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A Study on Synthetic OD Estimation Model based on Partial Traffic Volumes and User-Equilibrium Information

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요 약

본 논문은 교통망에서 관측 링크 교통량, 미관측 링크의 이용자평형 정보를 이용하여 O-D행렬을 수학적으로 생성하는 모형을 제시하고 있다. 교통량이 관측되지 않은 링크로부터 이용자 평형 상태에서 추출 가능한 정보를 바탕으로 일련의 논리적 연산을 거쳐 실제교통량에 근접하는 서브알고리듬을 유추하여 O-D행렬 추정의 정확도와 연산의 일관성을 제고하였다. 이를 위해 이용자평형상태에서 새로운 정리(Theorem)와 보조정리(Lemma)를 유도하여 적용하였다. 모형의 시험은 3개의 초기 O-D 행렬과 3개의 미관측 링크 교통량 시나리오를 각각의 모형에 적용하여 그 결과를 비교하였다. 적용 결과 본 논문에서 제시된 모형은 기존의 이용자균형 접근방식의 모형emf에 비해 추정된 O-D값의 실제 값과의 차이(O-D Trip RMSE)가 현저히 감소되는 것을 확인하였다.

Abstract

This research addresses the problem of estimating Origin-Destination (O-D) trip matrices from link volume counts, a set of unobserved link volumes and information of user equilibrium flows in transportation networks. A heuristic algorithm for estimating unobserved link flows is derived, which provides volume estimates that are approximately consistent with both observed flows and an assumption of user equilibrium conditions. These estimated link volumes improve the constraints associated with the synthetic OD estimation model, providing improved solution search procedure. Model performance is tracked in terms of the root mean square errors (RMSE) in predicted travel demands, and where appropriate, predicted linked volumes. These results indicate that the new model substantially outperforms existing approaches to estimating user-equilibrium based synthetic O-D matrices.

Key words : Transportation modeling, O-D estimation, traffic volume, land use

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I. INTRODUCTION

The Origin-Destination (O-D) matrix is a fundamental input for many problems regarding the planning and management of transportation systems. O-D matrices describe the number of trips between the origins and destinations in a transportation network for a specified time period. These values help describe the patterns of movement of persons and goods in a particular area of interest. Such data can help planners and engineers estimate the demand on existing transportation facilities, calibrate or verify travel forecasting models, determine the feasibility of new routes or facilities, identify travel characteristics to and from specific types of land use, and determine the adequacy of parking or other terminal facilities.

At present, several O-D matrix estimation methods are being used in the transportation planning process. Models commonly used for estimating an O-D matrix can be divided into three categories [1]. The first method, the transportation demand model approach, estimates the O-D matrix by applying a system of sub-models typically used in large scale transportation planning projects. The second method is a direct sample approach that obtains O-D matrices by conducting roadside interviews or license plate surveys. The third method is the synthetic method that mathematically estimates the O-D matrix directly from link volume counts.

The synthetic O-D estimation approach offers significant advantages by eliminating expensive and intrusive interview surveys and the burden of managing of survey data. Traffic volume count data represent a quick, inexpensive, and accurate source of input data for the synthetic O-D estimation model. In many urban areas, detectors have been installed on roads to provide traffic volume information. Appropriate utilization of these data in O-D matrix estimation models provides transportation planner and engineers with a powerful and cost effective tool.

Since the early seventies, several synthetic O-D estimating models have been developed. Depending on the assumptions concerning the user's route choice behavior, the approaches can be classified into two categories: uncongested and congested network cases. In the former cases, referred as constant route choice models, congestion effects in the network are assumed to be of minor importance. Instead, path use proportions for each O-D pair are assumed or estimated using prior information or transportation assignment models. In user equilibrium based model, in contrast, the effects of the network congestion on the user's route choice are considered in the O-D estimation process.

Each approach has its own inherent shortcomings. The output of a proportional assignment model is estimated based on fixed route choice assumptions. This creates an inconsistency in using one set of route choice proportions to obtain an O-D matrix from link flows, and another to obtain the link flow distribution by assigning the trip matrix to the network. This shortcoming becomes more apparent in a network with realistic congestion levels [2].

Compared to the constant route choice models, the user equilibrium assignment (UEA) based model has two inherent weaknesses. First, its output is most sensitive to the initial (input) trip table [3], [4], and [5]. The high sensitivity of the solution to the initial trip table implies that the quality of the input trip table determines the quality of the output. We cannot expect an acceptable output from the model unless we have an appropriate input trip table. Second, the model is applicable only when the flow counts on all links are available, which is hard to achieve in practical situations. Alternatively, a UEA based model can be applied to the network after the links with unobserved volumes are eliminated from the network. This elimination, from the user equilibrium assignment point of view, is equivalent of treating links with unobserved volume as having zero capacities and/or link travel times are infinity. In this situation the output of the model will result in a trip matrix and a set of corresponding link volumes in which the volumes of all links with unobserved volume are zero. Therefore, except for the special situation where all the links with unobserved volume are unused by the travelers, the output of such a model inevitably contains errors. Considering the high demand for urban roadways and usual rate of volume detector failure, the application of the existing model to urban area would be impractical or severely limited.

The purpose of this paper is to formulate a user equilibrium based O-D estimation algorithm that can address the problem of partially missed link volumes. The proposed algorithm will be different from the existing ones since it does not require observed volumes for all links. Although link volume data is a critical factor for the user equilibrium based O-D estimation model, links in a network have other valuable information such as free flow speed, link length, capacity, and link performance functions. When the link volumes are not available, the existing model discards all this information for the links with unobserved volumes by eliminating the links from the network. The new algorithm will not discard network links with unobserved volumes. Instead, it will utilize all the other information in addition to the available link volumes to estimate a better O-D matrix.

