Traffic Simulation-Based Dynamic Origin-Destination Traffic Demand Estimation for Intelligent Transportation Systems

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Introduction

Intelligent Transportation Systems (ITS) have received a great deal of attention in overcoming traffic-associated problems by implementing online traffic management, which inevitably depends on the accurate dynamic traffic demand. Dynamic Traffic Demand is a fundamental input for simulation-based Dynamic Traffic Assignment (DTA) models to describe and predict traffic conditions on the network over time and space, as well as to generate coordinated traffic control and information supply strategies for intelligent traffic network management. Dynamic Origin-Destination (OD) traffic demand matrix is recommended as perfect choice for demand, which captures spatial and temporal distribution of traffic demand in a transportation network.

Recent researches focus on dynamic OD demand estimation algorithms, which employ simulation-based DTA models. DTA models represent interactions between traffic 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 traffic simulation model; (b) adjustment of OD demand according to the deviation between predicted traffic states and corresponding latest field measurements of them. To solve state-space model Kalman filter is employed, which provides a recursive algorithm.

Simple state-space models, which are differentiable and can be expressed analytically, are solved by standard kalman filter (KF) or by extended kalman filter (EKF). When system dynamics is complex non-linear, analytically inexpressible, unscented kalman filter (UKF) is adopted. The UKF is numerically reliable and stable because it does not require any differential operations in execution that was requisite in the EKF.

In the context of traffic simulation models, there are numerous options available ranging from macro to micro. Popular examples for macro are cell transmission model (CTM), and Payne model. The macroscopic models faced severe criticisms because of their underlying hydrodynamic theory, from which they have been formed, is inadequate in describing real-traffic phenomenon. On the other hand, with the advancement in computational technology, microscopic simulation has evolved into software packages like VISSIM, AIMSUN, etc. They have become very popular because they are versatile, and simpler than conventional ones, such as general motor’s (GM) model, and excess critical speed (ECS) model. Some software packages are provided with Application Programming Interface (API), through which they can communicate with almost any external user-defined control modules.

Yet to develop a reliable dynamic OD demand estimation model is a more challenging, in some sense unresolved issue. Consequently, most of the existing dynamic OD demand estimation methods rule out issues related to noisy input data, require large amount of historical data to achieve considerable accuracy and hardly exploit the usage of sophisticated software packages. Moreover, computational efficiency of OD demand estimation methods remains another crucial issue as far as large-scale traffic networks are concerned. This research develops alternative formulations to address a series of critical and challenging issues in estimating and predicting dynamic OD traffic demand.

Statement of Problem

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

\[ x_{rs}^t = O_r^t \times b_{rs} \]  

(1)

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

Pueboobpaphan proposes a dynamic OD demand estimation 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. Prior to adopting Pueboobpaphan's method for large networks, it is inevitable to have clear perspectives for several issues.

The first issue is the number of unknowns to be dealt with, in the process of estimating OD demands. For example, analyzing a transportation network with \( n \geq 2 \) origins and \( m \geq 2 \) destinations requires computation of \((n -1) \times (m -1)\) number of unknown OD demands. For large networks, this number increases drastically. On the other hand, in a large scale network, defining and obtaining accurate traffic flow data from origin, destination zones is difficult, because there is a strong
possibility of ignoring some minor traffic flows. In addition, due to malfunction of measuring device, data on traffic flows are sometimes unobserved during a particular time interval. Therefore, Pueboobapahan’s method is likely to be computationally inefficient and may lead to erroneous results when accurate data on origin demands and destination demands are unavailable.

The second issue is, embedding and analysing different types of traffic simulation models in dynamic OD demand estimation method. Before introducing them, a careful inspection on their flaws is inevitable.

The third issue concerns the numerous parameters in a dynamic OD demand estimation system. In addition to OD demands, the main parameters in a dynamic OD demand estimation scheme may include model parameters, supply parameters, etc. The dynamic impact of rest of the parameters on OD demands is significant, which cannot be captured if all parameters including OD demands are estimated together. In addition, there is no clear understanding of the variation of each parameter.

The fourth issue is, dealing with urban transportation networks. In urban networks, complex traffic patterns and route choice are the major concerns.

**Research Objectives**

Developing a simulation-based dynamic OD demand estimation method is the ultimate goal of this research. The following objectives are defined to provide solutions to the existing drawbacks in the current approaches.

