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THE ESTIMATION OF FREEWAY ORIGIN-DESTINATION DEMAND USING REAL-TIME TRAFFIC DATA OF FREEWAY TRAFFIC MANAGEMENT SYSTEM (FTMS)

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Abstract: The goal of this paper is to develop the freeway Origin-Destination (OD) demand estimation model using real-time traffic data collected from Freeway Traffic Management System (FTMS). Although it is necessary for the dynamic OD demand between on and off-ramps to perform more effective traffic management strategies, Automated Vehicle Identification (AVI) systems are unable to assist to collect OD demand due to the limitation of construction and maintenance costs. The existing models use the simulation model to get a link distribution ratio of dynamic traffic flow by time process. It is difficult to load at FTMS and estimate a dynamic OD between on and off-ramps. The formulation of methodology proposed in this paper includes traffic flow techniques and dynamic OD demand estimation techniques using a real-time detector data. The proposed methodology is evaluated by using the real-time data of NAEBU Ring Road, a circulatory freeway system in Seoul, South Korea.

Key Words: Dynamic O-D demand estimation, FTMS, Traffic flow module, QUEENSOD

1. INTRODUCTION

Recently, Freeway Traffic Management System (FTMS) has been extended to most of urban freeway sections and puts it to several desirable means dealing with congestion management in Seoul. It is necessary for the dynamic OD demand between on and off-ramps to build the more effective traffic management strategies. To collect the OD demand, Automated Vehicle Identification (AVI) should be equipped at the entire on and off-ramps. Nonetheless AVI systems have been partially installed because of the limitation of construction and maintenance costs. The detectors are constructed at the whole section of mainline as an identical gap (usually 500m) and all the on and off-ramps at NAEBU Ring Road in Seoul. Traffic Management Center (TMC) has collected a useful real-time data, such as traffic volumes, travel speed and occupancy. Meanwhile, the current consideration involved with the estimation of freeway dynamic OD matrices have been taken increasing attention through the applicability to on-line traffic management systems.

The existing simple dynamic OD estimation model is mostly formulated in order to minimize the gap between observed and predicted link traffic volumes. It comprises two parts of algorithms - traffic flow theory and optimal solutions algorithm. Regardless of sophisticated techniques for the solutions, most of the models have been dealt with a few types of link distribution proportion of trips on time process by using micro simulation models. The link distribution proportion means the proportion of trips located at every link on time process and is used for calculating the estimated link traffic volumes by a specific period of time.

The existing dynamic OD estimation models that use micro simulation models (CORSIM, PARAMICS, INTEGRATION, AIMSUN, MITSIM and so on) to calculate the moving points of vehicles on time process have some difficulty in applying to FTMS, especially on line sections of freeways. Because there is an interrelation between link distribution proportion of trips estimated from the micro simulation models and dynamic OD demand estimated from optimal solution model, the existing dynamic OD estimation model have to be solved bi-level problem between the micro simulation model and the optimal solution model.
This paper attempts to develop the simple traffic flow technique which outputs the link distribution probability of trips on time process using average speed, occupancy collected from the detectors. The proposed traffic flow technique has several advantages. We can remove the interrelation between link distribution proportion of trips and dynamic OD demand. Therefore, bi-level problem that has been pointed out as difficulty of dynamic OD estimation model can be excluded. Because it describes traffic flow using observed traffic data, we need not to calibrate traffic flow models. We use QUEENSOD model of Van Aerde(1) for optimal solution algorithm. The approach makes it possible to estimate dynamic OD to minimize the gap between the observed and estimated link traffic volumes. In addition, this paper expects that the proposed model would be applied to the on-line traffic management systems.

2. MODELING DYNAMIC OD DEMAND ESTIMATION

2.1 Definition of Variables

This study attempts to estimate the dynamic OD on freeway based observed link traffic data, such as traffic volumes, travel speed, and occupancy. The following notations are used to express the dynamic OD estimation algorithm described in Section 2.

i , j , a , dt , t : Indices corresponding to origin, destination, link, time interval for departure time, time interval

v_a^t : Observed link volume at link a and time interval t

$\bar{v}_a^t$: Estimated link volume at link a and time interval t

OD_{ij}^{dt} : Trips leaving from origin i to destination j during time interval dt

$P_{ij,dt}^{a,t}$: Proportion of trips leaving origin i to destination j during time interval dt and traveling on link a during time interval t

