AN APPLICATION OF A NEURAL-KALMAN FILTER FOR DYNAMIC ESTIMATION OF O-D TRAVEL TIME AND FLOW WITH THE DIFFERENT NUMBER OF TRAFFIC DETECTORS*

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1. Introduction

The authors have been engaged in developing a new paradigm for estimating dynamic O-D travel time and flow on a freeway corridor. The fundamental framework is to 1) develop a Neural-Kalman filter (NKF) method, which is a new algorithm by integrating artificial neural network (ANN) model into a Kalman filter, 2) introduce a macroscopic model for predicting traffic states in advance and 3) estimate dynamic O-D travel time and flow simultaneously within one process. The NKF method was originally proposed by Nakatsuji et. al.[1)2)], and was modified in steps by Suzuki and Nakatsuji [3)4)5)] to estimate O-D travel time and flow on a freeway: A basic concept of the new model was briefly described in Suzuki and Nakatsuji [3)5)]. They presented how to formulate the Kalman filter to consider the influence of traffic situations for arbitrary number of time steps as long as necessary [3)5)]. This development enabled the NKF to be applied for the dynamic estimations of O-D travel time and flow on long freeways. The integration of ANN models into a Kalman filter was found effective in describing the non-linear features of dynamic O-D travel time and flow [3)5)]. An advance prediction of traffic states by the macroscopic traffic flow model contributed in improving the estimation precision [4)5)]. The parameters of a macroscopic model were independently optimized for each road link of the expressway to improve an estimation precision[3)], and a sigmoid function of ANN model was also modified to improve the training performance [4)]. Some numerical analyses were carried out using simulated traffic data on the expressways in Bangkok Metropolis, Thailand [3)4)5)]. In this way, the first and second objectives of the framework mentioned above have been almost realized and examined through some numerical analyses using traffic data simulated by a microscopic traffic simulation package, FRESIM [6)]. However, the last objective still remains unresolved.

The problem that lies in the third topic is the interaction between O-D travel time and flow. The interaction has not been considered in previous studies of dynamic O-D flow estimations, for instance, at an isolated intersection [7) 8)] on a small freeway [9)] and O-D travel time estimations [2) 10) 11)]. On the other hand, some researchers have used travel time information for dynamic O-D flow estimations on a long freeway. Ashok and Ben-Akiva [12)] applied a Kalman filter to estimate O-D flows from link traffic counts on a long freeway corridor. Travel time of specific O-D pairs was used for the estimations, assuming that the travel time was constant during the whole simulation period. This assumption is not realistic for an actual freeway because travel time varies with traffic situations. Chang and Wu [13)] investigated the influence of O-D travel time in O-D flows on a freeway. In order to avoid complexity in the formulation of Kalman filter and to reduce computational burden, they took into account the O-D travel time only for two time steps immediately before. Another Kalman filter approach was proposed by Madant et al.[14)] to estimate O-D flows considering dynamic changes in travel time. However, the approach has no feedback process from O-D flows to travel time because a traffic simulator independently calculated the travel time without considering dynamic changes of O-D flows. In this way, the O-D travel time has been solely treated as implicit variable and not been directly used in O-D flow estimations. Moreover, there has been no feedback process considered from O-D flow to travel time even though travel time varies over time according to O-D flows. Consequently, no model is successful yet in estimating both O-D travel time and flow simultaneously encompassing mutual interactions.

In addition, this new method is featured as an indirect estimation method based on a feedback technique. It estimates O-D travel time and flow in real time while measuring traffic variables, such as link traffic volumes, spot speeds and off-ramp volumes. It uses as much information as possible about traffic state available through traffic detectors to estimate O-D travel time and flow accurately. Hence, it is anticipated that the estimation precision will improve by installing more traffic detectors. Different from other western countries, traffic detectors are densely installed and well maintained in Japan. The traffic data measured are reliable enough for such a. feedback method to have a potential of providing satisfactory estimation precision. Still there are many issues to be addressed before practical application, nevertheless it is interesting to evaluate issues such as the relationship between installing more traffic detectors to the improvement in estimation precision. That is, the questions whether installation of more traffic detectors can improve the precision in the estimation of O-D travel time and flow , how many detectors should be installed to satisfy the estimation precision required, and so on, are relevant.

