real network heavy vehicles and passenger cars interact each other on the same link, thus such method is not realistic. To cope with the problem, multiple vehicle estimation technique is required. While there are not too many researches regarding multi-vehicle OD matrix estimation from multi-vehicle link counts. One of the methods is combined OD matrix estimation model with multiple-vehicle assignment to overcome the problem. Combined model can reduce the error of link counts by classifying target OD matrix and link traffic counts by vehicle types. And by separating the vehicles, it is possible to enhance the performance of OD matrix estimation.

This paper is the revised research of multiple-vehicle OD matrix estimation problem, which comes from Lim et al.(2000) that estimated OD matrix from link counts using genetic algorithm(GA) for the corridor and from Baek et al. (2001) that applied the method to urban network. The main purpose of this paper is that we show the performance of previous OD matrix estimation methods is deteriorated due to using one-vehicle type and suggested alternative method to overcome that problem. We suggest that multiple-vehicle OD matrix estimation from link counts using GA and compare the method with previous method such as Iterative Estimation Assignment (IEA) algorithm of Yang(1995). We introduce a new concept of OD matrix structure to show the previous method's dependancy on target OD matrix. Investigation into the performances of our model and previous model will be also given when OD matrix structure be changed. This paper describes the bilevel OD matrix estimation algorithm in section 2, new OD matrix estimation method using GA and multiple-vehicle assignment is described in section 3, comparison of the performance of estimation models is given in section 4. Finally conclusion and further work are suggested in section 5.

2. BILEVEL OD ESTIMATION METHOD

Target OD matrix may have some errors in survey procedure or in data processing and have time variation errors. Observed link flows also may have measurement errors as well as temporal fluctuations. To solve these problems, Generalized Least Square ; GLS) method is one of the efficient methods. A major attraction of GLS is that it allows the combination of survey relating directly to OD flows with traffic count data, where takes into account the relative accuracy of these data source (Bell, 1991). Yang et al. (1992) have shown that the bilevel programming approach can be used as an efficient technique to achieve the simultaneous estimation of OD matrix and route choice under congested traffic condition as follows.

$$\min \quad F(t) = (\bar{t} - t)^T U^{-1} (\bar{t} - t) + (\bar{v} - v)^T V^{-1} (\bar{v} - v) \tag{1a}$$

subject to

$$t \geq 0 , \tag{1b}$$

$$v = M(t) \tag{1c}$$

where, $\bar{t}$: target OD matrix

$\bar{v}$: link traffic counts
t : estimated OD matrix
v : link flow according to estimated OD
U : variance and covariance matrix for the error of OD matrices
V : variance and covariance matrix for the error of link flows

Equation (1a) is upper-level function which is OD matrix estimation, (1c) is lower-level function which is equilibrium. $M(t)$ that is known as traffic assignment map, describing the relation OD matrix t and estimated link flow v.
The bilevel problem is to estimate an OD matrix satisfying a user equilibrium condition. The problem calculates corresponding link flows, subject to the estimated OD matrix. A set of observed link flows are also calculated based on a target OD matrix.

Link flow $v = M(t)$ is called the response or reaction function. A successful solution of OD matrix greatly depends on how to evaluate the reaction function, or in other words, how to estimate link flow changes in response to OD matrix adjustment. In such model v is nonlinear and its functional form is not explicitly known, estimation of variations in link flows cannot be carried out explicitly. Yang (1995) suggested IEA and sensitivity analysis based (SAB) algorithm, which formulated a local linear approximation of successful solution of OD matrix greatly depends on how to evaluate the reaction function. Because this paper uses the diagonalization algorithm, we assume that nonseparable relation among vehicles and separable relation among link flows. Therefore we use IEA only in multiple-vehicle OD matrix estimation. The general form of IEA algorithm is as follows.