CL_a^t : Correction factor for link a and time interval t

CS_{ij}^{dt} : Correction factor summed between origin i and destination j

PO_{ij}^{dt} : Probabilities of link use summed for all links used for traveling from i to j during time interval t

CF_{ij}^{dt} : Correction factor finalized for between origin i and destination j at time interval t

S_a^t : Travel length at link a during time interval t

$TS_{i,dt}^t$: Cumulative moving length of trips leaving from origin i during time interval dt at time interval t

sp_a^t : Travel speed at link a during time interval t collected from detector

occ_a^t : Occupancy at link a during time interval t collected from detector

$l_{i,dt}^{a,t}$: Distributed length of trips leaving from origin i during time interval dt at link a during time interval t

L_i^a : Cumulative link length from entry ramp to link a

$P_{i,dt}^{a,t}$: Using proportion of link a at time interval t of trips leaving origin i during time interval dt

PR_{ij}^{dt} : OD proportion of trips leaving from origin i to destination j at time interval dt

O_i^{dt} : Traffic volume leaving from origin i during dt

2.2 Overview of the Dynamic OD Estimation Problems

As far as literatures are concerned, various approaches have already been applied for the estimation of dynamic OD demand. They can be categorized into two families - statistical method and state space method. The objective function of the dynamic OD demand estimation model is generally set up to minimize the gap between observed and estimated link flow as equation (1). According to some studies, the objective function consists of two terms related to traffic counts and historic OD matrix (Yang, 1992)

$$\min \ Z = \sum_a (v_a^t - \overline{v}_a^t)^2 \tag{1}$$

In order to solve the minimization problem, the approaches have been adopted, like Bayesian approach, Generalized Least Squares(GLS), Maximum Likehood(ML), Kalman Filtering(KF), QUEENSOD and so on. Maher(1983) presented a Bayesian statistical approach to estimate time varying OD flows for small networks. The basic assumption of this method is the multivariate normality of the existing information, observation, and accurate knowledge of the assignment matrix based on a proportional assignment algorithm.

Cremer and Keller(1987) and Nihan and Davis(1987) have presented GLS and weighted GLS procedures for the estimation of dynamic OD flows on small networks. These models began with assumption that the time should be taken by vehicles to traverse intersections or networks which are either small or ignored. However, the assumption was not acceptable enough to apply to a freeway or a general network, especially when congestion existed.

The KF algorithm is the most typical state space model that has been intensively investigated. Ashok and Ben-Akiva(1993) provided an OD matrix updating frameworks that could approach the problem as a Kalman Filtering regarding the state vector consists of OD flows deviations from previous estimates based on historical data. In the case study, the authors assumed that the assignment matrices would be time-invariant due to the constant speed assumption that there is no realistic condition in the view of traffic flow fluctuation. Zijpp and Hamerlag(1994) proposed an improved KF method for estimating dynamic freeway OD probabilities. This model offered a clue which approximates the noise in the KF algorithm by using a trip generation model. The simulated and empirical results indicated that the improved KF method combined with a historical data base could make a better performance than any other approach.

Van Aerde introduced the QUEENSOD model for generating dynamic synthetic O-D matrices. Not only is this model based on an iterative approach, but also starts the first iteration from a seed OD matrix. The adjustment on the seed OD matrix is conducted by the

process of the quantitative comparisons between observed and estimated link flows.
Most of the existing dynamic OD estimation models take it into account to adopt micro simulation models in a way of calculating a moving location of vehicle on time process. However, IIDA and KURAUCHI(2004) applied a simple traffic flow method that calculates the influence coefficient (the ratio of the vehicles whose OD is (i,j), running on path (h), departed at time interval (s) that will be on the link (a) at time interval (t)) using moving points of vehicles.

2.3 Proposed Dynamic OD Estimation Model

The proposed dynamic OD Estimation model has two modules - traffic flow module, OD estimation module. The traffic flow module calculates a link distribution proportion of each trips at every link ($P_{i,dt}^{a,t}$) on time process pertaining to link travel speed and occupancy. The dynamic OD estimation module estimates traffic volume by using a link distribution proportion at every link and calculates dynamic OD demand to minimize a gap between observed and estimated link traffic volumes. To estimate the dynamic OD demand, QUEENSOD model proposed by Van Aerde(1) is selected as a main tool.

