A NEURAL-KALMAN FILTER FOR REAL-TIME ESTIMATION OF O-D TRAVEL TIME AND FLOW ON THE EXPRESSWAYS IN BANGKOK *

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1. Introduction

So far, two different, feed-forward and feedback, approaches have been directed for estimating dynamic O-D travel time and flow. The feed-forward approach is based on drivers' behavior models which attempt to estimate dynamic O-D travel time and/or flow according to how drivers behave under certain traffic conditions. Experimental data have been created by various travel simulators to analyze and model the drivers' behaviors experimentally. In spite of extensive efforts, however, the drivers' behavior models are not reliable yet because the travel simulators are still not successful in providing more realistic driving environment and conditions [3].

The feedback approach is on the basis of measurement data: It estimates dynamic O-D travel time and flow using measured traffic variables such as link traffic counts and spot speed at some observation points. Kalman filter has been widely used to tackle these problems for a complicated intersection [4], a small network [5] and long freeway corridors [6][7][8]. Although the Kalman filter have a good potential of estimating either O-D travel time or flow, they still have some difficulties to be improved. Firstly, no model is so far applicable to estimate O-D travel time and flow simultaneously. The O-D travel time and flow are closely correlated each other especially when route choice problems are required on freeway networks. To enable precise estimation of O-D travel time and flow, they should be estimated within one process. Secondly, it is very complicated to describe the relationship between state variables such as O-D travel time and flow, and measurement data such as link traffic counts and spot speeds. It makes almost impossible to define state and measurement equations in analytical forms. In addition, those two equations have to be differentiable in the extended Kalman filter. Thus, another synthetic approach should be developed to overcome these difficulties. Finally, the Kalman filter gives the estimates of O-D travel time with large errors when it was applied for relatively long freeway corridors [8]. The large errors occurred because the detector data are not sensitive to O-D travel time due to the long distance of O-D pairs. This leads the way to predict the traffic states on the freeway corridors in advance.

This study aims to develop a new model for estimating dynamic O-D travel time and flow on freeway corridors. The objectives of this study are: (1) to develop a method of estimating both dynamic O-D travel time and flow simultaneously, (2) to formulate state and measurement equations using ANN models and compare with conventional regression models, and (3) to investigate how the macroscopic model improves the estimation precision of O-D travel time and flow.

2. Model description

(1) Kalman filter [9]

The Kalman filter is a filtering technique to estimate state variables indirectly from measurement variables. This study employs both O-D travel time and flow as state variables and estimate them from measurement variables such as link traffic counts, spot speeds and off-ramp volumes at some observation points. In general, the Kalman filter consists of two important equations; state and measurement equations. Let $\mathbf{z}(k)$ denote column vector of O-D flow and travel time at time k, then the current state variables are given by those of m previous time steps as follows:

$$\mathbf{z}(k)=\mathbf{A}(k-1)\mathbf{z}(k-1)+\mathbf{A}(k-2)\mathbf{z}(k-2)+\cdots+\mathbf{A}(k-m)\mathbf{z}(k-m)+\mathbf{b}(k)+\xi(k) \tag{1}$$

where

$\mathbf{A}(k-1),\mathbf{A}(k-2),\ldots,\mathbf{A}(k-m)$ = coefficient matrices,
$\mathbf{b}(k)$ = constant term of state equation,
$\xi(k)$ = system error vector..

Measurement equation denotes the relationship between current measurement variables $\mathbf{y}(k)$ and state variables. If the freeways are equipped with detectors to provide measurement variables such as traffic volume $q_i(k)$, spot speed $w_i(k)$ and off-ramp volume $s_i(k)$ at M observation points, the measurement equation is defined as

$$\mathbf{y}(k)=\mathbf{C}(k)\mathbf{z}(k)+\mathbf{C}(k-1)\mathbf{z}(k-1)+\cdots+\mathbf{C}(k-m+1)\mathbf{z}(k-m+1)+\mathbf{d}(k)+\zeta(k), \tag{2}$$

where

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$\mathbf{y}(k) = [q_1(k), w_1(k), s_1(k), \ldots, q_M(k), w_M(k), s_M(k)]^T$,
$\mathbf{C}(k), \mathbf{C}(k-1), \ldots, \mathbf{C}(k-m+1)$ = coefficient matrices,
$\mathbf{d}(k)$ = constant term of measurement equation,
$\zeta(k)$ = measurement error.