Step 0. Determined intial solution matrix $t^{(0)}$. Set the $k = 0$.
Step 1. Assign $t^{(k)}$
Step 2. Calculate the influence factor $Z^{(k)}$.
Influence factor Z is defined by link use proportions($Z = [\, p_{aw}]$), where p_{aw} is calculated from path flow by equation (2).

$$p_{aw} = \frac{\sum_{r \in R} f_R \, \delta_{ar}^{w}}{t_w}, \quad a \in A, \; w \in W \tag{2}$$

where, f_r, $r \in R$ is solution of equilibrium path flow related t, R is path set in network. δ_{ar}^{w} is 1 if path r between OD pair w uses link a, otherwise 0.
Step 3. Calculate $t^{(k+1)}$ by using upper-level problem
Approximate nonlinear function $v = v(t)$ to linear function as equation (3) based on influence factor.

$$v(t) \approx v(t^{*}) + Z(t - t^{*}) \tag{3}$$

,Solution matrix can be presented as equation (4).

$$t^{(k+1)} = (U^{-1} + Z^{(k)T} V^{-1} Z^{(k)})^{-1} (U^{-1} \bar{t} + Z^{(k)T} V^{-1} \bar{v}) \tag{4}$$

Step 4. If it meets the stopping criteria. Stop. Otherwise set $k = k+1$ and go to Step 1.

3. MULTIPLE-VEHICLE OD MATRIX ESTIMATION

3.1 Existing Research

Such researches relating to multiple-vehicle OD matrix estimation from link traffic counts have not been suggested despite of the necessity. Kim(2000) firstly estimated multi-vehicle OD matrix using the multi-class assignment with EMME/2. EMME/2 assumes that perceived cost of link, C, by traveller on vehicle type c is expressed as equation (5).

$$C_a^c(v_a) = C_a(v_a) + b_a^c \quad a \in A \tag{5}$$

Where $C_a^c(v_a)$ is cost on link a of vehicle type c and $C_a(v_a)$ is cost on link a, function of link flow v_a. b_a^c is additional cost term of vehicle type c, which represents the interaction among vehicle types.

Equation (5) has some limitations regarding multiple-vehicle OD matrix estimation. Firstly, it assumes that each vehicle has a different fixed bias b_a^c, although they have the same congestion impact by all link volume on the link. Because it has the same congestion impact by the traffic flows, it is similar to the method of one-vehicle OD matrix estimation. Secondly, although it is necessary to use the asymmetric cost function, it uses the separable type cost function representing the vehicle characteristics as a constant. Thus it is not suitable for the multiple-vehicle traffic assignment in which should be considered the asymmetric cost function. Finally, because EMME/2 set the possible paths beforehand and execute assignment, it produces a good results in large network. But its results are not suitable to real traffic pattern due to the simplification of the traffic behavior. Thereby it is difficult to expect that the method produce a correct estimated OD matrix.

3.2 multiple-vehicle OD matrix estimation using GA

For multiple OD matrix estimation, a bi-level program is formulated in this paper. To solve the bi-level problem, a global solution searching method is required. Genetic algorithm(GA) is used for upper-level problem. GA produces an optimal solution by using reproduction, cross-over, mutation steps iteratively. For lower-level problem, we use user equilibrium assignment technique.

In this paper to estimate OD matrix from traffic counts using GA. Equation (1) is formulated as least squared formula as follows.

$$Min\ F(t_{ij}) = \frac{1}{2}\sum_{c}\sum_{a \in A}(v_a^c - \overline{v_a^c})^2 + \gamma\frac{1}{2}\sum_{c}\sum_{ij \in W}(t_{ij}^c - \overline{t_{ij}^c})^2 \tag{6a}$$

subject to

$$t \geq 0 \tag{6b}$$

$$v = M(t) \tag{6c}$$

where, $t=\{t_{ij}^c\}$: OD trips of vehicle type c between OD pairs i-j

$v=\{v_a^c\}$: Volume of vehicle type c on link a

We assume that U and V in equation (1) are identity matrix. γ is parameter reflecting the reliability of the target OD matrix. W is the set of OD pairs.

To consider multi-vehicle traffic counts, a multiple-vehicle traffic assignment is required. That can be interpreted asymmetric problem. Asymmetric problem means that Jacobian matrix of objective function in traffic assignment is asymmetric. In this case, equivalency problem related Wardrop's equilibrium do not exists.