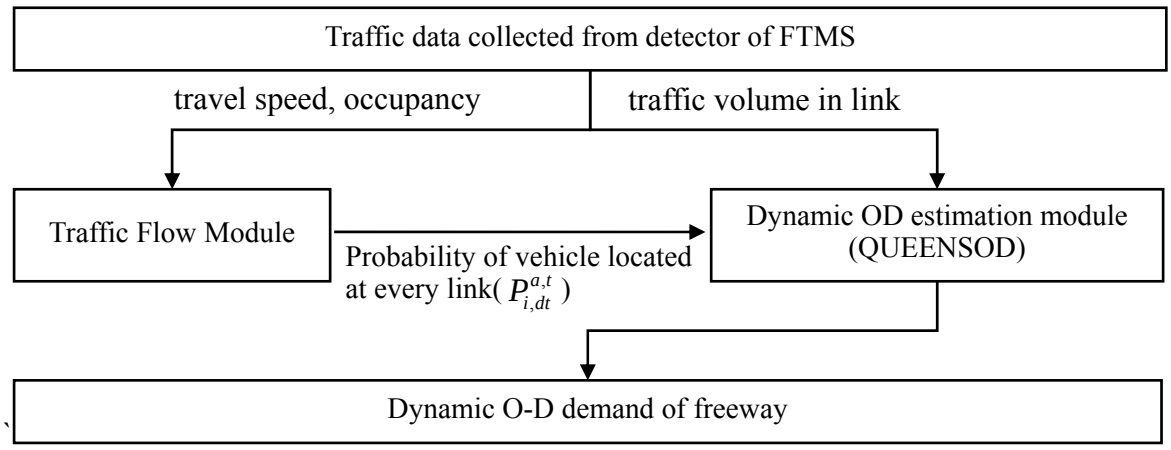

Figure 1. Dynamic O-D Estimation Model

2.3.1 Traffic Flow Module

The traffic flow module is an important part for the dynamic OD demand estimation on freeway. The principle of the module describes that vehicles are running, based on traffic flow theory to the destination on time process. In order to estimate OD demand to minimize the gap between observed and estimated link traffic volumes, the link traffic volume should be estimated based on the OD matrix and link distribution proportion calculated traffic flow module. The role of the traffic flow module is to calculate a link distribution proportion (parameter $P_{ij,dt}^{a,t}$, proportion of trips located at every link on time process). The existing OD estimation model is proposed at the use of the micro simulation models for link distribution proportion. In this case, dynamic OD estimation model have several shortcomings. In order to calculate the link distribution proportion using micro simulation model, dynamic OD must be input at micro simulation model. Therefore, Dynamic OD demand has influence on link distribution proportion estimated at traffic flow module and link distribution proportion has

influence on dynamic OD demand estimated at dynamic OD estimation module. Ultimately, dynamic OD estimation problem has to be solved bi-level approach between traffic flow module and dynamic OD estimation module. Also, the result of micro simulation model should be compared to the real data collected from the detectors, and the parameter used to micro simulation model should be calibrated on the exact same real traffic situation. It is not so much easy to perform a simultaneous implementation on FTMS.

The research of this paper proposes a new simple traffic flow technique to calculate a variable of link distribution proportion $P_{ij,dt}^{a,t}$ by using a real time traffic data collected detector such as average travel speed, occupancy, link volume and so on, so that bi-level problem need not to be considered and the dynamic OD demand estimation model is able to be applied to on-line traffic management systems. The traffic flow module draws the trajectory of a leading vehicle leaving at every on-ramp during every time interval on time process using average travel speed, and calculates the link distribution proportion of the entire link based on occupancy and distributed length of trips. For this process, three assumptions are made.

a) The traffic condition of each link is uniform; all of the vehicles running on the same link has the same speed, and the traffic density of the link is homogeneous.
b) The vehicle driving on the link complies the rule of the first-in first-out(FIFO) condition.
c) All of the trips leaving from the same entry ramp distribute in proportion to the occupancy of each link between the front and last vehicle at the same time