Eq.(2) makes it possible to estimate both O-D travel time and flow simultaneously and to take traffic conditions into account for any number of time steps. Both state and measurement equations can be rewritten as:

$$\mathbf{x}(k) = \Phi(k-1)\mathbf{x}(k-1) + \mathbf{B}(k) + \Xi(k), \tag{3}$$

$$\mathbf{y}(k) = \Psi(k)\mathbf{x}(k) + \mathbf{d}(k) + \zeta(k), \tag{4}$$

where

$\mathbf{x}(k) = [\mathbf{z}^T(k), \mathbf{z}^T(k-1), \ldots, \mathbf{z}^T(k-m+1)]^T$,
$\mathbf{B}(k) = [\mathbf{b}^T(k), \mathbf{O}, \mathbf{O}, \ldots, \mathbf{O}]^T$,
$\Xi(k) = [\xi^T(k), \mathbf{O}, \mathbf{O}, \ldots, \mathbf{O}]^T$,
$\Psi(k) = [\mathbf{C}^T(k), \mathbf{C}^T(k-1), \ldots, \mathbf{C}^T(k-m)]^T$,

$$\Phi(k-1) = \begin{bmatrix} \mathbf{A}(k-1) & \mathbf{A}(k-2) & \cdots & \mathbf{A}(k-m+1) & \mathbf{A}(k-m) \\ \mathbf{I} & \mathbf{O} & \cdots & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{I} & \cdots & \mathbf{O} & \mathbf{O} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \mathbf{O} & \mathbf{O} & \cdots & \mathbf{I} & \mathbf{O} \end{bmatrix}$$

Here, $\mathbf{I}$ and $\mathbf{O}$ are identity and zero matrices, respectively. When the actual measurement variables $\mathbf{y}(k)$ are detected at each time step, the estimates of state variables $\tilde{\mathbf{x}}(k)$ are updated into $\hat{\mathbf{x}}(k)$ by the following Eq. (5),

$$\hat{\mathbf{x}}(k) = \tilde{\mathbf{x}}(k) + \mathbf{K}(k)[\mathbf{y}(k) - \tilde{\mathbf{y}}(k)]. \tag{5}$$

(2) Macroscopic Traffic Flow Simulation Model (Macroscopic Model)

Drivers' expected O-D travel time and flow strongly depend on future traffic conditions along freeways. To estimate O-D travel time and flow more accurately, the traffic states are predicted in advance by the use of macroscopic traffic flow simulation model [10]. Traffic variables to be predicted are link volume, spot speed, off-ramp volume and O-D travel time. Consider a freeway corridor which consists of N road segments with some on- and off-ramps, as shown in Fig. 1.

The macroscopic model yields density $\rho_i(k)$, space mean speed $v_i(k)$, link volume $q_i(k)$ and spot speed $w_i(k)$ for each road segment $(i = 1,2,\ldots,N)$ at time step k by following recursive equations:

$$\rho_i(k+1) = \rho_i(k) + \Delta t/_{\Delta l}\,[q_{i-1}(k) - q_i(k) + r_i(k) - s_i(k)] \tag{6}$$

$$v_i(k+1) = v_i(k) + \Delta t/_{\tau}\left[v_f\left(1 - (\rho(k)/\rho_{jam})^l\right)^m - v_i(k)\right] + \Delta t \cdot \xi/_{\tau}\,[v_{i-1}(k) - v_i(k)] - \nu \cdot \Delta t/_{\tau \cdot \Delta l}\left[\rho_{i+1}(k) - \rho_i(k)/_{\rho_i(k) + \kappa}\right] \tag{7}$$

$$q_i(k) = \alpha \cdot \rho_i(k) \cdot v_i(k) + (1-\alpha) \cdot \rho_{i+1}(k) \cdot v_{i+1}(k) \tag{8}$$