The problem of synthetic O-D estimation with unobserved link volume is transformed to the problem of unobserved link volume estimation. Thus the proposed algorithm in essence consists of two sub algorithms; the unobserved link volume estimation algorithm and the optimal O-D estimation algorithm with all observed link volumes. The major contribution of this paper is the development of the unobserved link volume estimation algorithm and its integration with the existing optimal O-D estimation algorithm with all observed link volumes suggested by Cho and Moore's [6].

Ⅱ. LITERATURE REVIEW

Nguyen [7] suggested the first mathematical program for estimating an O-D matrix from traffic volume counts under user equilibrium assignment condition. The solution of this program is an O-D matrix satisfies user equilibrium assignment conditions and is consistent with the observed flow. Nguyen's work is distinctive because it takes into account link capacity or congestion and eliminates the assumption of proportional assignment. However, subsequent works by other researchers indicate that Nguyen's solution algorithm suffers from a number of major deficiencies.

Turnquist and Gur [3] noted that it does not address the problem of how to deal with the large number of potential solutions that reproduce the same observed link volumes. LeBlanc and Farhongian [8] and Spiess [9] also pointed that Nguyen's solution algorithm is inefficient when applied to large network due to immense computation time and storage requirements that arise in practical implementation. Turnquist and Gur improved Nguyen's algorithm. They developed an iterative descent algorithm. Under this approach, a trip table correction procedure defines the direction of the next feasible solution at each iteration by correcting the current trip table. The most important improvement of this approach concerns the efficiency of the solution search procedure.

Although Turnquist and Gur's algorithm resolved these deficiencies in Nguyen's algorithm, there are still several problems to be addressed. First, Turnquist and Gur's algorithm requires a definitive number for the volume on each link. Users should exclude links in the network when the volumes are not available. This stringent data requirement remains unchanged. Second, under their approach, a trip table correction function defines the next feasible solution at each iteration by correcting current trip table. Turnquist and Gur report that this trip table correction procedure is a crucial element of the algorithm, determining both the efficiency of the technique and the nature of the final solution. This trip correction function is heuristic, and its convergence to a solution is not guaranteed.

Gur [5], Han and Sullivan [4], Fisk [10], Oh [11], and Yang et. al. [12] have carried out further elaborations and modifications of Nguyen's and Turnquist & Gur's models. These extensions focus on improving the algorithm's efficiency, and on coping with the problem of underspecification in the original program or on modifying non-UE based models to accommodate the congestion effects. Recently, further improvement for the trip table correction procedure of the Turnquist and Gur's algorithm has been made by Cho and Moore [6] to address the second problem of Turnquist-Gur's model.

Williumsen [13] derived a model to estimate an O-D matrix that is consistent with the information available represented as constraints to maximization of an entropy function problem. He replaced the trip end constraints and cost constraints in Wilson's original entropy model with a set of observed link volume constraints. This model estimates an O-D matrix from link volume counts under proportional assignment conditions.

It should be noted that Willumsen's original model does not utilize the initial trip table. In effect, the model may be considered to generate the most likely trip table to minimizing the difference between a uniform initial trip table and the estimated matrix. Willumsen's entropy maximizing (EM) model was modified later to utilize an outdated or estimated initial trip table information [13].

In addition to the Willumsen's models, several other entropy-based models have been suggested. Van Zuylen [14] suggested an information minimizing (IM) model. This model is closely related to the Willumsen's entropy maximizing model except for the use of an initial O-D matrix. Van Zuylen and Willumsen [15] added the maximum likelihood to the original EM model to improve the solution accuracy. Other examples of various application of the EM approach can be found in Lam and Lo [1], Lo et. al. [16], Sivanada et. al. [17], Yang et. al. [2], Lee and Lee [18], and Lim [19].

Ⅲ. ESTIMATING VOLUMES FOR THE UNOBSERVED LINKS

This section demonstrates how the volumes of the unobserved links can be estimated. Illustrations with the simplest network are provided to give some insights on the procedures for the estimation of the unobserved link volumes. In the later section, user equilibrium related theorems needed for the estimation of unobserved link volumes of more complex and realistic networks are derived.

1. Information under User-Equilibrium Conditions

In real scale network problems, which have multiple paths for each trip interchange and multiple links in a path, the unobserved link volumes cannot generally be obtained by solving a set of simultaneous equations. Thus it is attempted to formulate a heuristic algorithm that estimates the missing volumes. To estimate the unobserved link volumes the proposed algorithm relies on additional clues provided by the user-equilibrium condition. Such clues are the manipulated combinations of user equilibrium theorems derived in following section.

(1) Definitions and Glossary

Big Network (BN): The complete network for the user equilibrium assignment and for the origin-destination estimation problem. BN contains both the links with observed volumes and the links with unobserved volumes.

Small Network (SN): A subset of the BN. SN contains only the links with observed volumes.

LUV: Links with unobserved volume.

Free Flow Travel Time for Big Network (FTBN(i,j)): The free flow travel time from zone i to zone j in the BN.

Free Flow Travel Time for Small Network (FTSN(i,j)): The free flow travel time from zone i to zone j in the SN.

Observed Travel Time for Big Network (OTBN(i,j)): The observed travel time from zone i to zone j in the BN.

Observed Travel Time for Small Network (OTSN(i,j)): The observed travel time from zone i to zone j in the SN.