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This paper aims to 1) re-formulate the NKF model so as to estimate O-D travel time and flow simultaneously, 2) investigate how precise simultaneous estimations are , and 3) the influence of measurement points on the estimation precision. Here, a macroscopic model is not used because the analyses fully investigated the effect of the simultaneous estimations or the number of measurement points on estimations of O-D travel time and flow. Firstly, the theory of a NKF model is briefly reviewed with the modification done in the NKF model to treat both O-D travel time and flow simultaneously. Then, the subjects mentioned above are investigated taking the Second-Stage Expressway in Bangkok as the experiment field. Finally, a conclusion and a recommendation are given based on the discussions of the numerical analyses.

2.Model Description

The fundamental structure of the NKF model and the computational procedure are almost same as described in the previous studies by Suzuki and Nakatsuji[3)4)5)]. To avoid the duplication with the preceding papers, here only a brief description of NKF model is presented. In this study, however, the macroscopic model was not included in the NKF model to examine the effect of the number of measurement points more clearly.

(1) Kalman Filter for Simultaneous Estimations of O-D Travel Time and Flow

Let:

$t_i(k)$ = O-D travel time for O-D pair i at time k $\quad$ $f_i(k)$ = O-D flow for O-D pair i at time k

N = the number of O-D pairs

MA, MB = the number of measurement points on a freeway mainline and off-ramps

$\mathbf{t}(k) = [t_1(k), t_2(k), \ldots, t_N(k)]$ $\quad$ $\mathbf{f}(k) = [f_1(k), f_2(k), \ldots, f_N(k)]$

$\mathbf{z}(k) = [\mathbf{t}^T(k), \mathbf{f}^T(k)]^T$ $\quad$ $\mathbf{y}(k) = [q_1(k), w_1(k), \ldots, q_{MA}(k), w_{MA}(k), s_1(k), \ldots, s_{MB}(k)]^T$

$\mathbf{I}$, $\mathbf{O}$ = Identity and zero matrices, respectively. $\quad$ m = the number of time steps to be considered

$\mathbf{x}(k) = [\mathbf{z}^T(k), \mathbf{z}^T(k-1), \ldots, \mathbf{z}^T(k-m+1)]^T$ $\quad$? $(k), \xi(k)$ = state and measurement errors

$\mathbf{B}(k), \mathbf{d}(k)$ = constant terms of state and measurement equations

$\mathbf{A}(k-m)$ = coefficient matrix that denotes the contribution of $\mathbf{z}(k-m)$ to $\mathbf{z}(k)$

$\mathbf{C}(k)$ = coefficient matrix that denotes the contribution of $\mathbf{z}(k)$ to $\mathbf{y}(k)$

$\Psi(k) = [\mathbf{C}^T(k), \mathbf{C}^T(k-1), \ldots, \mathbf{C}^T(k-m)]^T$

$\mathbf{y}(k) = [q_1(k), w_1(k), \ldots, q_{MA}(k), w_{MA}(k), s_1(k), \ldots, s_{MB}(k)]^T$

$\tilde{\mathbf{x}}(k)$ = predicts of state variable $\mathbf{x}(k)$ before measuring $\mathbf{y}(k)$

$\tilde{\mathbf{y}}(k)$ = predicts of measurement variable $\mathbf{y}(k)$

$\hat{\mathbf{x}}(k)$ = corrected state variable $\mathbf{x}(k)$ after measuring $\mathbf{y}(k)$

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

What is different from the previous model is that the vector z(k) has both O-D travel time and flow in order to estimate them within one process. A Kalman filter consists of the following Equations:

$$\tilde{\mathbf{x}}(k) = \Phi(k-1)\hat{\mathbf{x}}(k-1) + \mathbf{B}(k) + \exists(k) \qquad (1)$$

$$\tilde{\mathbf{y}}(k) = \Psi(k)\tilde{\mathbf{x}}(k) + \mathbf{d}(k) + \xi(k) \qquad (2)$$

$$\hat{\mathbf{x}}(k) = \tilde{\mathbf{x}}(k) + \mathbf{K}(k)[\mathbf{y}(k) - \tilde{\mathbf{y}}(k)] \qquad (3)$$

where:

$\mathbf{K}(k) = \mathbf{M}(k)\Psi^T(k)[\Psi(k)\mathbf{M}(k)\Psi^T(k) + \Omega]^{-1}$