Although many researchers have shown the asymmetric cost function, the most representative function is BPR type function, which is suggested by Lawphongpanich and Hearn(1984), Mahmasani and Mouskos(1988) etc. We also use the equation suggested by Mahmassani et al.(1988) as traffic cost function for each vehicle.

$$t_{aA}(x_{a,a}, x_{aT}) = t^0_{aA}[1 + 0.15 (\frac{x_{aA} + 1.5x_{aT}}{C_a})^4] \tag{7a}$$

$$t_{aA}(x_{aT}, x_{a,t}) = t^0_{aT}[1 + 0.43 (\frac{x_{aA} + 1.5x_{aT}}{C_a})^3] \tag{7b}$$

where, t^0_{aA}, t^0_{aT}= Free-flow time on link a for passenger car and truck
X_{aA}, X_{aT}= link volume on link a for passenger car and truck
C_a = PCU(passenger Car Unit) capacity on link a

Because link cost function is asymmetric in this paper and Jacobian of that function is generally not positive definite, it is difficult to guarantee that the solution of that function is unique. But it is possible to apply diagonalization method to multiple-vehicle assignment problem, with a small modification of the Frank-Wolf (F-W) algorithm which is used in convex mathematical program. Mahmassani et al. (1988) have shown that diagonalization method has a convergence in nonseparable and asymmetric problem. We develop IEAMUC(IEA Multiple User Class) which is combined IEA with diagonalization and GAMUC which is combined GA with diagonalization.

The solution algorithm of GAMUC is as follows.

[step 0] Initialization (Random Generation)

① Set *mutratio* (mutation ratio)
max*iter* (maximum number of iteration)
$n=1$(generation or the number of iteration)

② Generating random values for $X^c_{1,n}[m][ij]$ and $X^c_{2,n}[m][i]$ within the specific range.
$X^c_{1,n}[m][ij]$ is choice proportion of vehicle c of m^{th} chromosome between origin i and destination j in n generation
$X^c_{2,n}[m][i]$ is proportion of vehicle c of m^{th} chromosome between origin I in n generation

③ Calculating

$$X^{c*}_{1,n}[m][ij] = \frac{X_{1,n}[m][ij]}{\sum_{r\in D} X_{1,n}[m][ir]} \tag{8}$$

where, $\sum_{j \in D} X^{c*}_{1.n}[m][ij] = 1.0 \quad \forall \ i \in O, \ j \in D$

[step 1] Estimating vehicle OD $t^c_{ij}[m]$

① Calculating

$$t^c_{ij}[m] = X^*_{1.n}[m][ij] \cdot X_{2.n}[m][i] \cdot O_i \tag{9}$$

where O_i is historical trips generated from origin i

[step 2] Diagonalization (traffic assignment)

To calculate v^c_a from assigning $t^c_{ij}[m]$, execute the multiple-vehicle assignment, diagonalization in multiple-vehicle OD estimation.

① Initialization
Calculate the shortest path of each vehicle by using the free-flow link cost and execute the all-or-nothing assignment. set n=0.

② Increase the number of iteration
n=n+1

③ Diagonalize the link cost function
Calculate the link cost of specific vehicle by fixing the volume of the other vehicle as latest value. Thus C^n_a is the composed of only v_a.

$$C^n_a = C_a(v_a, \ v^{(n-1)}_t) \tag{10}$$

④ Search the equilibrium traffic patterns(search the solution of current minimization)
Assume that link cost function $C^n_a(v_a)$ and link flow $v^{(n-1)}_a$ in ③, find the user equilibrium traffic patterns of diagonalized vehicle type using the F-W algorithm to calculate link flow v^n_a

⑤ Test convergence for the inner calculation.
If the change of volume of diagonalized vehicle on link is under the predetermined value, stop and go to ③, diagonalize the other type vehicle. If not converge, go to ④ and do the optimalization step iteratively.

⑥ Test convergence for the outer calculation.
If the change of total travel cost is under the predetermined value, stop. Otherwise, go to step ②.

[step 3] Fitness Calculation

① Calculating the fitness value by (6)

② Sorting the fitness values in ascent order.