- To reduce the number of unknown variables to be dealt with, in the process of estimating OD demands. In addition, to provide solutions to prevailing noise in origin demands and destination demands.
- To examine different traffic simulation models and their impact on accuracy of OD demand estimation. To investigate the improvement on OD demands when additional information is introduced and further addresses computational efficiency.
- To evaluate the possibilities of improving accuracy of OD demand estimates with the application of Dual Kalman Filter for concurrent noise control.
- To extend the application of the developed dynamic OD demand estimation approach to urban networks with route choice.

**Solution Scheme**

Consider a transportation network with \( n \geq 2 \) origins and \( m \geq 2 \) destinations. It consists of at most \((n-1) \times (m-1)\) number of unknown OD demands. When OD demands are replaced with origin demands and destination demands, the number of unknowns reduces to \( n + m - 1 \). Especially the reduction \((n-1) \times (m-1) - (n + m - 1)\) could be significant in large networks. Fundamental relationship between OD demands and, origin demands and destination demands such network can be given as follows:

\[
\sum_{i=1}^{n} x_{ri}^t = O_r^t, \quad (r = 1, 2, \ldots, n) \quad (2)
\]

\[
\sum_{j=1}^{n} x_{js}^t = D_j^t, \quad (s = 1, 2, \ldots, m) \quad (3)
\]

where, superscript \( t \) refers to time interval. \( x_{ri}^t \) denotes the OD demand from origin \( r \) to destination \( i \). \( O_r^t \) is the origin demand from \( r \). \( D_j^t \) is the destination demand at \( s \). Both relationships are purely static, must be satisfied within a stipulated time interval in case of dynamic estimation.

When OD demands are replaced with origin demands and destination demands, joint estimation provides two stages method to disaggregate origin demands/destination demands, and to assign them to the network that is requisite in mapping with traffic simulation model.

**Research Framework**

The research framework includes development of joint OD demand estimation algorithm, direct OD demand estimation algorithm based on origin demands, and dual OD demand estimation algorithm based on origin demands to estimate model parameters, along with OD demand.

**Joint OD demand Estimation**

The joint estimation considered that, estimation of OD demands directly from origin demands and OD proportions is computationally expensive, and might not be accurate, unless the availability of accurate and uninterrupted data on origin demands was guaranteed.

**Trip distribution model**

Let the analysis time period is divided into multiple time intervals \( t = 1, 2, \ldots, T \). At each time interval \( t \), trip distribution process computes the most likely OD trip pattern, provided that the origin and destination demands are known and fixed. The most likely OD trip pattern is the average of OD demands from entropy distribution and from destination demand based.

Entropy distribution assumes that traffic flow in the network is distributed according to the transportation cost between OD pairs, and is devised as follows:

\[
\min Z(x) = \sum_{s=1}^{n} \sum_{r=1}^{m} c_{rs} x_{rs,E} \quad (4)
\]

subject to constraints in equations (2) and (3) where \( Z(x) \) is the optimization process of OD demands. \( c_{rs} \) denotes the transportation cost between OD pair \( rs \). \( x_{rs,E} \) represents the OD demand between OD pair \( rs \), derived from entropy distribution. Transportation cost between OD pair \( rs \) was defined as an exponential function as follows:
where $u_{rs}^{t+1}$ is the shortest travel time between OD pair $rs$ during time interval $t+1$. $\gamma$ is a model parameter. During every time interval, the shortest travel time was estimated with simulation model and hence transportation cost was updated in order to reflect the effect of latest traffic condition on trip distribution. However, before performing simulation, the shortest travel times remain unknown. To avoid this problem, the shortest travel time in the previous time interval $t-1$ was considered for the computation of transportation cost in the current time interval, $t$.

Demand based OD demand computation is given as follows:

$$x_{rs,D}^t = \frac{D_{rs}^{t+1}}{\sum_{i=1}^{k} D_i^{t+1}} \times O_i^t$$

(6)

where $x_{rs,D}^t$ denotes the OD demand calculated from ratio of destination demand. $D_i^{t+1}$ represents traffic demand at destination $i$ during time interval $t+1$. $O_i^t$ denotes traffic demand at origin $r$ during time interval $t-1$.