$\mathbf{P}(k) = \mathbf{M}(k) - \mathbf{K}(k)\Psi(k)\mathbf{M}(k)$

$\mathbf{M}(k) = \Phi(k-1)\mathbf{P}(k-1)\Phi^T(k-1) + \Gamma$

Γ, Ω = variance- covariance matrices of state and measurement equations

(2) Neural-Kalman Filter (NKF)

Let:

W_{ij}, W_{jk} = connection weights between input and hidden, hidden and output layers

θ_j, θ_k = offsets in a middle and output layer

x_i = input signal of an ANN model at I-th neuron

y_k = output signal of an ANN model at k-th neuron

$g(x)$ = a sigmoid function

u_0 = a parameter to define the shape of the sigmoid function

A multi-layered ANN model yields output signals y_k by giving some input signals x_i ($i = 1,2,\ldots$):

$$y_k = g\left[\sum_j W_{jk} \cdot g\left(\sum_i W_{ij} x_i + \theta_j\right) + \theta_k\right] \quad (k = 1,2,\ldots) \tag{4}$$

The entry of coefficient matrices $\Phi(k-1)$ and $\Psi(k)$ is defined the partial derivative $\partial y_k / \partial x_i$, as derived in the previous studies, which made it possible to integrate the neural network model into Kalman filter.

$$\partial y_k / \partial x_i = \cdots = (2/u_0) \cdot y_k \left[1 - y_k\right] \cdot \sum_j \left(W_{jk} \cdot (2/u_0) y_j \left(1 - y_j\right) \cdot W_{ij}\right) \tag{5}$$

(3) Estimation Procedure

The procedure of estimations of O-D travel time and flow by a NKF is as follows: First of all, an initial state variable and an error covariance matrix are given to a NKF. Then, prior to the measurement of y(k), the state variables $\tilde{\mathbf{x}}(k)$ are predicted using an ANN model for the state equation of Eq. (1). At the same time, partial derivatives $\partial y_k / \partial x_i$ are calculated by Eq. (5) to yield coefficient matrix $\Phi(k-1)$. Similarly, the predicts of $\tilde{\mathbf{y}}(k)$ are computed by another ANN model for the measurement equations of Eq. (2) as well as the coefficient ? (k) by Eq. (5). Those error covariance and coefficient matrices define the Kalman gain $\mathbf{K}(k)$ at time step k. Finally, the predicts $\tilde{\mathbf{x}}(k)$ are corrected into new estimates $\hat{\mathbf{x}}(k)$ by Eq. (3) when actual new measurement data $\mathbf{y}(k)$ are observed. This correction is what is called feedback in Kalman filter. After the error covariance matrix is updated, the above procedures are iterated over the whole simulation period.

3. Effect of Simultaneous Estimation

(1) Field Data Collection

A simultaneous estimation was carried out on the Expressways in Bangkok, as illustrated in Fig. 1. The distance between Thammasat (TU) on-ramp to Bang Na (BN) off-ramp is 49.03 km. Drivers are able to enter and exit the expressways at thirteen and eleven on- and off-ramps between TU and BN. Three O-D pairs with large traffic volumes were selected for the numerical analysis. These are: Chiang Wattana (CW) to BN, Ngam Wongwan (NW) to BN, and Rachada Phiseki (RP) to BN. The distance of each O-D pair is 25.88, 21.40 and 17.79 km, respectively.