[step 4] Cross-over

① Alternate the lower 50% of total chromosomes for next generation

$$X^{c*}_{1.n+1}[m][ij] = \alpha X^{c*}_{1.n}[k][ij] + (1-\alpha) X^{c*}_{1.n}[k+1][ij] \tag{11a}$$

$$X^c_{2.n+1}[m][i] = \alpha X^c_{2.n}[k][i] + (1-\alpha) X^c_{2.n}[k+1][i] \tag{11b}$$

where, α : random number(0 ~ 1)

[step 5] Mutation

① For each $X^{c*}_{1,n+1}[m][ij]$ and $X^{c}_{2,n+1}[m][i]$
Generate random real number r in (0,1)
② If $r \leq mutratio$ Then
Generating random values for $X^{c*}_{1,n+1}[m][ij]$ and $X^{c}_{2,n+1}[m][i]$ within the specific range.

[step 6] Fitness Calculation
① Calculating

$$t_{ij}[m] = X^{c*}_{1,n+1}[m][ij] \cdot X^{c}_{2,n+1}[m][i] \cdot O_i \tag{12}$$

② The below is the same procedures as [step 1]
[step 7] Stopping Criteria
If $n \leq \max iter$ then $n = n+1$ and go to [step 2]. Otherwise, stop

GAMUC computes equilibrium flows simultaneously with respect to each feasible set of OD matrix, not iterative computing. GA is intrinsically multiple point searching method and searches the solution in parallel. Thus it is possible to produces multiple traffic assignment map for multiple OD matrix. Since the relationship between OD matrix and link flow is considered simultaneously, the solution is optimum or at least better than that of IEA algorithm for solving bilevel approach.

4. A NUMERICAL EXAMPLE

4.1 Network Input Data

In this section, we report on the computational results of the proposed algorithm and compare the results with IEA, IEAMUC algorithm. To test on the efficiency of the algorithms, we provide a simple network shown in Figure 1. The network includes 9 nodes and 16 links with eight origin-destination pairs, whose true OD matrices are shown in Table 3.

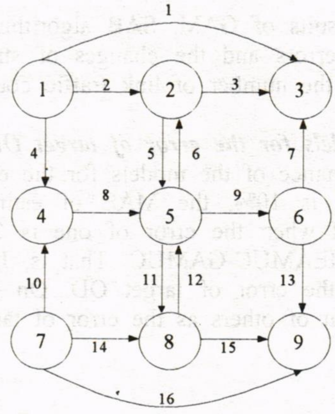

Figure 1. Test Network

The network link costs are calculated from Bureau of Public Roads (BPR) type formula and its data for the example are displayed in Table 2.

Table 1. Data for Network example

Link number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Free flow speed for passenger car(km/h)	70	75	75	75	75	75	75	80	80	75	75	75	75	75	75	70
Free flow speed for truck (km/h)	50	60	60	60	60	60	60	70	70	60	60	60	60	60	60	50
Capacity(veh.)	1500	2000	2000	2000	2000	2000	2000	2500	2500	2000	2000	2000	2000	2000	2000	1500

Additional data are required in this paper with regard to GAMUC. The parameters are as follows.

- Population size is 20.
- X1 has 30% variation with average of 1.0 ($0.7 \le X_{1.n}[m][ij] \le 1.3$)
- X2 has 20% variation with average of 1.0 for target OD ($0.8 \le X_{2.n}[m][i] \le 1.2$)
- Mutation ratio is different to the number of iterations.
- Maximum iteration is 500

Important parameters in GA are cross-over probability, mutation ratio, population size and the maximum number of iteration. As the results of several experiments in the paper, we found that parameters in GA have relations mainly with the efficiency of GA, but they have not so much influence on the results. Only computing time to meet convergence criterion depends on these parameters.

Relative mean absolute error (MAE) is used as a statistical measure of error so as to compare the estimated and true O-D trip matrices.

$$MAE(\%) = \left(\sum_{w \in W} | t_w - t_w^{+} | / \sum_{w \in W} t_w^{+} \right) \times 100 \tag{13}$$

Where, t_w and t_w^{+} denote the estimated and true OD matrix respectively.