$$w_i(k) = \alpha \cdot v_i(k) + (1-\alpha) \cdot v_{i+1}(k) \tag{9}$$

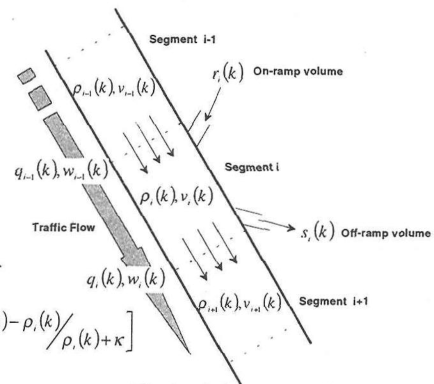


Fig. 1. A freeway corridor

where $r_i(k)$ and $s_i(k)$ are on-and off-ramp volumes, respectively. Δt represents the time interval (Δt = 4 sec) and Δl is the segment length. α, τ, ξ, ν, l m, κ, v_f and ρ_{jam} are all macroscopic parameter to be optimized. Since the space mean speed $v_i(k)$ is given by Eq. (7), the link travel time $T_i(k)$ of road segment i can be computed as: $T_i(k) = \Delta l / v_i(k)$. The actual O-D travel time $tt_{ij}(k)$ of O-D pair $i-j$ is then calculated by summing up these link travel times along the O-D pair. $tt_{ij}(k)$ is given as follows:

$$tt_{ij}(k) = tt_{i,j-1}(k - T_j(k)/\Delta t) + T_j(k). \tag{10}$$

(3) Neural-Kalman Filter (NKF) Technique

a) Artificial Neural Network (ANN) Models [11]

Fig. 2 illustrates an ANN model to describe state and measurement equations; Eqs. (3) and (4). It consists of three layers; input, hidden and output layers. Each layer has some specific number of neurons. The connection of neurons between adjacent layers allow the signal to propagate forward or backward beyond the layers. Let W_{ij}^{BC} and W_{jk}^{CD} denote connection weights between input and hidden, hidden and output layers, respectively, then all input signals in the input layer x_i ($i = 1,2,\ldots$) produce the output signal from the k-th neuron y_k according to the following equation.

$$y_k = f\left(\sum_j W_{jk} \cdot f\left(\sum_i W_{ij} x_i\right)\right) \quad (k = 1,2,\ldots) \tag{11}$$

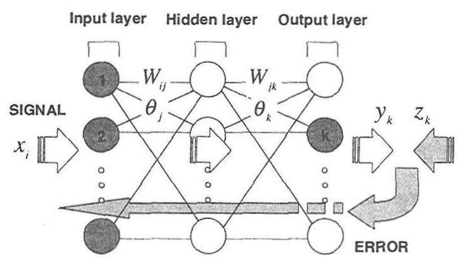


Fig. 2. An ANN model

where $f(\cdot)$ is a sigmoid function. The error information between y_k and desired outputs (actual data) z_k, are propagated backward from the output layer to input layer, following back propagation algorithm. It is assumed that an ANN model $\mathbf{F}$ yields current state variables $\mathbf{x}(k)$ from previous state variables $\mathbf{x}(k-1)$. Similarly, an ANN model $\mathbf{G}$ outputs current measurement variables $\mathbf{y}(k)$ from the current state variables $\mathbf{x}(k)$. The extended Kalman filter requires derivative functions of state and measurement equations. The

ANN models enable to formulate these derivative functions. Differentiating Eq.(11) with respect to each input signal x_i yields the following formula,

$$\partial y_k / \partial x_i = (2/u_0) y_k (1 - y_k) \sum_j \left(W_{jk} \cdot (2/u_0) \cdot y_j (1 - y_j) \cdot W_{ij} \right) \tag{12}$$

b) NKF technique [12]

The procedure of estimation of O-D travel time and flow by NKF technique is illustrated in Fig. 3. Some initial settings are required before starting the estimation. Firstly, the macroscopic model predicts some traffic variables in advance such as link traffic counts, spot speeds, off-ramp volumes and O-D travel times. Next, these predicted variables are used to define the state and measurement equations by ANN models $\mathbf{F}$ and $\mathbf{G}$. Finally, the weight matrices of ANN models can be obtained as a results of formulating the state and measurement equations. After these initial settings, the estimation is carried out by following Steps 1 to 8 described below:

Step 1: Give initial state variables $\mathbf{x}(0)$ and error covariance matrix $\mathbf{P}(0)$,