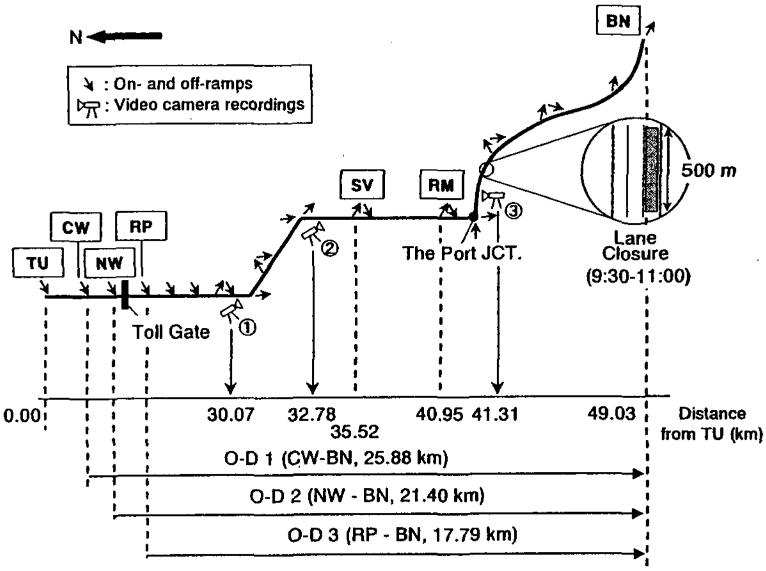

Fig. 1. Study area

The basic filed data were collected on 22 (Tue) and 23 (Wed) December 1998 by manual counting as well as video camera recordings since the traffic surveillance system has not been operational in Bangkok yet. The data of on- and off-ramp volumes, spot speeds and link traffic volumes are collected at three observation points, which are located at 30.07, 32.78 and 40.95 km downstream of TU. In addition, O-D travel time and flow were also measured by a license plate number matching. All data were aggregated every five minutes for ten hours time duration from 7:00 a.m. until 5:00 p.m. for each day.

A NKF requires a lot of data sets to calibrate ANN models of state and measurement equations of a Kalman filter. The traffic data sets must cover extensive traffic situations from light to congested states. However, it is almost impossible to collect such traffic flow data only from the real world. Therefore, an expressway network, which imitates the expressways in Bangkok, was virtually created by a microscopic traffic simulation package called FRESIM.[6] The actual field data collected on the first day were used to calibrate the FRESIM model parameters. The second day traffic data were used for validating the FRESIM model. After validating the FRESIM model, traffic data were generated by FRESIM for various traffic situations.

The inflow volumes and the ratios of heavy vehicle were not measured at minor on-ramps. They were determined from the traffic data collected by the Expressway and Rapid Transit Authority of Thailand (ETA) on 22nd November 1997.[15]

(2) Calibration and Validation of a FRESIM Model

The parameters of FRESIM models must be carefully adjusted in order to simulate actual traffic flows as precisely as possible. Two parameters were specified to be influential; a free flow speed and a car-following parameter. The free flow speed on each link was estimated from actual speed data collected at the nearest measurement point. The car-following parameter was calibrated on a trial and error basis so as to minimize the difference between the estimated and measured link flow volumes and spot speeds on three measurement points.

Tab. 1. Result of a t-test for validating a FRESIM model

	Link flow volumes	Spot speeds
Measurement points	t-value	
1	1.8428	1.3605
2	1.5532	1.7926
3	1.5773	1.5713

critical value=2.0687, degree of freedom = 23, two-sided hypothesis test

After the calibration, the FRESIM model was validated to check whether it was capable of simulating the actual traffic flows of the second data. Tab. 1 depicts the result of a t-test, comparing the difference between the averages of actual and simulated measurement variables. Since all t-values in Tab. 1 were less than the critical value of 2.0687, it was justified that there was no significant difference between the actual and simulated volumes and spot speeds.

(3) ANN models

The ANN model of state equation is different from the one of the measurement equation. The ANN model for state equation has three layers; input, hidden and output layers. Since both O-D travel time and flow were simultaneously estimated within one process, the number of neurons in input and output layers are 40 and 6, respectively. Here, traffic states for preceding five steps were considered in Eqs. (1) and (2). The number of hidden layer was fixed to be 1 with twenty neurons, which was the half number of that in the input layer.

This study assumed that traffic detectors were installed at three measurement points ①, ② and ③ on mainline freeways and at three off-ramps SV, RM and BN, as shown in Fig.1. The detectors on the mainline freeway give both link traffic volumes and spot speeds, while those on the off-ramps yield outflow volumes only. Therefore, the total number of measurement variables are 9. Similar to the ANN model for the state equation, another ANN model with three layers was defined for measurement equation. The number of neurons in each layer was, therefore, 40-20-9, respectively.

(4) Procedure

No heavy traffic congestion occurred during the two-days field data collection. However, to evaluate simultaneous estimations of O-D travel time and flow under congested flow states, traffic data were virtually created by FRESIM, assuming that

- A lane out of three was closed for about 500 meters long near Port Junction from 9:00 a.m. to 10:30 a.m., as shown in Fig. 1. The lane closure caused a heavy congested flows propagating backwards the expressways,
- During a lane closure, some traffic volumes that were supposed to exit at Bang Na (BN), diverted at SV and RM off-ramps to avoid the traffic congestion ahead of them.