Initial Shortest Path (ISP(i,j)): The shortest path for trips from zone i to zone j at free flow condition. Incase of multiple shortest paths, the shortest path algorithm breaks the tie.

tk(i,j): Travel time from zone i to zone j via path k.

tk0(i,j): Free flow travel time from zone i to zone j via path k.

T(i,j): The number of trips from zone i to zone j.

(2) Theorem and Lemma

Lemma: *At user equilibrium condition, ISP(i,j) is always used by T(i,j).*

Proof: At the first All-Or-Nothing assignment stage of the user equilibrium assignment algorithm, T(i,j) is assigned to ISP(i,j). After the path impedances are updated, T(i,j) is reassigned to the new (updated) shortest path (USP(i,j)). The net assignment of T(i,j) on ISP(i,j) is decided as follows:

α * T(i,j) on ISP(i,j) and

(1-α) * T(i,j) on USP(i,j) .

where, $0 \leqq \alpha \leqq 1$ that minimizes the user equilibrium assignment objective function.

If α is zero, then all T(i,j) is assigned to USP(i,j) and ISP(i,j) is not used for T(i,j). This is impossible because all T(i,j) cannot be assigned to the paths, which are not the shortest path for each O-D pairs (Assignment priority must be given to the shortest path by principle).

If α is not zero, than a fraction of T(i,j) is assigned to the ISP(i,j) (i.e., ISP(i,j) is used for T(i,j).) Unless any α in the next iterations is zero, a fraction of T(i,j) is using ISP(i,j). In principle, the convex combination algorithm cannot have an extreme α value such as zero or 1 while the objective function is strictly convex. Therefore, a fraction of T(i,j) is always assigned to the ISP(i,j) at user equilibrium condition and the proof is completed.

Theorem 1: *At user equilibrium condition, the observed travel time of all paths that is not the ISP is greater than or equal to that of ISP.*

Proof: According to the Lemma, ISP(i,j) is used by T(i,j). The observed travel time of used paths for T(i,j) is equal, and less than or equal to the observed travel time of any unused path. Therefore, the observed travel time of all paths that is not the ISP is greater than or equal to that of ISP and the proof is completed.

Theorem 2: *At user equilibrium condition, if FTSN(i,j) is greater than FTBN(i,j), then OTSN(i,j) is greater than or equal to OTBN(i,j).*

Proof: If FTSN(i,j) is greater than FTBN(i,j), then the ISP(i,j) is in BN, not in SN. The ISP(i,j) is used for T(i,j) (by Lemma) and the observed travel time of ISP(i,j) is OTBN(i,j) at user equilibrium condition. And, by Theorem 1, OTBN(i,j) is less than or equal to the travel time of any other path. Therefore, OTSN(i,j) should be greater than or equal to OTBN(i,j) and the proof is completed.

2. Volume Estimation Algorithm for the Unobserved Links

This section derives an algorithm that estimates the volumes of LUVs under UE assignment conditions. The suggested algorithm is a manipulated combination of the Theorems 1 and 2 shown in previous section.

Step 0: *Preliminaries:* Set the upper bound equal to big M and lower bound equal to zero for the all unobserved links. Compute FTSN, FTBN, OTSN, and

OTBN for all O-D pairs.

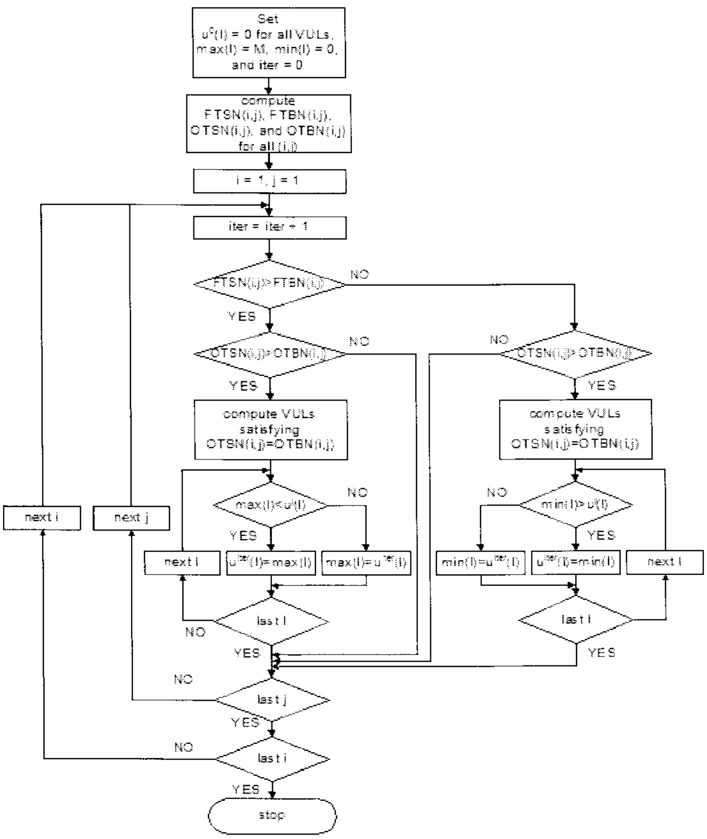
Step 1: *Initialization.* Set i = 1, j = 2, and iteration =1.

Step 2: *Identification of ISP Location.* Check whether FTSN is greater than FTBN. If FTSN is greater than FTBN, then the ISP is in BN. Other wise, the ISP is in SN.

