Application of Dual-Filter to Incorporate Model Parameter Effect in Traffic Simulation-based Origin-Destination Traffic Demand Estimation

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Traffic simulation model provides accurate mapping between unknown OD demand and known traffic states so that OD demand could be estimated more accurately. The method involves numerous parameters that have crucial influence on OD demand, which may affect the accuracy of OD demand output. This paper presents the development of dual-filter system to accommodate the influence of model parameter on OD demand in such estimation system. The proposed method is tested with various traffic simulation models including a software package. Results from the case study on a freeway corridor shows 2-5% overall improvement and 7-10% during AM and PM peak hours for the dual-filter method.

Key Words: *OD demand, Traffic Simulation, Kalman Filter, Dual-Filter*

1. INTRODUCTION

Recently, researchers focus on dynamic OD demand estimation algorithms, which employ traffic simulation models [1-3]. They represent interactions between OD demand in the transportation network and network supply parameters more accurately. The interactions are formulated as state-space models to implement dynamic estimation. The state-space model for simulation-based dynamic OD demand estimation comprising the following steps: (a) prediction of traffic states with current OD demand using a traffic simulation model; (b) adjustment of OD demand according to the deviation between predicted traffic states and corresponding latest field measurements. The state-space models can be solved with Kalman filter, which provides a recursive algorithm.

(1) Statement of problem

The general conceptual problem for estimation of OD demand can be written as follows:

$$x_{rs}^{t} = O_{r}^{t} \times b_{rs}^{t} \tag{1}$$

where, superscript t refers to discrete time interval. x_{rs}^{t} denotes the OD demand from origin r to destination s. O_{r}^{t} is the traffic demand departed from origin r. b_{rs}^{t} stands for the OD proportion between pair rs.

Pueboobpaphan *et al.* [1] propose a dynamic OD demand estimation method by adopting the concept in Eq.1. Starting with initial OD proportions, by assuming error-free data on real-time origin demands are available, the authors predict traffic states over time by feeding origin demand and OD proportions during a specific time interval onto Cell Transmission Model (CTM). The simulation outputs are compared with the latest traffic measurements obtained during the specific time interval. The deviation is used to compute accurate OD proportions.

There have been couple of crucial issues still remaining in Pueboobpaphan *et al.*'s method. First is, the influence from dynamic characteristics of other model parameters in the simulation-based OD demand estimation system, on OD demand is neglected. Second is, the presence of CTM may lead to poor representation of real-traffic phenomenon especially in non-equilibrium traffic conditions due to inherent first order characteristics of CTM. Both issues may lead to erroneous OD demand estimates.

This study attempts to include the effect from model parameter by estimating it concurrently with OD demand using dual-filter. In addition to that, the application of various types of traffic simulation models is also examined.

2. SOLUTION SCHEME

Fig. 1 illustrates the simulation-based dynamic OD demand estimation approach proposed by Pueboobpaphan *et al.* [1]. The state vector $\mathbf{b}_{rs}^{t}$ represents OD proportions. Superscript t denotes time interval. The algorithm is started by predicting the current OD proportions based on the previous estimates. The mapping between OD proportions and measurements with traffic simulation model, $g[.]$, is performed as follows: during time interval t+1, load vectors of OD proportions, and vectors of origin demands ($\hat{\mathbf{O}}_{r}^{t}$) as exogenous input from time interval t-p to t+1 ($\hat{\mathbf{b}}_{rs}^{t-p}, \ldots, \hat{\mathbf{b}}_{rs}^{t}, \tilde{\mathbf{b}}_{rs}^{t+1}, \hat{\mathbf{O}}_{r}^{t-p}, \ldots, \hat{\mathbf{O}}_{r}^{t}, \hat{\mathbf{O}}_{r}^{t+1}$) onto the simulator. The inputs form OD demand. Execute traffic simulation with the OD demands and record the latest measurements ($\tilde{\mathbf{y}}_{l}^{t+1}$) during time interval t+1. $\mathbf{v}_{rs}^{t}$ and $\mathbf{w}_{l}^{t+1}$ are noise parameters. The purpose of including the inputs from t-p to t+1 is to consider the contribution from previous OD demands on the current traffic condition. These recorded outputs are then compared with the field measurements ($\mathbf{y}_{l}^{t+1}$) during the corresponding time interval. The error is then used to adjust the predicted OD proportions, and hence OD demands are estimated.