Due to the lane closure, O-D travel times for all three O-D pairs increased during this time period. Also, the O-D flow to BN slightly decreased as outflow volumes at two off-ramps of SV and RM increased. For those traffic situations, the O-D travel time and flow were estimated separately and simultaneously using NKF models. The effectiveness in simultaneous estimationwas evaluated based on the Root Mean Square (RMS) errors between the two.

(5) Experimental Results

(a) O-D Travel Time

Fig. 2 shows the variation of O-D travel time for O-D pair, No.2, for both separate and simultaneous scenarios. It can be seen that the simultaneous estimates follow the target O-D travel time more precisely than the separate estimates, although the simultaneous estimates fluctuated at around 10:20, 10:55 and 12:00 a.m. The fluctuations were due to drastic changes of traffic conditions at 10:20, 10:55 and 12:00 a.m. The NKF sensitively reflected the changes of traffic conditions to the estimates.

Fig. 3 summarized RMS errors between separate and simultaneous estimations of dynamic O-D travel time for all three O-D pairs. By estimating them with O-D flows, the estimates were improved at 31.3, 32.0 and 15.5 % for O-D pairs No. 1, 2 and 3, respectively. Also, the ratio of the RMS errors to the average O-D travel time was 16.3 % in the average among three O-D pairs. The ratio should be improved for an actual implementation of dynamic O-D travel time and flow estimations by eliminating the fluctuations of O-D travel time estimates.

(b) O-D Flow

Fig. 4 depicts the comparison between separate and simultaneous estimates of O-D flow for O-D pair No. 2. The separate estimation method caused a significant under-estimation state at the beginning of simulation period, between 7:25 to 8:55 a.m., while the simultaneous method resulted in better estimations. Also, a sensitive fluctuation that occurred at around 10:20 a.m. in the separate method is captured with fair accuracy using simultaneous method.

Similarly, RMS errors for separate and simultaneous O-D flow estimations were summarized for three O-D pairs, as illustrated in Fig. 5. It shows that the simultaneous method gives better estimates of O-D flows for all three O-D pairs than the separate estimations. The simultaneous method reduced the RMS errors at 22.9, 30.1 and 50.5 % for O-D pairs No. 1, 2 and 3, respectively. However, the ratio of RMS errors in simultaneous method to average O-D flows was 26.4 % in the average among three O-D pairs. It suggests an improvement of a NKF, although it is capable of estimating non-linearity of dynamic O-D flows.

(6) Discussion

The numerical analysis showed that the simultaneous approach yielded more accurate estimates for both O-D travel time and flow than separate method. In other words, the premise that an O-D flow information is an important factor for estimating dynamic O-D travel time and vice versa was justified. However, as shown in Fig. 2, the NKF itself was sensitive to a drastic change of traffic situation and caused significant errors, especially in estimating O-D travel time. This is because the ANN models encountered traffic conditions that they did not learn in advance. The use of more learning data sets covering extensive traffic situations may improve the estimation precision. Another reason seems to be the parameters used in ANN model; u_0, θ_j and θ_k in Eq. (5), where u_0 is a shape parameter of sigmoid function and the θ_j and θ_k are offsets. They are said to be influential in the training of neural network models. But, at present, there exists no rational method except trial and error basis to identify them.