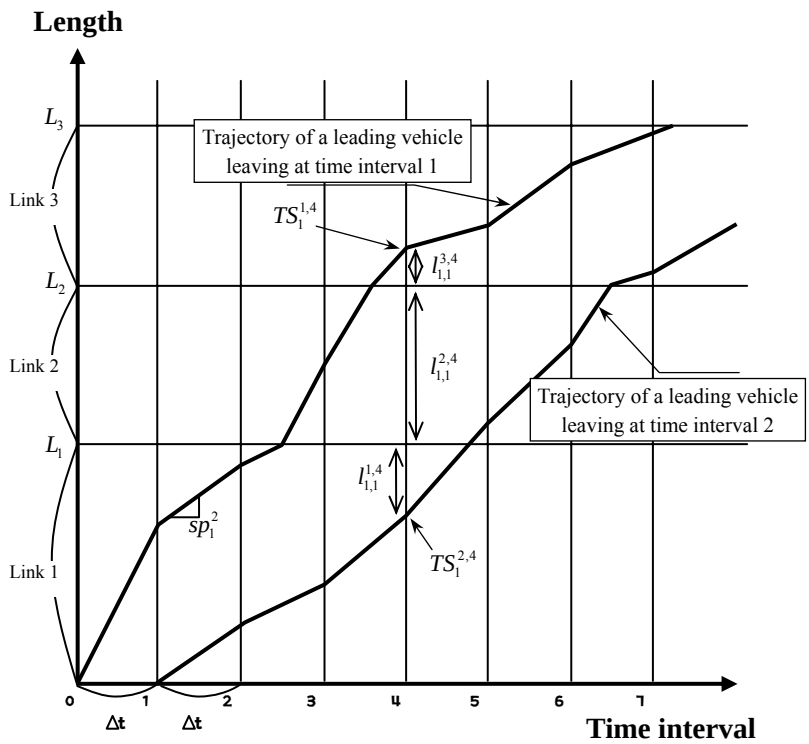

Figure 2. Trajectory of a Leading Vehicle Leaving at Every Interval

The slope of the trajectories at every link and time interval in Figure 2 means average travel speed. Traveling length to be capable of moving during every time interval is calculated by travel speed of the link, on which the leading vehicle is located, and time interval as follows.

$$S_a^t = sp_a^t \times \Delta t \tag{2}$$

In order that trips leaving from each entry ramp move at average speed of the located link at every time interval, the position of a leading vehicle should be tracked on time process. If the average speed is high at time interval t, the leading vehicle can pass more than one link. In this case, the trajectory of leading vehicle and link length has to be considered as the cumulative value from the connecting link of entry ramp. The traffic flow module should include a routine to determine whether leading vehicle pass the ending point of the link at time interval t or not. The calculation process of trajectory is as equation (3).

$$\begin{aligned} &if \quad TS_{i,dt}^{t-1} + S_a^t > L_i^a \\ &\qquad TS_{i,dt}^t = L_i^a + (\Delta t - \frac{L_i^a - TS_{i,dt}^{t-1}}{sp_a^t}) \times sp_{a+1}^t \\ &else \quad TS_{i,dt}^t = TS_{i,dt}^{t-1} + S_a^t \end{aligned} \tag{3}$$

The distributed length of trips at every link can be valued by using moving trajectory of leading vehicle. It is calculated by the point of the front and last vehicle at every time slice. It is assumed that the point of the last vehicle is same as the point of the front vehicle at next time slice. The equation for calculating the link distribution length of trips is as equation (4).

$$\begin{aligned} &if \quad TS_{i,dt}^t \le L_i^a \;\; and \;\; TS_{i,dt+1}^t > L_i^{a-1} \\ &\qquad l_{i,dt}^{a,t} = TS_{i,dt}^t - TS_{i,dt+1}^t \\ &if \quad TS_{i,dt}^t > L_i^a \;\; and \;\; TS_{i,dt+1}^t > L_i^{a-1} \\ &\qquad l_{i,dt}^{a,t} = L_i^a - TS_{i,dt+1}^t \\ &if \quad TS_{i,dt}^t \le L_i^a \;\; and \;\; TS_i^{dt+1,t} \le L_i^{a-1} \\ &\qquad l_{i,dt}^{a,t} = TS_{i,dt}^t - L_i^{a-1} \\ &if \quad TS_{i,dt}^t > L_i^a \;\; and \;\; TS_{i,dt+1}^t \le L_i^{a-1} \\ &\qquad l_{i,dt}^{a,t} = L_i^a - L_i^{a-1} \end{aligned} \tag{4}$$

The link distribution proportion of trips can be calculated by using link distribution length of trips and occupancy of each link. The link distribution proportion is suitable to be calculated based on link density rather than link occupancy. Nevertheless, we substitute link occupancy for link density because the link density can not be collected from detector. The link distribution proportion of trips can be calculated as equation (5).