The most likely OD demand at time interval $t$ ($x_{rs}^t$) was then computed as follows:

$$x_{rs}^t = 0.5x_{rs,E}^t + 0.5x_{rs,D}^t$$

(7)

Traffic assignment model Traffic assignment is similarly performed each time interval $t$, considering route choice options. It puts premium to route overlapping, commonly observed phenomenon in urban traffic networks. We adopted multinomial Probit model based stochastic traffic assignment process to estimate route choice fractions, which can effectively take account of route-overlapping issues. The superior performance of Probit model over Logit model is demonstrated by Sheffi.

Traffic Simulation

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

Cell Transmission Model

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

$$\rho_i^{t+1} = \rho_i^t + \frac{dk}{dx_i} (O_i^t - Q_i^t + R_i^t - \Delta_i^t);$$

(8)

$$v_i^t = \frac{V_e(\rho_i^t)}{\Delta_i^t};$$

(9)

$$q_i^t = \rho_i^t v_i^t$$

(10)

where $k (\neq t)$ is simulation time step $\rho_i^t$, $v_i^t$, and $q_i^t$ 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. $Q_i^t$ represents the boundary flow from cell $i$ to cell $i+1$. $R_i^t$ and $S_i^t$ stand for on-ramp and off-ramp flows, respectively. $V_e(\cdot)$ represents equilibrium speed-density relationship.

Modified Payne model

The Payne model, introduced by Payne and later modified by Cremer & Papageorgiou is considered for higher order macroscopic simulation. In addition to equations (6) and (8), modified Payne model describes speed-density relationship through a second order equation, given as follows:

$$v_i^{t+1} = v_i^t + \frac{dk}{\tau} [V_e(\rho_i^t) - v_i^t] + \frac{dk}{dx_i} v_i^t [v_i^{t+1} - v_i^t] - \frac{\alpha k}{dx_i} \frac{\rho_i^{t+1} - \rho_i^t}{\rho_i^t + \kappa}$$

(11)

where $\tau$, $\alpha$, $\kappa$ are model parameters for which the values stated by Cremer et al. were used in this study.

Before using Payne model for simulation purposes, we attempt to overcome the critics from Daganzo 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 models by converting them into approximate finite difference equations.

The traffic flow between cells (boundary flow) 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. 10.

$$Q_i^t = \text{Min} \left[ \Delta_i(\rho_i^t), \Sigma(\rho_i^{t+1}) \right]$$

(12)

where $\Delta_i(\rho_i^t)$ and $\Sigma(\rho_i^{t+1})$ denote local demand and local supply, respectively.

Excess Critical Speed Model

We consider ECS model proposed by Gurusinghe et al. for microscopic simulation purposes. ECS model is formed by adding a headway-dependant stimulus term with the existing relative speed stimulus term in the GM model. The formulation of ECS is given as follows:

$$\bar{d}_s^{i+1} = a_0 + a_1 \left\{ \frac{2a_s d_{s-1} - d_s}{d_s} \right\} + a_2 \left\{ d_{s-1} - d_s \right\}$$

(13)

where $k (\neq t)$ represent simulation time interval. $d_s$, $\bar{d}_s$, and $\bar{d}_s$ denote position, speed and acceleration of nth car, respectively. $\Gamma$ is the reaction time. $a_s$ represents the maximum braking rate. $a_0$, $a_1$, and $a_2$ are constants. According to Ranjitkar et al, $a_0$ is fixed at 0, while parameters $a_1$, and $a_2$ are allowed to vary from 0 to 1.

VISSIM

VISSIM is a microscopic simulation software package originally based on Wiedemann’s psycho-physical car-following model. VISSIM model consists of two different modules: a traffic simulator and a signal state generator.

The network model in VISSIM is created by series of links and its connectors. The dynamic traffic demand can be defined either in terms of OD matrix for dynamic assignment or origin demands and OD proportions.
Development of Dynamic OD Demand Estimation Methods

State-space modeling for Joint Estimation
State-space model for joint dynamic OD demand estimation considers origin demands and destination demands as state variables. To account for the errors in origin demands and destination demands due to data collection, ignorance of minor flows, and so on, a noise term was included in the state transition model.