Step 3: *Computation of Unobserved volume.* If the ISP is in BN and, if OTSN is greater than OTBN, then the volume of the unobserved links in the ISP can be increased until OTBN is equal to OTSN (Theorem 2). This procedure defines the upper bounds of the unobserved volumes in the path. If the ISP is in SN and OTSN is greater than OTBN, then it is against the Theorem 1. Therefore the volume of the unobserved links must be increased until OTBN is equal to OTSN, consistent with Theorem1. This procedure defines the lower bound for the unobserved volumes in the path for T(i,j). If OTSN is not greater than OTBN, go to Step 5.

Step 4: *Updating Upper/Lower bounds.* If the current upper bound of a link is greater than the maximum in the path of one of O-D pairs reviewed, then this violates Theorem 2. Therefore the current upper bound should be set equal to the maximum upper bound. If the current upper bound of a link is not greater than the maximum upper bound, then the maximum upper bound should be set equal to the current upper bound so that flow on the current path conforms to Theorem 1.

If the current lower bound of a link is smaller than the minimum lower bound1 in a path for one of O-D pairs reviewed, then this violates Theorem 1. Therefore the current lower bound should be set equal to the minimum lower bound. If, for the current path, the current lower



<Fig. 1>Unobserved link volume estimation algorithm

bound of a link is not smaller than the minimum lower bound, then the minimum lower bound should be set equal to the current lower bound to conform to Theorem 1.

Repeat this procedure for the all LUVs in the path.

Step 5: *Stopping Rule*. If there are no more O-D pairs, stop. Otherwise, repeat Steps 2, 3, and 4 for next O-D pair.

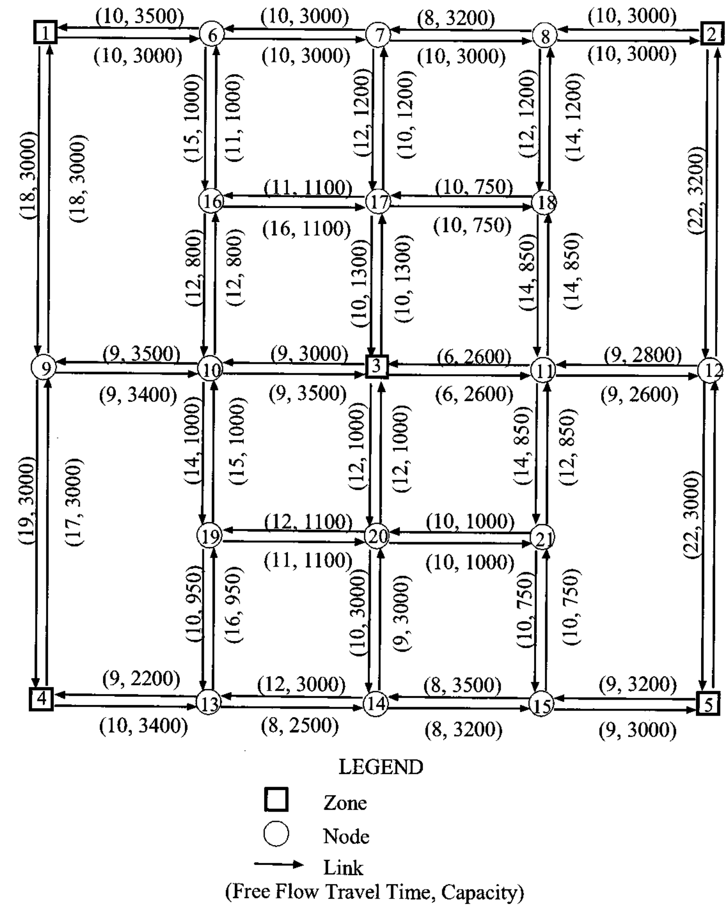
<Fig. 1> shows the flowchart of the suggested volume estimation algorithm.

Ⅳ. MODEL TEST AND RESULTS

The existing optimal solution search algorithm [6] and the new unobserved link volume estimation algorithm are integrated into the new user equilibrium based O-D matrix estimation model (New model hereafter). Then it is compared to Turnquist and Gur's original procedure and Cho and Moore' model [6] in the case of a simple synthetic network and representative trip tables.

1. Model Measures of Effectiveness

The test network is a synthetic network, shown in <Fig. 2>. The free flow travel times and capacities for each link are defined so that 32 links function as part of major arterials, and the other 32 links function as minor arterials or collectors. The capacities of major arterials range between 2,500 and 3,500 veh/hr, and those of the minor



<Fig. 2> Test network

arterials or collectors range from 750 to 1,300 veh/hr. The travel time on each link is given by the BPR performance function, with typical parameter values α = 0.15 and β = 4.0. To demonstrate the effects of the unobserved link volume data to the estimated matrices, three link volume-missing cases are prepared for the input data. <Table 4> shows the test network scenarios and the number of links omitted from the network.

Three different initial trip tables (ITTs) are used as the model input data to assess the performance of the new algorithm and sensitivity to starting conditions. ITT-1 <Table 1> is the same as the true trip table. It is used to test how accurately both models can replicate the true trip table. This measures the intrinsic limitation of the models. The total number of trips accounted for in ITT-2 <Table 2> is about 20 percent less than the total number of trips in true trip table. ITT-2 is obtained by decreasing the each cell values of the true trip matrix by 20 percent, and then randomly increasing or decreasing each value by up to 10 percent based on the computer generated random numbers. ITT-2 represents an out-dated trip table for an area in which travel demand has increased. ITT-3 <Table 3> is an initial trip table in which the numbers of trips are increased relative to the true trip table by 20 percent, and then each cell value in the matrix is increased or decreased randomly up to 10 percent.