Step 2: Create state variables $\hat{\mathbf{x}}(k-1)$ as inputs of state Eq. (3). $\hat{\mathbf{x}}(k-1)$ consists of updated O-D flow $\hat{\mathbf{f}}(k-1)$ and O-D travel time $\mathbf{t}_{macro}(k-1)$ predicted by the macroscopic model,

Step 3: Calculate state variables $\tilde{\mathbf{x}}(k)$ by the ANN model $\mathbf{F}$,

Step 4: Compute $\partial y_k^F / \partial x_i$ by Eq. (12),

Step 5: Formulate $\mathbf{A}(k-1), \ldots, \mathbf{A}(k-m)$ and convert them to $\Phi(k-1)$,

Step 6: Input the estimates of state variables $\tilde{\mathbf{x}}(k)$ into the ANN model $\mathbf{G}$ and yield the estimates of measurement variables $\tilde{\mathbf{y}}(k)$,

Step 7: Formulate the coefficients $\mathbf{C}(k), \ldots, \mathbf{C}(k-m+1)$ and yield $\Psi(k)$,

Step 8: Compute Kalman gain $\mathbf{K}(k)$ and update $\tilde{\mathbf{x}}(k)$ into $\hat{\mathbf{x}}(k)$ by Eq. (5) when the actual measurement data $\mathbf{y}(k)$ are detected.

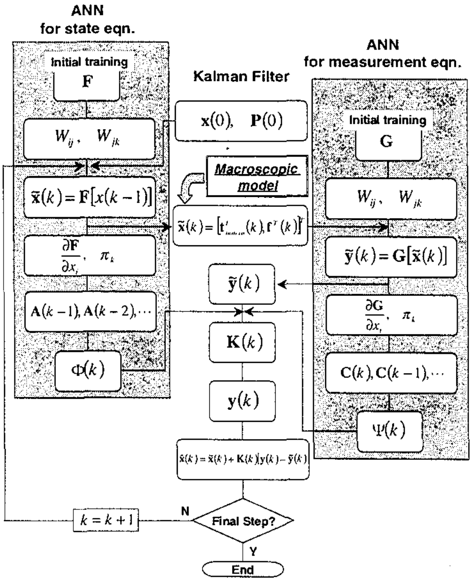


Fig. 3. Procedure of NKF

3. Numerical analyses

(1) Field Data Collection

The proposed model was applied to an approximately 50 km long road section of the Expressways in Bangkok. Three O-D pairs are selected because they have relatively large traffic volumes. The basic filed data were collected on 22 (Tue) and 23 (Wed) December 1998 by manual counting as well as video camera recordings. The data collected are: dynamic O-D travel time and flow, on and off-ramp volumes, spot speeds and link traffic volumes at three observation points. All data were aggregated every five minutes for ten hours time duration from 7:00 AM until 5:00 PM for each day.

(2) Estimation of Dynamic O-D Travel Time and Flow

a) Evaluation Procedures

To evaluate the effect of ANN models and macroscopic model on the estimation of O-D travel time and flow, the estimation was carried out by following three steps:

Step 1. Estimate O-D travel time and flow without using both NKF and macroscopic model. State and measurement equations of the KF technique are defined by conventional linear multiple regression models. Here, the KF with regression models are referred to Regression Kalman Filter (RKF).

Step 2. Apply ANN models instead of using multiple regression models for defining state and measurement equations of KF technique. In other words, the estimation was carried out by NKF technique. The estimates of O-D travel time and flow by NKF are compared to those of RKF. At this stage, the macroscopic model was not integrated into the estimation system yet.

Step 3. Use macroscopic model to predict traffic states in advance, and compare the estimation results by the NKF model in Step 2.

b) Scenarios of Numerical Analyses

To evaluate the proposed estimation model for extensive traffic states, following two scenarios were assumed:

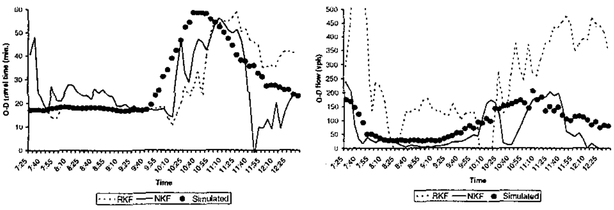
Case 1: Free flow state: Dynamic O-D travel time and flow were estimated using actual observed field data. Since traffic flows were almost steady and no congestions was found during the observation period, O-D travel times were constant for any departure times. Also, the O-D flows were very low except the morning peak period.