Prediction Step The prediction model was built as a simple random walk model as follows:

\[
\begin{bmatrix}
\hat{O}_t^{r+1} \\
\hat{D}_t^{r+1}
\end{bmatrix} = 
\begin{bmatrix}
\hat{O}_t^r \\
\hat{D}_t^r
\end{bmatrix} + \zeta_t
\]  
(14)

where \(\hat{O}_t^r\) and \(\hat{D}_t^r\) represent the vectors of origin demands and destination demands, during time interval \(t\). \(\hat{O}_t^{r+1}\) and \(\hat{D}_t^{r+1}\) are the vectors of priori origin demands and destination demands during time interval \(t+1\). \(\zeta_t\) is state modelling noise with Gaussian distribution, zero mean and \(\Phi_{t}^\zeta\) covariance, accounts for the aforesaid error.

The definition of measurement equation was as follows:

\[
\hat{y}_t^l = g[l(\hat{O}_{t-p}^r, ..., \hat{O}_t^r, \hat{D}_{t+1}^r)] + \xi_t
\]  
(15)

where \(\hat{y}_t^l\) denotes the vector of estimated traffic measurements at link \(l\) during time interval \(t+1\), \(g[l]\) denotes the simulation mapping. \(\hat{O}_{t-p}^r, ..., \hat{O}_t^r, \hat{D}_{t+1}^r\) are the vectors of OD demands from time interval \(t-p\) to \(t\) between OD pair \(rs\). \(\hat{O}_t^r\) represents the vector of priori OD demands during time interval \(t+1\) between OD pair \(rs\). Including OD demands from the past time intervals in addition to the current interval was to capture the influence of vehicles which had departed during past intervals that remain on the network and had not yet reached their destinations. OD demands were computed using trip distribution model. \(\xi_t\) is measurement noise with Gaussian distribution zero mean and \(\Psi_t^\xi\) covariance.

Update Step By getting the feedback from the corresponding traffic measurements \(y_t^{r+1}\), the vectors of priori state estimates \(\hat{O}_t^{r+1}\) and \(\hat{D}_t^{r+1}\) were adjusted as follows:

\[
\begin{bmatrix}
\hat{O}_t^{r+1} \\
\hat{D}_t^{r+1}
\end{bmatrix} = 
\begin{bmatrix}
\hat{O}_t^{r+1} \\
\hat{D}_t^{r+1}
\end{bmatrix} + K_t^{r+1}(y_t^{r+1} - \hat{y}_t^l)
\]  
(16)

where \(K_t^{r+1}\) is the kalman gain during time interval \((t+1)\).

State-space modeling for Direct OD demand Estimation based on Origin demand
State-space model for the OD traffic demand estimation based on origin demands and OD proportions, introduced by Pueboobapaphan considers OD proportions \((b_s^r)\) as state variable. Other formulations are similar to the state-space modelling for joint estimation. Figure 2 illustrates the schematic diagram of OD demand estimation based on origin demands.

State-space modeling for Dual Estimation
Dual estimation in this study considered OD proportions \((b_s^r)\) as state variables and state modelling noise \((\zeta_s)\) as parameter, which has a significant influence in state transition modelling. Other parameters were kept constant throughout the analysis. Two separate state-space models for state and parameters were formulated and run concurrently.

Unscented Kalman Filter This study employs UKF to solve nonlinear state-space models. In the UKF, a number of deterministically selected sample points are produced to represent a Gaussian random variable. This is called unscented transformation and the sample points refer to as sigma points. When sigma points propagated through a nonlinear system, they capture the posterior mean and covariance of the random variable to the second order Taylor series expansion, preserving nonlinearity of the estimation.
Case Study

A freeway corridor and an urban arterial network are selected in this dissertation to evaluate proposed dynamic OD demand estimation.

The freeway section used in this case study is the Matsubara line of Hanshin freeway in Japan, depicted in Figure 4. 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 feasible OD pairs. 15-minute detector data on link traffic flows and flow speeds were collected at 68 detector locations.

The urban arterial network used in this case study is located in Minami-ward of Sapporo city, Hokkaido, Japan. Figure 5 shows the general layout of the study network. The network approximately spans 4 km north-south and 2 km east-west. It is composed of 10 origin zones, 10 destination zones and 54 feasible OD pairs.

Figure 4: Freeway Corridor
Figure 5: Urban Network

Table 1 summarizes the nine schemes organized for the case study on freeway corridor. Similarly, Table 2 tabulates the six schemes organized for the case study on urban network. In both tables, 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 and urban network.