$$P_{i,dt}^{a,t} = \frac{l_{i,dt}^{a,t} \times occ_a^t}{\sum_{a \in A} (l_{i,dt}^{a,t} \times occ_a^t)} \tag{5}$$

Described in the above, the value of link distribution proportion($P_{i,dt}^{a,t}$) is calculated by using the real-data, such as traffic volume, travel speed and occupancy, collected from VDS and not

influenced by OD proportion at all, because it is a value calculated without any variables about destinations. Therefore, we can overcome the existing bi-level problem between traffic flow module and dynamic OD estimation module. In addition, we can save the analysis time to estimate dynamic OD trips by running a program just once because the proposed link proportion does not still change even if dynamic OD matrices estimated from optimal solution algorithm are renewed

2.3.2 OD Estimation Module

A variety of optimal solution algorithms to be used for dynamic OD demand estimation, like Generalized Least Square algorithm, Kalman Filter algorithm, Genetic algorithm and so on, have been proposed for the decades of years. The research of the paper selects QUEENSOD algorithm proposed by Van Aerde to evaluate dynamic OD demand estimation. The QUEENSOD model initiates the first iteration form as a seed OD matrix. The seed OD can be either a uniform or a historical OD matrix. The seed OD matrix is adjusted through the quantitative comparison between the observed and the estimated link flows. By implementing the multiple iterations of these processes, the seed OD matrix is systematically modified to generate a newer and better OD matrix.
The flow of dynamic OD demand estimation using QUEENSOD is as follow. We applied the algorithm that used existing study of Ilsoo Yun and Byungkyu Park[5]

- Step1 : Determining a dynamic seed OD matrix(uniform OD)
- Step2 : Estimating link volume using link distribution proportion ($P_{i,dt}^{a,t}$) estimated at traffic flow module, OD proportion matrix (PR_{ij}^{dt}) and traffic volumes of on-ramp (O_i^{dt})

$$\overline{v}_a^t = \sum_{i<a}\sum_{j>a}\sum_{dt}(P_{i,dt}^{a,t} \times O_i^{dt} \times PR_{i,j}^{dt}) \tag{6}$$

- Step3 : Calculating link error correction factors. After estimating link traffic volume, the link error correction factor should be calculated to consider errors between observed and estimated traffic volumes for every link.

$$CL_a^t = \begin{cases} \dfrac{v_a^t}{\overline{v}_a^t} & if \quad \overline{v}_a^t > 0 \\ 1.0 & if \quad \overline{v}_a^t = 0 \end{cases} \tag{7}$$

- Step4 : Estimating OD error correction factors. The process is so essential that the error of link traffic volume between observed and estimated value could be reflected to OD matrix. OD error correction factor is calculated as follow.

$$\begin{aligned} CS_{ij}^{dt} &= \prod_{a,t}(PR_{ij,dt}^{a,t} \times CL_a^t) \\ PO_{ij}^{dt} &= \sum_t \sum_a PR_{ij,dt}^{a,t} \end{aligned} \tag{8}$$

$$CF_{ij}^{dt} = \begin{cases} CS_{ij}^{dt^{(PO_{ij}^{dt})^{-1}}} & if \quad PO_{ij}^{dt} > 0 \\ 1.0 & if \quad PO_{ij}^{dt} = 0 \end{cases} \tag{9}$$

- Step5 : Updating a new OD matrix

$$OD_{ij}^{dt}(n+1) = OD_{ij}^{dt}(n) \times CF_{ij}^{dt} \tag{10}$$

where, $OD_{ij}^{dt}(n+1)$ = dynamic OD matrix at iteration $n+1$
n = iteration identifier

- Step6 : Repeating above steps until convergence criterion is met. If convergence criterion is not met, go to step 2.