4.2 Estimation Results

We show the estimation results of GAM, SAB algorithm and compare the estimation accuracy according to the errors and the changes of structure of target O-D matrix. We also compare them for the number of link traffic counts.

1) Performance of the models for the error of target OD matrix

Figure 2 shows that performance of the models for the error of target OD. When The error of target OD matrix is 10%, the MAE of estimated OD matrix is ordered IEA-IEAMUC-GAMUC, but when the error of one is 20%, The MAE of estimated OD matrix is ordered IEA-IEAMUC-GAMUC. That is, IEA has the highest value the MAE in all cases despite the error of target OD. On the other hand, the MAE of GAMUC is smaller than that of others as the error of target OD matrix increase.

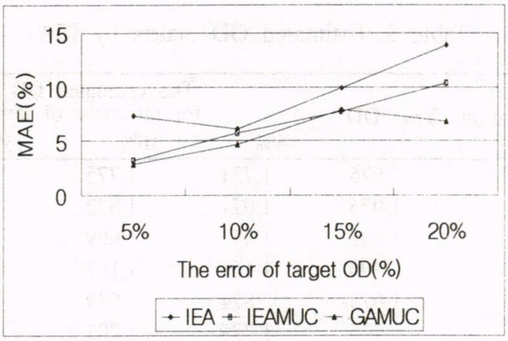

Figure 2. Performance of the models for the error of target O-D
(The error of count flow is 3%, The number of link count is 10)

2) Performance of the models for the error of counts flows

Table 2 shows that the MAE of estimates OD matrix when the number of link count is 10. When the error is 3%, it is possible to estimate despite the error of target OD matrix. But When the error is 6%, IEA, IEAMUC cannot estimate. This means that if the error of link count is more specific value, IEA which consider one-vehicle type only has a significant error and IEAMUC has a high estimate error.

In addition to, when the error of target OD matrix is 5%, IEA, IEAMUC and GAMUC all have the value of MAE over 5%. This means that it is possible to estimate only at that the error of link counts is smaller than the error of OD matrix. Also this means that the smallest error in the error of target OD matrix and of link counts is lower bound of the error of estimated OD matrix.

Table 2. performance of models for the error of target OD and of count flow

The error	The error of target OD matrix							
	5%		10%		15%		20%	
The error of count flow	3%	6%	3%	6%	3%	6%	3%	6%
IEA	7.311	12.698	6.111	14.979	9.922	17.407	13.810	20.586
IEAMUC	3.207	7.436	5.790	9.897	7.765	13.079	10.390	15.808
GAMUC	2.863	6.344	4.691	6.777	7.888	7.982	6.839	8.764

3) Performance of the models for the change of O-D matrix structure

To compare IEAMUC, GAMUC with IEA algorithm. we describe that the estimated OD for the error of target OD by one-vehicle in table 3, 4 and 5, which are the product estimated multi-vehicle OD by PCE of truck.

(1) IEA

Table 3 reports the estimated OD matrix by IEA. The results show that IEA estimate only 1 OD matrix structure correctly when the error of target OD matrix is 5%. This means that the estimation method by one-vehicle may produce different from the true OD matrix. Compared with Table 4, MAE of IEA is relatively higher than that of IEAMUC.

Table 3. Estimated OD matrix by IEA

Origin	Destination	True OD	The estimated OD matrix for the error of target OD 5%	10%	15%	20%
1	3	1,625	1,731	1,775	1,851	1,928
1	5	1,075	1,071	1,022	990	957
1	9	1,650	1,471	1,609	1,556	1,501
5	3	990	1,166	1,167	1,208	1,247
5	9	1,075	874	1,039	992	944
7	3	1,725	1,779	1,702	1,635	1,568
7	5	1,175	1,130	1,129	1,100	1,069
7	9	1,600	1,633	1,741	1,812	1,886
MAE			7.311	6.111	9.922	13.807

note) Bold line shows origins that OD matrix structure is changed, shadow shows origins that OD matrix structure is estimated correctly.