Table 1 Prepared schemes for the case study on freeway corridor

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Traffic Simulation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTM_Joint</td>
<td>Cell Transmission Model</td>
</tr>
<tr>
<td>Payne_Joint</td>
<td>Modified Payne Model</td>
</tr>
<tr>
<td>ECS_Joint</td>
<td>Excess Critical Speed Model</td>
</tr>
<tr>
<td>CTM_Single</td>
<td>Cell Transmission Model</td>
</tr>
<tr>
<td>Payne_Single</td>
<td>Modified Payne Model</td>
</tr>
<tr>
<td>VISSIM_Single</td>
<td>VISSIM</td>
</tr>
<tr>
<td>CTM_Dual</td>
<td>Cell Transmission Model</td>
</tr>
<tr>
<td>Payne_Dual</td>
<td>Modified Payne Model</td>
</tr>
<tr>
<td>VISSIM_Dual</td>
<td>VISSIM</td>
</tr>
</tbody>
</table>

Table 2 Prepared schemes for the case study on urban network

<table>
<thead>
<tr>
<th>Scheme</th>
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<tr>
<td>CTM_Single</td>
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<td>Modified Payne Model</td>
</tr>
<tr>
<td>VISSIM_Dual</td>
<td>VISSIM</td>
</tr>
</tbody>
</table>

Results

Table 3 and 4 tabulate the comparison between the schemes, discussed in Tables 1 and 2, based on average values of Root Mean Square Error (RMSE) and percentage Relative Error (%RE) of major OD demands, and computation time consumed to execute estimation for 1 hour time span.

Table 3 Summary of results from the case study on freeway corridor

<table>
<thead>
<tr>
<th>Scheme</th>
<th>RMSE*</th>
<th>%RE**</th>
<th>Computation Time ***</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTM_Joint</td>
<td>75</td>
<td>20</td>
<td>0.8</td>
</tr>
<tr>
<td>Payne_Joint</td>
<td>74</td>
<td>20</td>
<td>0.8</td>
</tr>
<tr>
<td>ECS_Joint</td>
<td>145</td>
<td>57</td>
<td>8.6</td>
</tr>
<tr>
<td>CTM_Single</td>
<td>82</td>
<td>17</td>
<td>1.4</td>
</tr>
<tr>
<td>Payne_Single</td>
<td>89</td>
<td>17</td>
<td>1.4</td>
</tr>
<tr>
<td>VISSIM_Single</td>
<td>93</td>
<td>20</td>
<td>25.0</td>
</tr>
<tr>
<td>CTM_Dual</td>
<td>75</td>
<td>16</td>
<td>2.8</td>
</tr>
<tr>
<td>Payne_Dual</td>
<td>79</td>
<td>15</td>
<td>2.8</td>
</tr>
<tr>
<td>VISSIM_Dual</td>
<td>78</td>
<td>15</td>
<td>47.0</td>
</tr>
</tbody>
</table>

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

Table 4 Summary of results from the case study on urban network

<table>
<thead>
<tr>
<th>Scheme</th>
<th>RMSE*</th>
<th>%RE**</th>
<th>Computation Time ***</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTM_Single</td>
<td>83</td>
<td>54</td>
<td>52.0</td>
</tr>
<tr>
<td>Payne_Single</td>
<td>108</td>
<td>66</td>
<td>52.0</td>
</tr>
<tr>
<td>VISSIM_Single</td>
<td>75</td>
<td>54</td>
<td>52.0</td>
</tr>
<tr>
<td>CTM_Dual</td>
<td>66</td>
<td>48</td>
<td>102.0</td>
</tr>
<tr>
<td>Payne_Dual</td>
<td>94</td>
<td>56</td>
<td>102.0</td>
</tr>
<tr>
<td>VISSIM_Dual</td>
<td>86</td>
<td>56</td>
<td>102.0</td>
</tr>
</tbody>
</table>

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

Conclusions

This study proposes alternative schemes for simulation-based dynamic OD demand estimation. The proposed methods are flexible to accommodate any traffic simulation model. In freeway corridors, joint estimation method is capable of handling noisy data and computational efficiency related issues. Dual filter provides a method to include the influence of model parameters on OD demand.

The application of the proposed approach to urban networks is theoretically possible, but still requires employment of more advanced traffic data such as, probe vehicle data, GPS data, in order to improve the accuracy of OD demand estimation.

References