The performance of the New Model is tested in terms of two measures; estimation of the unobserved link volumes, and the estimation of the O-D trip matrix. The New Model estimates the unobserved link volume via two steps. The first step is carried by the volume estimation algorithm that was shown in previous Section. The result of the algorithm is the initial estimated link volumes for the New Model. The *initial estimated link volumes* for the LUV and the observed link volumes are then calibrated within the O-D estimation algorithm during the solution O-D matrix is estimated in the New Model. The *finalized volumes* satisfy the user equilibrium assignment condition in association with the estimated O-D matrix.

The volume RMSE defined by following equation measures the performance of the unobserved link volume estimation of the integrated model.

<Table 1> True trip table / Initial trip table - 1

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
Zone 1	0	3500	5500	1500	1000
Zone 2	2500	0	3000	1200	700
Zone 3	2500	2200	0	2200	2200
Zone 4	2000	1500	3000	0	2000
Zone 5	1300	1800	2700	1100	0

<Table 2> Initial trip table - 2

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
Zone 1	0	2716	4180	1080	768
Zone 2	2200	0	2257	1017.6	526.4
Zone 3	2140	1777.6	0	1689.6	1865.6
Zone 4	1728	1176	2520	0	1664
Zone 5	1102.4	1382.4	2030.4	915.2	0

<Table 3> Initial trip table - 3

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
Zone 1	0	4326	6930	1980	1248
Zone 2	2700	0	3816	1353.6	890.4
Zone 3	2790	2613.6	0	2745.6	2481.6
Zone 4	2208	1836	3420	0	2304
Zone 5	1466.4	2246.4	3434.4	1267.2	0

<Table 4> Volume unobserved network scenarios

		Total Number of LUVs (Percentage)	LUV Link Number (Origin Node - Destination Node)
Network Scenario	Net-1	0 (0 %)	
	Net-2	8 (12.5 %)	16-17, 17-16, 17-18, 18-17, 19-20, 20-19, 20-21, 21-20
	Net-3	24 (37.5 %)	6-16, 8-18, 10-16, 10-19, 11-18, 11-21, 13-19, 15-21, 16-6, 16-10, 16-17, 17-16, 17-18, 18-8, 18-11, 18-17, 19-10, 19-13, 19-20, 20-19, 21-11, 21-20, 20-21, 21-15

$$Unobserved\ Volume\ RMSE = \sqrt{\frac{\sum_{n} (v_l - \bar{v}_l)^2}{n}}$$

where, v_l = the estimated volume of the unobserved link l estimated by the integrated model algorithm

or

= 0 when the volume is unobserved and is not estimated,

$\bar{v}_l$ = the user equilibrium volume of the unobserved link l, and

n = the number of unobserved links.

Another performance measure is Trip Root Mean Squared Error (Trip RMSE). This is the average number of squared trip errors in the non-zero cells of the trip table matrix.

$$Trip\ RMSE = \sqrt{\frac{\sum_{j} \left(T_j - \bar{T}_j\right)^2}{n}}$$

where,

T_j = the number of trips estimated for non-zero trip interchange j,

$\bar{T}_j$ = the true number of trips for non-zero trip interchange j, and

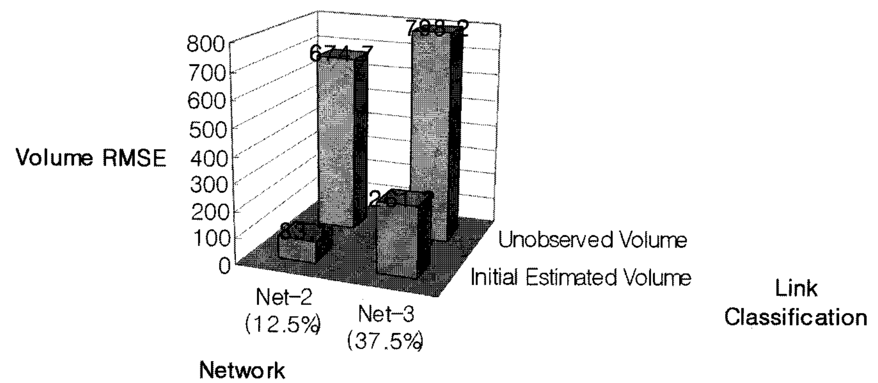
n = number of non-zero trip interchanges.

2. Comparing Estimated Volume Errors of the Unonserved Links

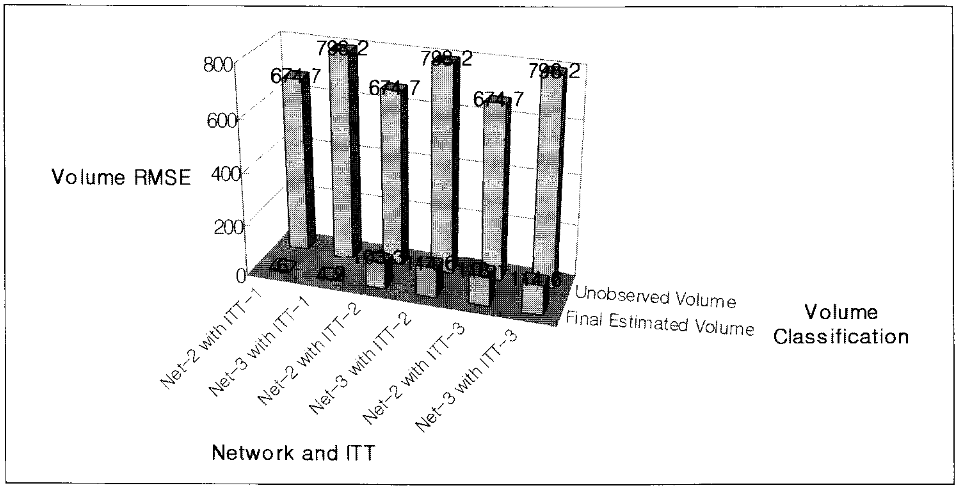
<Fig. 3> compares the RMSEs of the unobserved link volumes and the initial estimated volumes across the four network scenarios. In case of NET-2, where 12.5 percent of the link volumes are unobserved, the initial estimated volume reduced the volume RMSE by 87.7 percent.