2.3.3 Calibration of Detector Data

The dynamic OD demand is estimated on the basis of comparison between the observed and estimated link traffic volumes. The link traffic volumes($\bar{v}_a^t$), which are estimated by using OD proportion matrix, traffic volume of on-ramp and link distribution proportion calculated at traffic flow module, means strictly the number of vehicles running at link a and time t. Therefore, it is requested that a real traffic volume collected from detector should be modified for the sake of being compared with the estimated link traffic volume. We assume that the density of each cell is in proportion to the value of occupancy collected from detector. Thus, we use parameter λ to calibrate between density and occupancy. The traffic volumes can be calculated by length of cells, occupancy and number of the lane as equation (11)

$$v_a^t = \lambda \times \sum_{k \in a} (Occ_k^t \times L_k \times N_k) \tag{11}$$

where, Occ_k^t = Occupancy collected from detector at cell k and time t
λ= Calibration parameter between density and occupancy
L_k = Length of cell k
N_k = Number of the lane of cell k

Detectors are installed in the sections of mainlines at the distance interval of 500m on NAEBU ring road in Seoul <figure 4>.

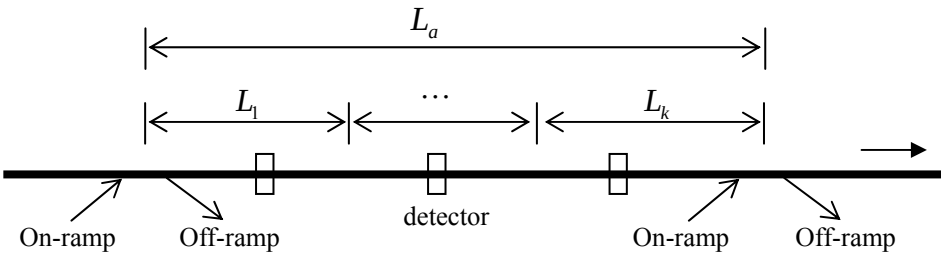

Figure 3. Organization of Cells in a Link

The parameter λ must be calibrated using real density and occupancy of every link. But it is difficult to observe density of every link. Thus, we search the value of λ that minimizes the gap between observed and estimated link traffic volume dependent on variation of λ. <Figure 5> shows the variation of RMAE and RMSE between estimated and observed link volume

dependent on value of λ at SOHAEAN freeway in KOREA. When λ is 1.5, all of RMAE and RMSE between have the minimum value. Thus we determined the value of λ as 1.5.

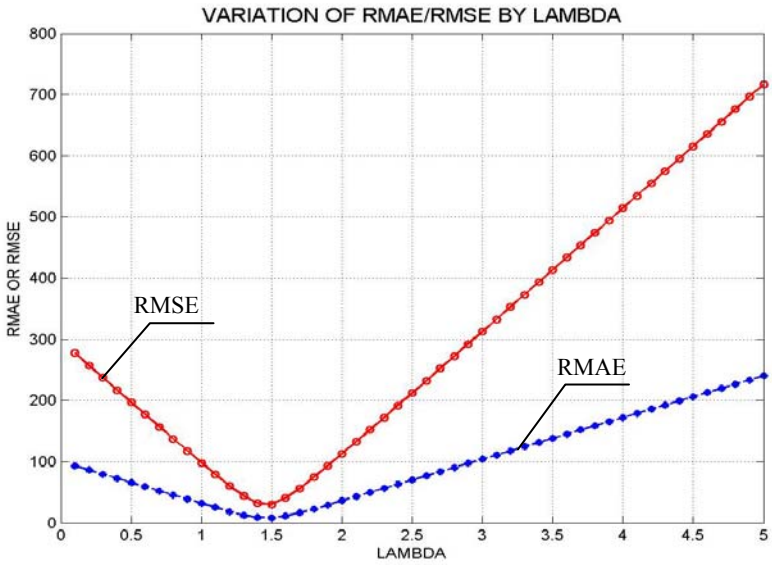

Figure 4. Variation of RMAE and RMSE between Estimated and Observed Link Volume Dependent on Value of λ

3. CASE STUDY

We programmed using MATLAB(version 6.5) to evaluate the dynamic OD estimation model proposed in this paper. In order to verify and analyze this model, we determined the site of NAEBU Ring Road that the length is 27.58km and it consists of four on-ramp and five off-ramp. We use a real traffic data, such as link traffic volume, travel speed, occupancy, collected from the detector.