Case 2: Congested flow state: To evaluate the proposed model under the congested flow state, traffic condition was assumed that a lane out of three is closed over 500 meters long near Port junction from 9:30 AM to 11:00 AM. By giving inflow volumes at entry links and off-ramps, a traffic flow simulation software package FRESIM 15) computed the artificial traffic data such as O-D travel time and flow, link traffic counts, spot speeds and off-ramp volumes.

This study mainly concentrates on estimating the dynamic O-D travel time and flow on the congested flow state (Case 2). Therefore, experimental results are given for Case 2 only. The first data on 22 (Tue) was set as the data on free flow state, and used to calibrate the proposed model. Then, the model was validated using the artificial congested flow data on 23 (Wed).

c) Experimental Results

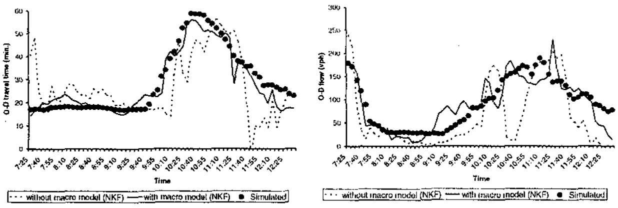
Fig. 4 shows the comparison between RKF and NKF in estimation of dynamic O-D travel time and flow for an O-D pair from Rachada Phisek (RP) to Sukhumvit (SV). As seen in Fig. 4 (a), NKF technique is able to avoid the time delay at the point where the O-D travel time started increasing. Also, the peak O-D travel time (60 minutes) comes earlier than the estimates by RKF technique. But, there is a significant under-estimation at the end of simulation time step. In Fig. 4 (b), the NKF is found to be capable for describing dynamic O-D flow rather than RKF.



(a) O-D travel time (b) O-D flow

Fig. 4. Comparison between RKF and NKF

The contribution of macroscopic model in the NKF technique can be seen in Fig. 5. No large error is found in the estimation of O-D travel time during whole simulation time (Fig. 5 (a)), and the fluctuation of O-D flow is not as big as that without using macroscopic model (Fig. 5 (b)).



(a) O-D travel time (b) O-D flow

Fig. 5. Comparison between NKF with and withoug macroscopic model

Tab. 1 depicts the changes of Root Mean Square (RMS) errors through the three steps described in evaluation procedures. It can be found that the NKF model (***Step 2***) is capable to yield the better estimates than RKF (***Step 1***) for all O-D pairs except one pair in O-D flow estimation. The O-D flow of the pair no. 2 is almost stable during the simulation time period except for the morning peak. Since the NKF technique works very sensitively, it seems to be difficult for the NKF to describe stable condition of O-D flow. In ***Step 3***, the RMS errors were very much reduced for all O-D pairs by integrating the macroscopic model into the NKF technique. It reveals how macroscopic model works effectively in O-D travel time and flow estimations by NKF technique.

Tab. 1. Root Mean Square Error (RMSE)

	O-D travel time			O-D flow		
Evaluation Procedure / O-D pair	1	2	3	1	2	3
Step 1 (RKF w.o. macro model)	29.91	13.07	13.03	203.09	92.26	230.39
Step 2 (NKF w.o. macro model)	**21.20**	**10.44**	**11.40**	**82.13**	254.12	**58.00**
Step 3 (NKF with macro model)	**10.66**	**7.51**	**4.37**	**50.00**	**113.80**	**29.39**

4. Concluding remarks

A new model was developed to estimate real time O-D travel time and flow on freeway corridors by integrating ANN models and macroscopic model with KF technique. The model supports simultaneous estimation of both O-D travel time and flow within one process. Conventional KF model was modified to take into account any number of previous time steps of state and measurement variables. Experimental analyses lead to the conclusion that the ANN models and macroscopic model were effective to improve the O-D travel time and flow estimations for some O-D pairs. Further studies will address: (1) to apply the new proposed model for freeway networks which requires route choice behaviors and (2) to investigate effect of the simultaneous estimation.

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