Volume RMSE values for NET-3 is higher than that of NET-2, but its volume RMSE value is reduced by 67.3 percent when it is compared with the original unobserved link volumes.

The final estimated volume RMSEs are the results of the New Model. The New Model modifies the initial estimated link volumes in conjunction with the initial trip table in the way to minimize the objective function using initial trip table. Therefore the final estimated volumes are affected by the initial trip table. <Fig. 4> shows the final estimated volume RMSEs of



<Fig. 3> Initial estimated volume RMSE comparison



<Fig. 4> Final estimated volume RMSE comparison

the two missing volume network scenarios (Net-2 and Net-3) across the three different initial trip tables.

It shows that the RMSE values are very small regardless of the network scenarios. When compared with the matching RMSE values of the initial estimated volumes, the final estimated volume RMSE values are all decreased. It is also shown that the final estimated volume RMSEs are less sensitive to proportions of the unobserved links.

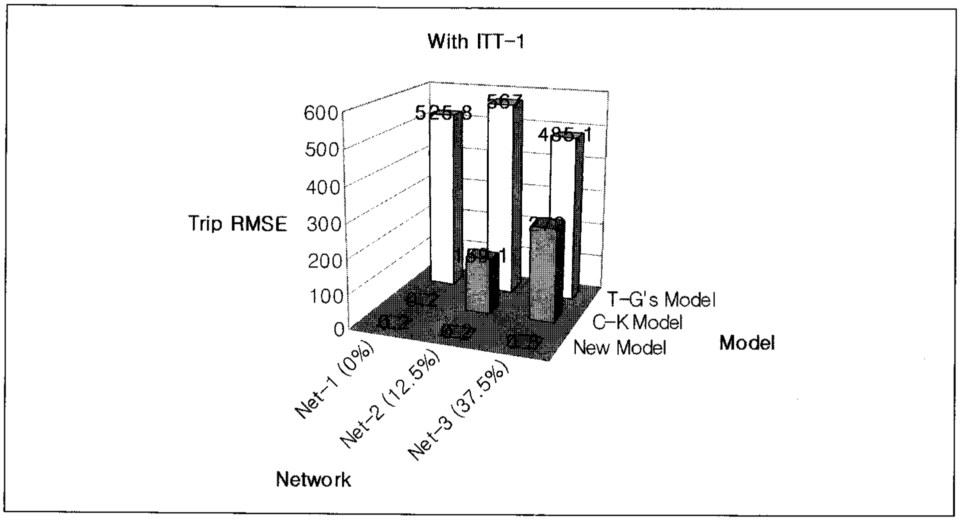
3. Comparing Trip Errors

The output O-D matrices of the three different models are compared to measure the performance of each model. The Existing Model 1 is the Turnquist and Gur's model and Existing Model 2 is the Cho and Moore's model. The network scenarios and the initial trip tables are same to those used to compare the volume RMSEs in previous section.

<Fig. 5> compares the trip RMSE values of the three models across the five network scenarios and ITT-1. All the RMSE values of Turnquist and Gur's model are larger than those of other two models. The RMSE values of Turnquist and Gur's model narrowly ranged between 485.1 and 605.6. Turnquist and Gur's RMSE value for ITT-1 and Net-1 is similar to the values for Turnquist and Gur's model based on other, poorer network information. The proportion of the unobserved links does not affect the trip RMSEs of Turnquist and Gur's model very much.

In contrast, the trip RMSE values of the Cho and Moore's model are steeply increased as the proportion of the unobserved links are increased. However Cho and Moore's model performs noticeably better than Turnquist and Gur's model regardless of the proportion of unobserved links. The New Model performs even better then the Cho and Moore's model. It performs consistently when up to 37.5 percent of the link volumes are not observed. The consistently low trip RMSE values of the integrated model with ITT-1 shows the internal consistency of the New Model. The low and consistent trip RMSE values of the New Model were predictable when the low link RMSE values of the final estimated link volumes were resulted in <Fig. 4>.