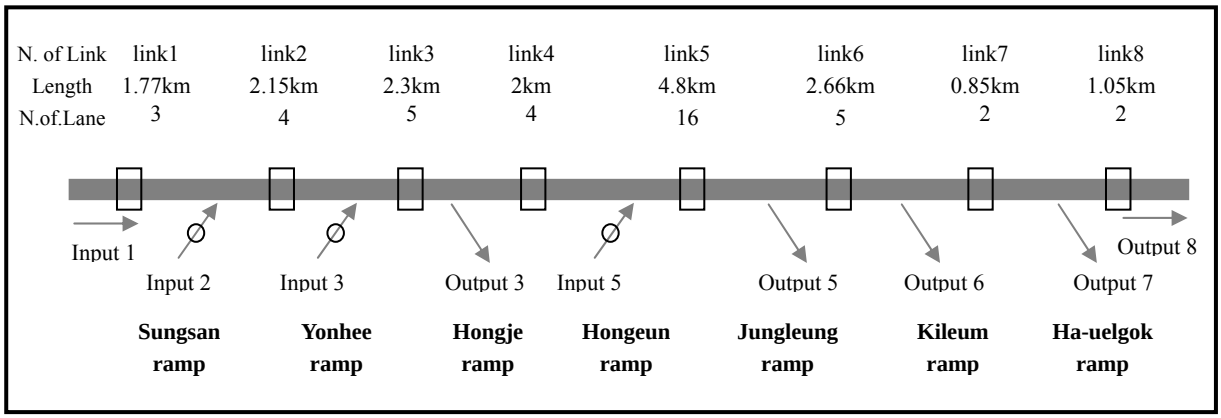

Figure 5. Detector on Freeway in Seoul

<Figure 6> represents a trajectory of a leading vehicle entering into on-ramp 1 during four time interval(dt1, dt2, dt3, dt4) by using real-traffic data collected from VDS of NAEBU ring road. <Table 1> represents the calculating process of link distribution proportion ($P_{i,dt}^{a,t}$) of trips at time slice 5($dt5$) that departing from on-ramp 1 during time interval 1($dt1$).

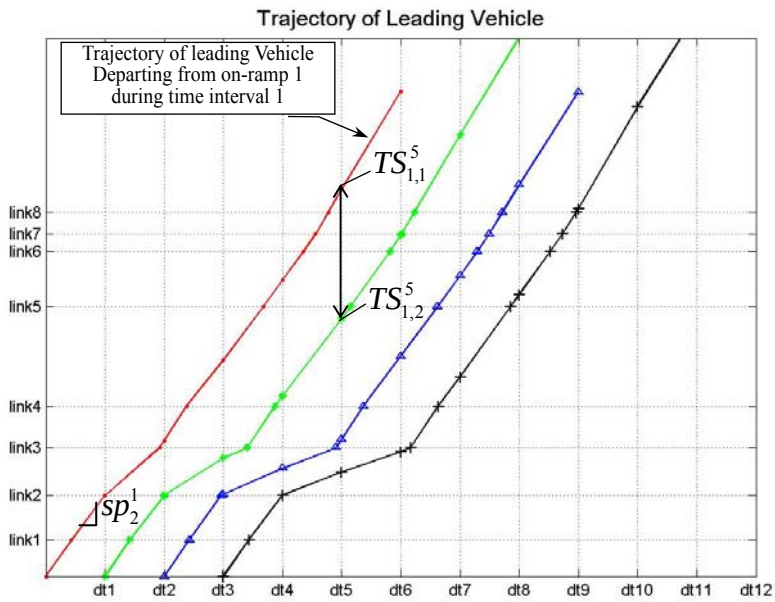

Figure 6. Trajectory of a Leading Vehicle

Table 1. Calculating Process of Link Distribution Length

	Link 5	Link 6	Link 7	Link 8	Link 9	Sum
Link distribution length (A)	0.56	2.66	0.85	1.05	1.14	6.26
Occupancy (B)	12.92	8.75	4.51	2.5	2.5	-
(A) (B)	7.30	23.27	3.83	2.62	2.84	39.88
Link distribution length ($P_{i,dt}^{a,t}$)	0.183	0.584	0.096	0.066	0.071	1

<Table 2> shows the result of OD estimation between on and off-ramp. Because we didn't survey the real OD demand, it is impossible to compare the estimated with observed OD demand. Judging from the real historical travel pattern, it is assumed that the result of dynamic OD estimation is reasonable.

Table 2. Result of OD Estimation(Sum of Total Time Interval)

	output3	output5	output6	Output7	output8	sum
input 1	1,362	290	1,160	1,003	229	4,044
input 2	707	361	512	388	281	2,250
input 3	231	163	176	169	160	899
input 5	-	371	408	399	372	1,550
Sum	2,300	1,185	2,256	1,959	1,043	8,743

<Figure 7> shows the result of comparison between estimated link volume and observed link volume at link 6. In order to apply to the practice, this model requires the complements and future researches with real-time data to reduce the error between observed and estimated value related link traffic volume and O-D demand.