(1) Dual-filter

The prediction model shown on Fig. 1 contains a noise parameter ($\mathbf{v}_{rs}^{t}$), which dynamically changes and produces significant impact on OD demand estimation. To estimate the dynamic variation of noise parameter and to accommodate the influence from it in OD demand, we developed a dual-filter OD demand estimation framework as shown in Fig.2. To be specific, two parallel filters, one on the OD demand and the other on the noise parameter are run concurrently. In the dual setting, the noise parameters are treated as known within the OD demand filter at any given time, while the OD demand are treated as known in the parallel noise parameter filter.

(2) Traffic Simulation

Two conventional models (CTM and Modified Payne) and a simulation software package (VISSIM) were employed for traffic simulation in this study.

(a) Cell Transmission Model

CTM is a first order macroscopic simulation model proposed by Daganzo [4], given as follows:

$$\rho_i^{k+1} = \rho_i^{k} + \frac{dk}{dx_i}\left(Q_{i-1}^{k} - Q_i^{k} + R_i^{k} - S_i^{k}\right); \qquad (2)$$

$$v_i^{k} = V_e\left(\rho_i^{k}\right); \qquad (3)$$

$$q_i^{k} = \rho_i^{k}\, v_i^{k} \qquad (4)$$

where k ($\neq t$) is simulation time step. ρ_i^{k}, v_i^{k}, and q_i^{k} denote density, space mean speed and traffic flow at cell i. dx_i and dk represent the length of each cell and discrete time step for simulation, respectively. Q_i^{k} represents the traffic flow from cell i to cell i+1. R_i^{k} and S_i^{k} stand for on-ramp and off-ramp flows, respectively. $V_e(.)$ represents equilibrium speed-density relationship.

(b) Modified Payne Model

The Payne model, introduced by Payne and later modified by Cremer & Papageorgiou [5] is considered for higher order macroscopic simulation. In addition to equations (2) and (4), modified Payne model describes speed-density relationship through a second order equation, given as follows:

$$v_i^{k+1} = v_i^{k} + \frac{dk}{\tau}\left[V_e\left(\rho_i^{k}\right) - v_i^{k}\right] + \frac{dk}{dx_i} v_i^{k}\left[v_{i-1}^{k} - v_i^{k}\right] - \frac{\upsilon dk}{\tau dx_i}\frac{\rho_{i+1}^{k} - \rho_i^{k}}{\rho_i^{k} + \kappa} \qquad (5)$$

where τ, υ, κ are model parameters for which the values were taken from Cremer *et al.* [5].