The RMSE value difference between Turnquist and Gur's model and the Cho and Moore's model is solely due to the optimal solution search function in the Cho and Moore's model. And the RMSE value difference



Existing model 1 (T-G Model): Turnquist and Gur's model
Existing model 2 (C-M Model): Cho and Moore's solution search direction optimized model
New Model (NM): Model with the unobserved volume estimation algorithm and solution search direction optimized algorithm

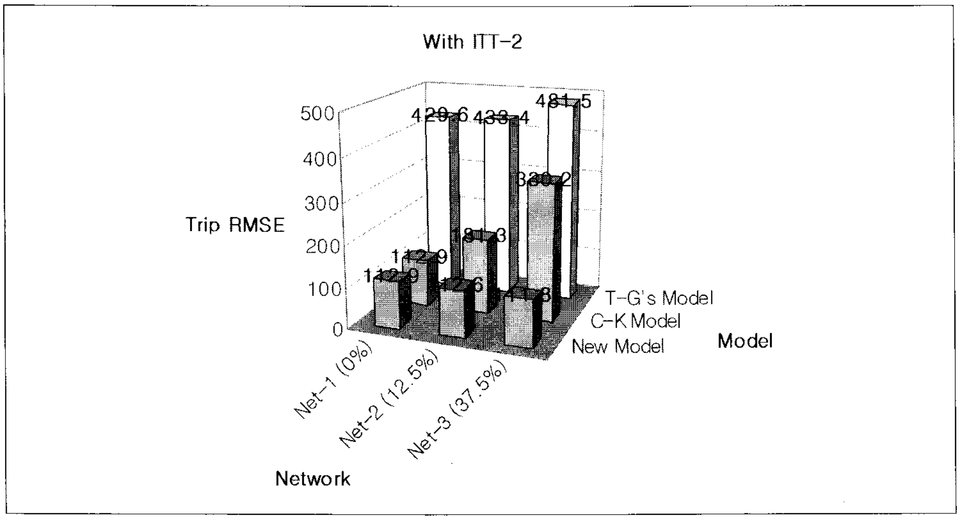
<Fig. 5> Trip RMSE comparison (with ITT-1)

between the Cho and Moore's model and New Model is the result of the volume estimation algorithm of the New Model. Thus the RMSE value difference Turnquist and Gur's model and the New Model is the result of the combined effects of the optimal solution search direction function and the volume estimation algorithm in the New Model .

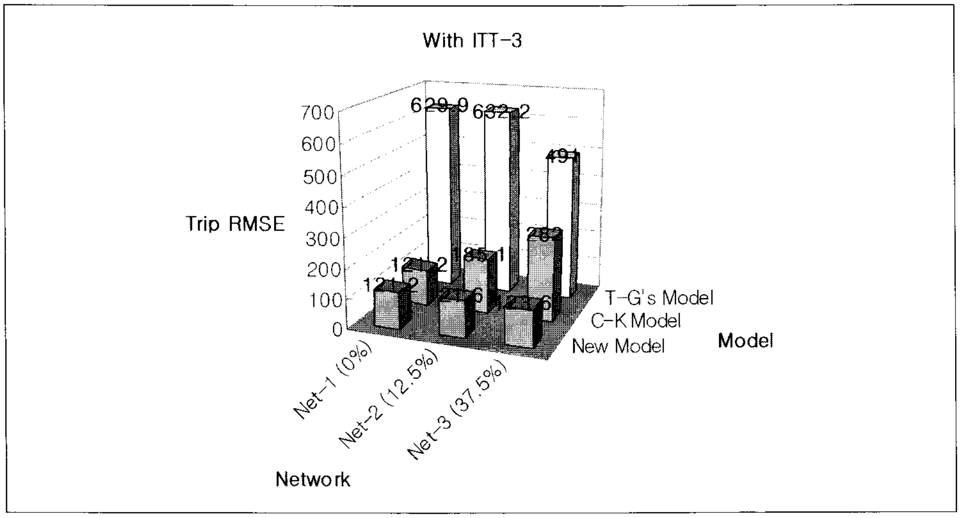
For the two other ITTs, which are imperfect initial trip tables, the Cho and Moore's model performs better than Turnquist and Gur's model and the New Model performs better than Cho and Moore's model <Fig. 6 and 7>. With ITT-2, the RMSE values of Turnquist and Gur's model distribute between 429.6 and 481.5 and, as before, they are not sensitive to the proportion of the unobserved link volumes. When compared with RMSE values of Turnquist and Gur's model, the RMSE values of the Cho and Moore's model are reduced by between 31.0 percent (with Net-3) and 73.7 percent (with Net-1). Overall, the RMSE values of the New Model 2 are gradually increased as the proportion of the unobserved link volumes are increased.

The New Model reduces the RMSE values of the Cho and Moore's model further. Compared with the trip RMSE values of the Cho and Moore's model, the New Model reduced the trip RMSE values up to 66.1 percent when 37.5 percent of the link volumes are not observed. Due to the unobserved link volume estimation algorithm, the New Model yielded much consistent solutions regardless of the proportion of unobserved links.

Similar performance improvements of the New Model are achieved when the ITT-3 is used <Fig. 7>. The New Model 2 performs consistently better than Turnquist and Gurs's model although its RMSE values are proportionally increased as the proportions of the unobserved link volumes are increased. The New Model overcomes the effects of the unobserved link volumes and resulted in stable trip RMSE values regardless of the proportion of the unobserved link volumes. Trip RMSE value of the New Model increased by only 2.0 percent when 37.5 percent of



<Fig. 6> Trip RMSE comparison (with ITT-2)-1)



<Fig. 7> Trip RMSE comparison (with ITT-3)

the link volumes are not observed.

V. CONCLUSIONS

This paper has addressed the synthetic estimation of the O-D matrices from link volume counts and user-equilibrium information. The volume estimation algorithm for the unobserved links is derived as the sub-algorithm of the suggested O-D estimation model. A lemma and two theorems concerning user-equilibrium conditions are suggested with proofs for the development of the volume estimation algorithm.