(2) IEAMUC

Table 4 shows that although IEAMUC seems that it has a high performance of estimation in estimating, compared with IEA that considers just one-vehicle type, in reality the method cannot estimate OD matrix structure when the error of target OD matrix is for upper 10%. In estimating by multiple-vehicle, because IEAMUC can estimate only two pairs from origin 7 at 5% error. This means that IEAMUC may not estimate the changes of OD matrix structure correctly.

Table 4. Estimated O-D matrix by IEAMUC

Ori.	Des.	Type	The estimated OD for the error of target OD by multiple-vehicle: True OD	5%	10%	15%	20%	The estimated OD for the error of target OD by one-vehicle: True OD	5%	10%	15%	20%
1	3	a	1,100	1,155	1,210	1,265	1,320	1,625	1,662	1,714	1,741	1,805
		t	350	338	336	317	323					
1	5	a	700	668	654	647	634	1,075	1,034	1,001	986	976
		t	250	244	231	226	228					
1	9	a	1,200	1,149	1,128	1,118	1,097	1,650	1,584	1,556	1,547	1,517
		t	300	290	285	286	280					
5	3	a	600	624	657	686	722	990	1,025	1,074	1,111	1,157
		t	260	267	278	283	290					
5	9	a	700	670	654	641	623	1,075	1,026	1,004	988	941
		t	250	237	233	231	212					
7	3	a	1,200	1,151	1,125	1,089	1,064	1,725	1,649	1,611	1,547	1,510
		t	350	332	324	305	297					
7	5	a	800	777	767	753	741	1,175	1,142	1,129	1,107	1,100
		t	250	243	241	236	239					
7	9	a	1,000	1,050	1,100	1,150	1,200	1,600	1,613	1,658	1,686	1,731
		t	400	375	372	357	354					
MAE				4.243	7.055	9.970	12.667		3.207	5.790	7.765	10.394

note 1) a : auto, t : truck
note 2) Bold line shows origins that OD matrix structure is changed, shadow shows origins that OD matrix structure is estimated correctly.

(3) GAMUC

Table 5 shows that in estimation by one-vehicle GAMUC can estimate all OD pairs from origin 1, while it cannot estimate OD matrix structure of origins 5, 7 correctly. But in estimation by multiple-vehicle GAMUC estimates correct OD matrix structure of origin 7 only. This shows that GAMUC has a different performance between by one-vehicle estimation and by multiple-vehicle one.

Table 5. Estimated O-D matrix by GAMUC

Ori.	Des.	The estimated OD for the error of target OD by multiple-vehicle						The estimated OD for the error of target OD by one-vehicle				
		Veh.	True OD	5%	10%	15%	20%	True OD	5%	10%	15%	20%
1	3	a	1,100	1,133	1,201	1,194	1,216	1,625	1,658	1,750	1,728	1,762
		t	350	350	366	356	364					
1	5	a	700	662	642	638	659	1,075	1,033	1,001	947	952
		t	250	247	239	206	195					
1	9	a	1,200	1,189	1,191	1,170	1,153	1,650	1,626	1,625	1,682	1,626
		t	300	291	289	341	315					
5	3	a	600	605	658	669	611	990	1,006	1,077	1,142	1,100
		t	260	267	279	315	326					
5	9	a	700	637	644	597	627	1,075	997	1,009	890	930
		t	250	240	243	195	202					
7	3	a	1,200	1,168	1,149	1,104	1,151	1,725	1,683	1,662	1,565	1,636
		t	350	343	342	307	323					
7	5	a	800	768	787	805	750	1,175	1,130	1,146	1,225	1,116
		t	250	241	239	280	244					
7	9	a	1,000	981	1,022	1,039	1,046	1,600	1,569	1,642	1,651	1,658
		t	400	392	413	408	408					
MAE				2.945	4.779	8.033	6.921		2.863	4.691	7.888	6.839

note 1) a : auto, t : truck
note 2) Bold line shows origins that OD matrix structure is changed, shadow shows origins that OD matrix structure is estimated correctly.

The results of analysing the OD matrix structure shows that it is possible to estimate correct OD matrix only when applied method uses the multiple-vehicle OD matrix and link count flow data.