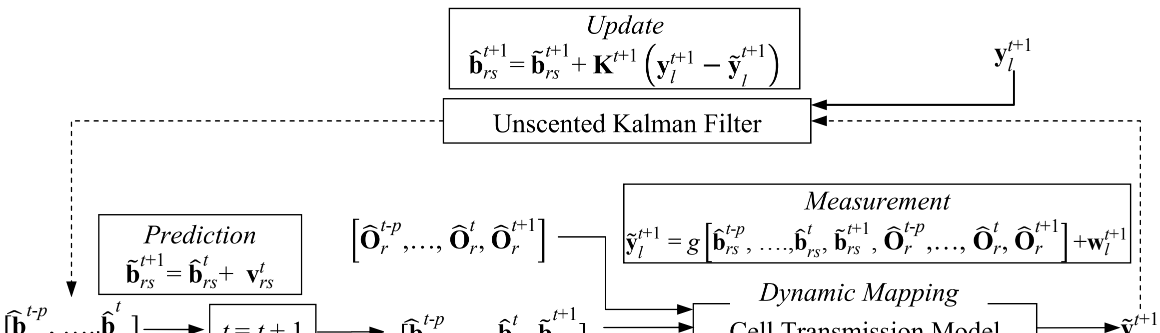

Fig. 1 Simulation-based Dynamic OD Demand Estimation Scheme

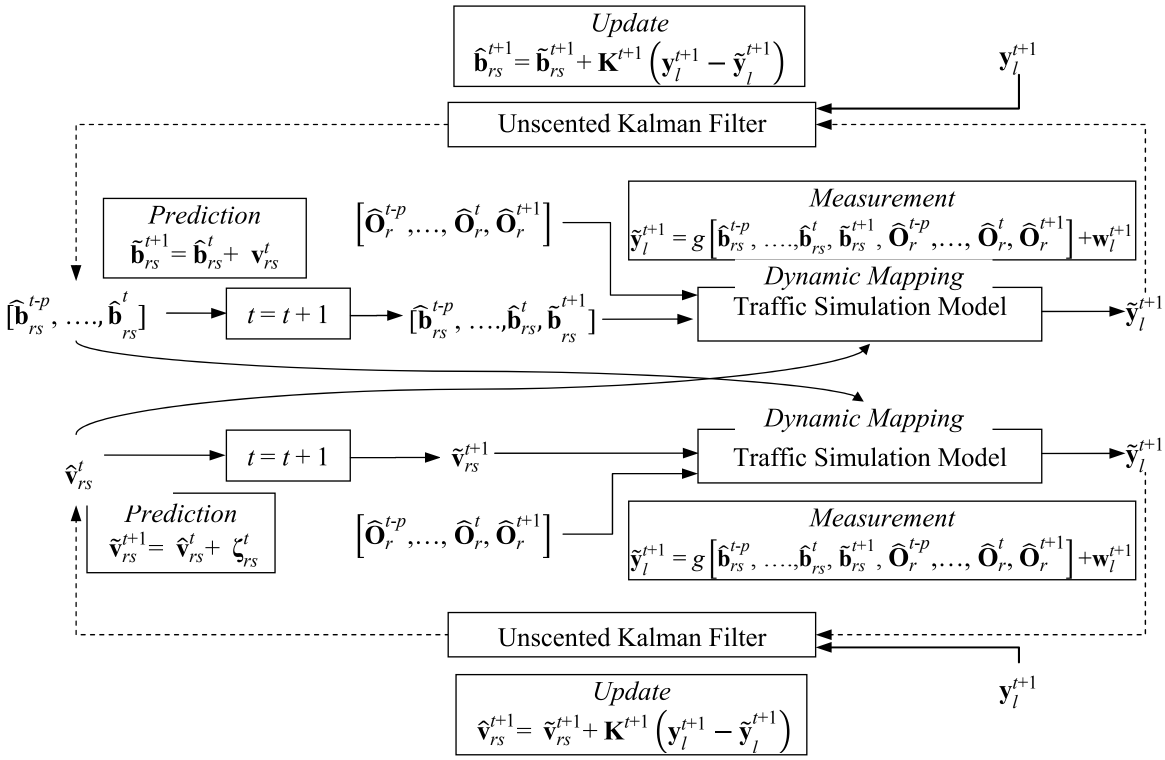

Fig. 2 Simulation-based Dynamic OD Demand Estimation Scheme based on Dual-filter

Before using Payne model for simulation purposes, we attempt to overcome the critics from Daganzo [6] by introducing Godunov scheme in Payne model. **Godunov scheme** The Godunov scheme proposes a time-space discretization to solve the partial differential equations in macroscopic simulation models by converting them into finite difference equations.

It further provides means to compute the traffic flow between cells (boundary flow), which is computed based on local demand-supply concept. The local demand function holds the maximum possible outflow that the upstream can transfer to downstream. Similarly, the local supply function holds the maximum possible inflow that the downstream can receive. The boundary flow is the minimum of both, as in Eq. 6.

$$Q_i^k = \text{Min}\left[\triangle(\rho_i^k), \Sigma(\rho_{i+1}^k)\right] \tag{6}$$

where $\triangle(\rho_i^k)$ and $\Sigma(\rho_{i+1}^k)$ denote local demand and local supply, respectively.

(c) VISSIM

VISSIM is a microscopic simulation software package originally based on Wiedemann's psycho-physical car-following model. Traffic simulation with VISSIM model involves the following procedure: preparing traffic network, loading OD traffic demand and execute traffic simulation, and unloading simulation outputs such as traffic states.

3. CASE STUDY

The freeway section used in this case study is the Matsubara line of Hanshin freeway, depicted in Fig. 3. It is 11.22 km long with two lanes. The two on ramps and a mainline entry were treated as origins ("O") and five off ramps and a mainline exit were as destinations ("D"). It is composed of 15 OD pairs. 15-minute detector data on link traffic flows and flow speeds were available at eight detector locations.