The suggested volume estimation algorithm is designed to estimate the unobserved link volumes that are as close to the true link volumes as possible. Performance of the algorithm depends on the proportion of the unobserved links and the link use patterns. The information about user-equilibrium conditions obtained from the observed link volumes is crucial for the estimation of the unobserved link volumes. The suggested theorems are the tools to systematically extract information from observed flows and on assumption of user-equilibrium conditions. The volume estimation algorithm is a combination of the theorems.

Compared with the existing models, the suggested model possesses a clear advantage. The new model approximates the unobserved link volumes using user equilibrium assignment conditions. The estimated link volumes provide additional useful constraints to the given optimization program. Thus the estimated link volumes provide the model with better starting conditions for solving given problems. The effectiveness of the new model was tested with a synthetic network with several unobserved link scenarios. The test results make it clear that the suggested model performs consistently better than the existing model. In the all tests with the synthetic network, the suggested model performs better than the existing model by large margins in terms of RMSE values.

The suggested model is applicable in places where the conventional or the existing synthetic O-D estimation procedures are used as long as the input data is available. Therefore, the suggested model can be applied for transportation studies, where O-D trip tables are required such as transportation modeling, network design problems, traffic impact studies, land-use and transportation simulation studies, and etc.

Current land-use patterns largely determine existing traffic pattern. More specifically, the observed link flows are the combined results of individuals' spatial activities. In the context of trip distribution and assignment, the number of trips between zones aggregately quantifies individuals' activities. When a new network is added to the existing network system, it can be used by those who previously used the other paths. On the other hand, the new network will improve the accessibilities of some zones and, therefore, trip productions and attractions of such zones are supposed to be changed. When the new network is regarded as the volume unobserved links, the suggested model estimates a new O-D matrix. This matrix is one that, when assigned to the network, replicates the observed volumes of the existing links and allocates additional trips on the new network. This means that the output O-D matrix is the sum of the existing spatial activities and the additional spatial activities stimulated by the new network. The interpretation of this new O-D matrix requires more rigorous studies, but this example shows the potential usefulness of the suggested model for the simulation of transportation and land-use relationship.

References

[1] W. H. K. Lam and H. K. Lo, "Estimation of origin-destination matrix from traffic counts: A comparison of entropy maximizing and information minimizing models," *Transportation Planning and Technology*, vol. 16, pp. 85-104, 1991.

[2] H. Yang, T. Sasaki, Y. Iida, and Y. Asakura, "Estimation of origin-destination matrices from link traffic counts on congested network," *Transportation Research*, vol. 26B, pp. 417-434, 1992.

[3] M. Turnquist and Y. Gur, "Estimation of trip tables from observed link volumes," TRB *Transportation Research Record*, vol. 730, pp. 1-6, 1979.

[4] A. Han and E. Sullivan, "Trip table synthesis for CBD networks: Evaluation of the LINKOD model," *TRB Transportation Research Record*, vol. 944, pp. 106-112, 1983.

[5] Y. Gur, "Estimating trip tables from traffic counts: Comparative evaluation of available techniques,"

TRB Transportation Research Record, vol. 944, pp. 113-117, 1983.

[6] S. Cho and J. E. Moore, "Improved user equilibrium based method for estimating trip tables," *J. Transportation Engineering*, vol. 126, no. 6, pp. 492-497, Nov. 2000.

[7] S. Nguyen, *Estimating an O-D matrix from network data: A network equilibrium approach*, Publication 87, Centre de recherché sur les Transports, University de Montreal, Montreal, Canada, 1977.

[8] L. LeBlanc and K. Farhangian, "Selection of a trip table which reproduces observed link flows," *Transportation Research*, vol. 16B, pp. 83-88, 1982.

[9] H. Spiess, *A gradient approach for the O-D matrix adjustment problem*, Centre De Recherché Sur Les Transports Publication no. 693, 1990.

[10] C. Fisk, "Trip matrix estimation from link traffic counts: The congested network case," *Transportation Research*, vol. 23B, pp. 331-356, 1989.

[11] J. Oh, *Estimation of trip matrices from traffic count: An equilibrium approach*, Mathematics in Transport Planning and Control, Clarendon Press, pp. 35-44, 1992.

[12] H. Yang, Y. Iida, and T. Sasaki, "The equilibrium-based origin-destination matrix estimation problem," *Transportation Research*, vol. 28B, pp. 23-33, 1994.

[13] L. Willumsen, "Simplified transportation models based on traffic counts," *Transportation*, vol. 10, no. 3, pp. 257-278, Sept. 1981.

[14] H. V. Zuylen, *The information minimising method: validity and application to transport planning*, New developments in modelling travel demand and urban systems, Saxon, Fahnborough, 1978.

[15] H. V. Zuylen, and L. G. Willumsen, "The most likely trip matrix estimated from traffic counts," *Transportation Research*, vol. 14B, pp. 281-293, 1980.

[16] H. Lo, W. Lam, and N. Zhang, "Estimation of an origin-destination matrix with random link choice proportions: a statistical approach," *Transportation Research* vol. 30B, pp. 309-324, 1996.

[17] R. Sivanada, D. H. Sherali, and A. Hobeika, "A new approach for estimating origin-destination trip tables from traffic counts," *Proc. Transportation Research Board 73rd Annual Meeting*, 1994.

[18] H. J. Lee and S. J. Lee, "The estimation of O-D matrix from traffic counts using conjugate gradient method in nationwide network," *J. Korean Society of Transportation*, vol. 23, no. 3, pp. 61-71, June 2005.

[19] Y. T. Lim, "Solution method for OD trip estimation in stochastic assignment," *J. Korean Society of Transportation*, vol. 24, no. 4, pp. 141-159, June 2006.

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