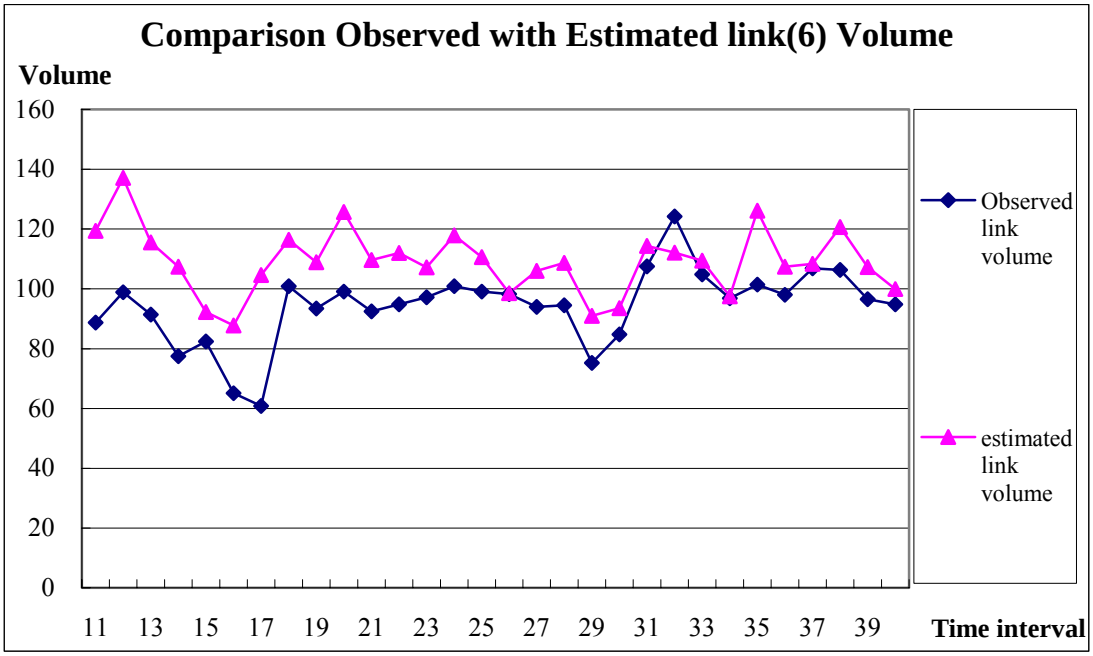

Figure 7. Comparison Observed with Estimated Link Volume(Link 6)

4. CONCLUSION

The development of dynamic OD estimation model using real time traffic data such as link volumes, speed and occupancy from FTMS is the main point of this research. As mentioned before, there have been realistically entangled problems in the existing models, since they have simulation models involved with the link distribution proportion on time process. The critical problems of existing dynamic OD estimation model can be categorized two parts.

First, the existing dynamic OD estimation model must be approached bi-level problem between traffic flow module and OD estimation module because of correlation between link distribution proportion and dynamic OD. It is resulted from using micro-simulation that OD value must be input initially to calculate link distribution proportion. In this research, we propose a new traffic flow technique using traffic data collected from detector such as travel speed, occupancy. Therefore, we can overcome the existing bi-level problem between traffic flow module and OD estimation module. In addition, we can save the analysis time to estimate dynamic OD demand by running a program just once because the proposed link distribution proportion does not change even if dynamic OD matrices estimated from OD estimation module are renewed.

Second, the dynamic OD estimation is in general an undetermined problem, because at each time interval the number of system equations that formulate the relationship between the time-varying OD flows and observed link traffic counts is usually far less than the number of OD pairs. Because QUEENSOD that applied in this study as dynamic OD estimation module use only observed link volume at objective function, it is difficult to obtain a unique solution. In order to reduce the error between observed and estimated OD demand according to undetermined problem, it is necessary to set up more constraints using historical OD data, off-ramp volumes, AVI data and so on.

Before applying to the practice, this model requires the complements and future researches with real-time data. In addition, for more advanced model, the sensitivity analysis of the dynamic OD demand in the proportion of the time interval should be implemented, and within

the initial analysis period of time the management of vehicle flow should be considered as well.

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