Table 6 describes that whole performance of models presented by Table 3, 4 and 5. When the OD matrix structure is changed, IEA cannot estimate the change, IEAMUC can estimate only OD matrix structure of one origin when the error of target OD is 10%. By contrast, GAMUC can estimate at least one OD matrix structure despite the error of target OD matrix.

Table 6. Numbers of correct estimation of O-D matrix structure

	The error of target OD matrix							
	5%		10%		15%		20%	
	NC	NCE	NC	NCE	NC	NCE	NC	NCE
IEA		0		0		0		0
IEAMUC	1	0	3	1	3	0	3	0
GAMUC		1		1		1		1

Note) NC is the Number of Change of the O-D matrix structure.
NCE is the Number of Correct Estimation of the O-D matrix structure.

4) The performance of model for the number of link traffic counts

Figure 3 shows that the performance of GAMUC is better than that of IEA and IEAMUC at whole number of link counts. Although all model have a similar performance when all link is counted, the difference of GAMUC and others is high when the number of link counts is 8.

As the number of link counts increase, the performance of models is not increase. This is occurred from that the error of link counts is different and relation OD matrix and path is varied due to the network topology. By these problems the performance of OD matrix different according to counting location of link flow. We exclude the counting location problem of link flow in this paper.

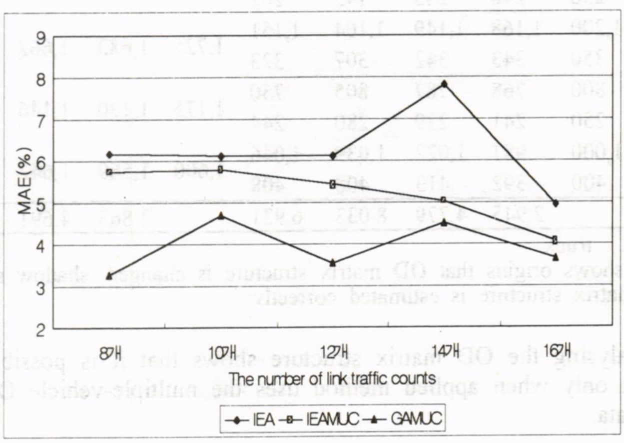

Figure 3. The performance of model for the number of link traffic counts
(The error of count flow is 3%, The error of target OD matrix is 10%)

From the numerical experience, we find that GAMUC is superior to IEA algorithm irrespective of any travel patterns. Therefore if we use GAMUC, it is possible to estimate current OD matrix correctly by using target OD matrix, which was surveyed before change in trip pattern. In addition to, as we use a model combined with multiple user class assignment, it is possible to enhance the ability of estimating OD matrix.

In this paper we tested the algorithm with only one example network. We have another experimental test for the verification of the solution algorithm(Lim et al, 2000). Seoul Inner Ring-road, 25km long, is used. The Ring-road connects east area to west area of Seoul City, including 8 on-ramps (implying origins) and 4 off-ramps (destinations). But we did not include the results in this paper due to mismatching of application methods, these results showed the superiority of the model developed in this paper.

5. CONCLUSIONS

Existing methods for OD matrix estimation have focused on minimizing the difference of target OD matrix and estimated OD matrix under the assumption that there have not been significant changes in travel pattern. These methods, however, have a serious dependency on the target OD matrix, thus if the structure of true OD matrix and target OD matrix is not similar, there occurs a reliability problem regarding estimated OD matrix. In addition to, those models consider traffic counts as single vehicle type only.

In this paper, with OD matrix estimation using GA which is global solution searching method we suggested the method that mitigate the dependency of OD matrix estimation on the error of target one. And with multi-vehicle data and assignment we suggested the method that mitigate the dependency of estimation on the error of count flow.

The results of estimation show that the previous method cannot estimate the OD matrix structure correctly when the OD matrix structure is different between target OD matrix and true one. Also the results show that the methods using one-vehicle data may have a significant error of estimation and the applicability may low. GAMUC using multi-vehicle data have a good performance of estimation in comparing IEA, IEAMUC in respect to the error of target OD matrix and of link counts. Thus we may conclude that the performance of GAMUC is better than the previous methods in urban network in which we do not usually known true OD matrix.

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