Six schemes were organized as summarized in Table 1 for the case study. The first and second columns refer to the names of schemes and the traffic simulation models used in each scheme. Except traffic simulation models the other execution modules in each scheme are the same. Each scheme was tested separately for the freeway corridor.

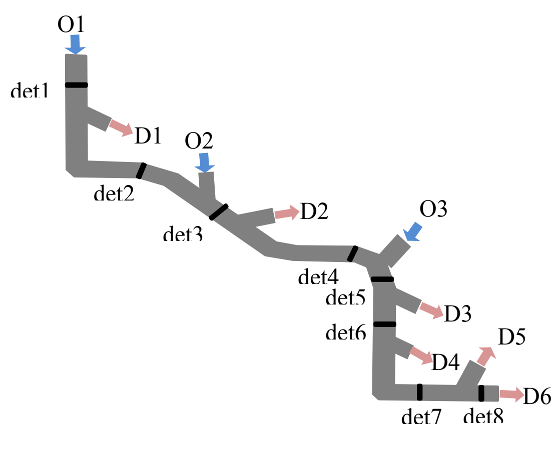

Fig. 3 Study area

Table 1 Prepared schemes for the case study

Scheme	Traffic Simulation Model
CTM_Single	Cell Transmission Model
Payne_Single	Modified Payne Model
VISSIM_Single	VISSIM
CTM_Dual	Cell Transmission Model
Payne_Dual	Modified Payne Model
VISSIM_Dual	VISSIM

Table 2 Summary of results

Scheme	RMSE*	%RE**	Computation Time ***
CTM_Single	82	17	1.4
Payne_Single	89	17	1.4
VISSIM_Single	93	20	25.0
CTM_Dual	75	16	2.8
Payne_Dual	79	15	2.8
VISSIM_Dual	78	15	47.0

*in veh/hr ** in percentage ***in minutes

4. RESULTS AND DISCUSSIONS

Figure 4 illustrates the variation of estimated OD demand between origin 1 and destination 6 (OD pair 16) by each scheme and their actual values with time, in 15-minute intervals. The term "Actual" in legend stands for the actually measured OD demands. Similarly, other terms stand for the estimated OD demands by each scheme described in Table 1. The schemes that employ dual-filter capture the dynamics of OD demand well and provide more accurate estimates over single-filter.

Table 2 tabulates the comparison between six schemes, discussed in Table 1, based on average values of Root Mean Square Error (RMSE) and percentage Relative Error (%RE) of major OD demands (from OD11 to OD 16), and computation time consumed to execute estimation for 1 hour time span. The first column lists the name of the schemes tested. The second and third columns summarize RMSE and %RE values, respectively. The fourth column refers to the computation time.

The dual-filter schemes display low error percentages than single filter schemes. The computation time is quite still remains high for them, particularly for VISSIM.

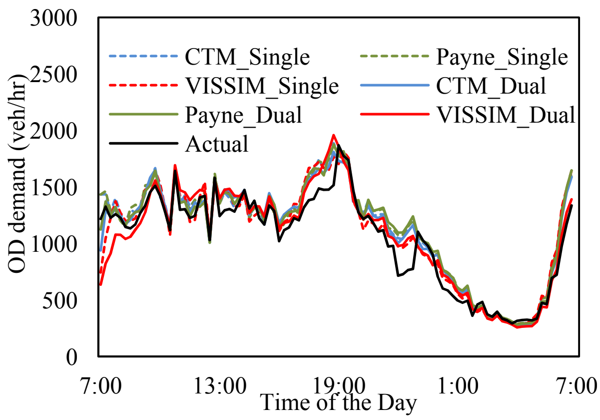

Fig. 4 Comparison of OD Demand for OD pair 16

4. CONCLUSIONS

The study presented in this paper proposed a dual-filter system to consider the influence of model parameter on OD demand, or a traffic simulation-based OD demand estimation system. In addition to that, it integrated various traffic simulation models including a software package. The results from the case study show that dual filter provides 2-5% overall improvement and 7-10% during AM and PM peak hours. However, the dual-filter schemes are computationally expensive.

The study provides ways to consider the effect of other model parameters on OD demand.

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