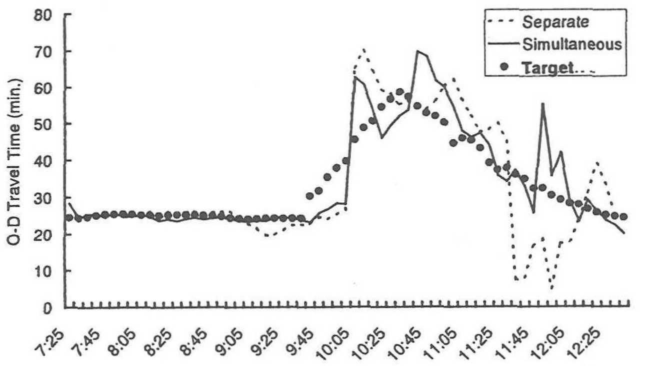

Fig. 2. Comparison of separate and simultaneous estimates of O-D travel time

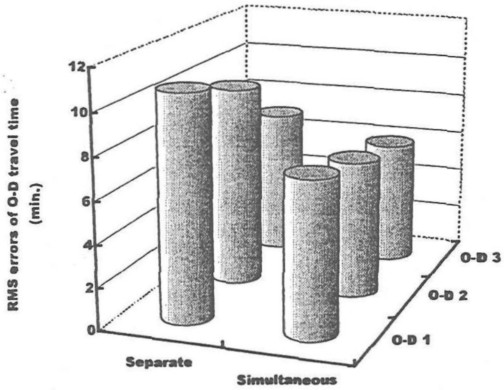

Fig. 3. RMS errors of separate and simultaneous estimations of O-D travel time

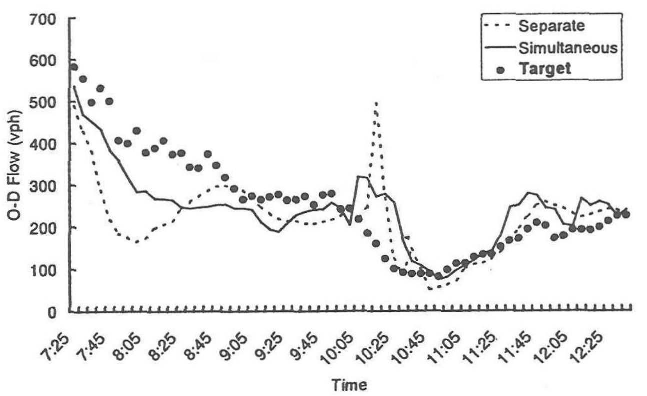

Fig. 4. Comparison of separate and simultaneous estimates of O-D flow

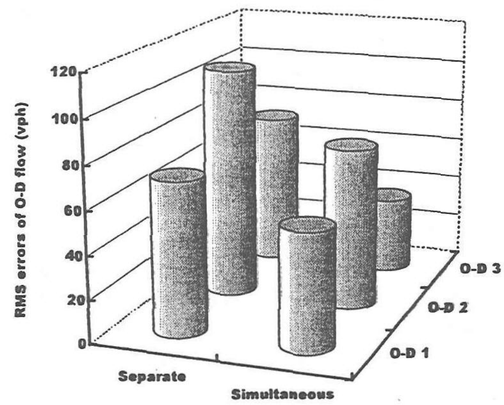

Fig. 5. RMS errors of separate and simultaneous estimations of O-D flow

4. Effect of Number of Measurement Points

The simultaneous estimation of O-D travel time and flow was carried out using the limited number of measurement points along the expressway. Link traffic volumes/spot speeds were measured at three points and outflow volumes ~~were~~ also observed at three off-ramps. Although results are good but it goes without saying that the limited observed traffic data is not fully capable of capturing the dynamics in traffic flow for the long expressway in the true sense.. In order to get a better picture, therefore, the influence of the number of measurement points on dynamic O-D travel time and flow estimations should be numerically examined for the NKF model. The O-D travel time and flow were simultaneously estimated again by virtually installing more traffic detectors along the expressways. The RMS errors were compared among the NKF models for different measurement points.

(1) Traffic Data

Another virtual freeway corridor was modeled imitating the expressways in Bangkok, as shown in Fig. 6. The freeway is approximately 30 km long with several on- and off-ramps. The number of on- and off-ramps remained the same as that on the previous expressways in Fig. 1. It was assumed that the freeway was equipped with at most ten traffic detectors; seven were used to observe link traffic volumes and spot speeds on the mainline, the other three were for outflow volumes at off-ramps D1, D2 and D3. The detectors were installed every one or two kilometers from the first measurement point ①, which was located at 10.52 km downstream of an origin O1. The same three O-D pairs, O1-D1, O1-D2 and O1-D3, were adopted. The distance of each O-D pair is 15.97, 21.40 and 29.48 km, respectively Similar to the previous analysis, traffic data were simulated by FRESIM. The traffic simulation was done based on the following assumptions:

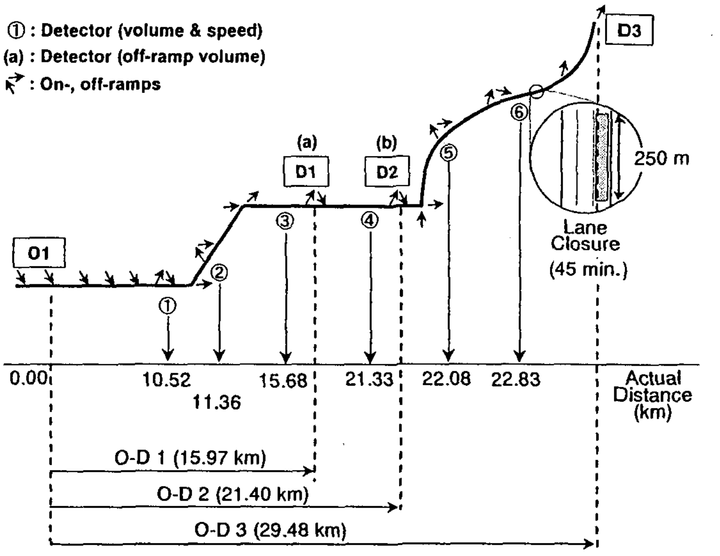

Fig. 6. A freeway Model

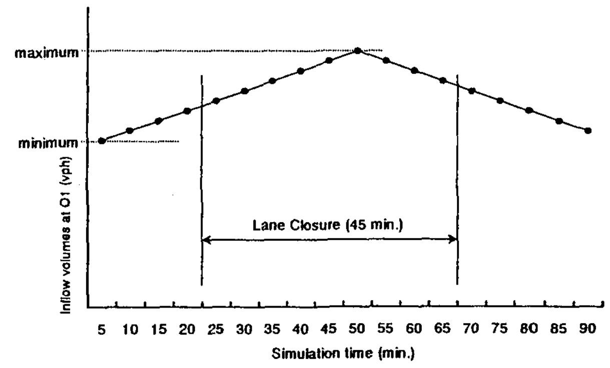

Fig. 7. Inflow volumes of each data pattern

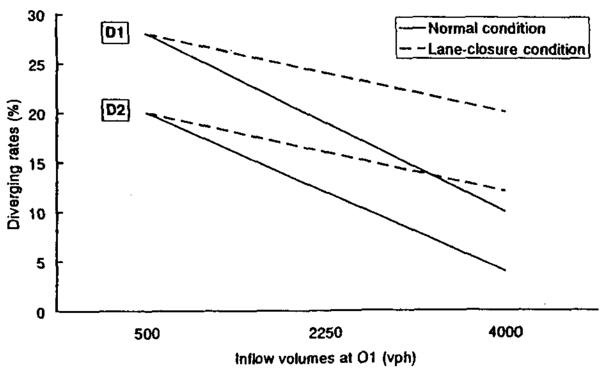

Fig. 8. Change of Diverging Rates at D1

- Inflow volume at an origin O1 takes twelve patterns according to traffic situations. The first data pattern changes the volume from 500 to 770 vehicle per hour (vph), varying linearly from the minimum, 500 vph to the maximum, 770 vph, over the simulation period of 1.5 hours, as illustrated in Fig. 7. The second data pattern has an inflow volume between the minimum of 770 vph and the maximum of 1,040 vph. Similarly, the last data pattern is in the range of 3,730 to 4,000 vph. The inflow volume of each data pattern changes every 5 minutes over the whole simulation period.
- The actual on-ramp volumes on the expressways in Bangkok are allocated to the inflow volumes at minor on-ramps. The inflow volumes were randomly selected at each on-ramp for the simulation period.
- One lane out of three is closed over a length of 250 meters, 430 meters downstream of the measurement point ⑦. The lane is closed for 45 minutes, i.e. just half of simulation time. Here, the traffic condition during the lane closure is referred to as lane-closure condition and the condition without the lane closure is as normal condition.
- During the lane closure, some traffic volumes diverted at off-ramps D1 and D2 to avoid traffic congestion. The diverging rates determined by travel time on diverting routes, vary with inflow volumes at O1, as illustrated in Fig. 8. The light inflow volume give slightly higher diverging rates for lane-closure condition than for normal condition. The higher the inflow volume, the lesser are the diverging rates; moreover, the difference between normal and lane closure conditions gets larger with the increase in inflow volume.

The O-D travel time/flow and measurement variables, such as link traffic volume, spot speed and off-ramp volumes, were aggregated every 5 minutes. Three time steps, which theoretically provide 15 data sets of O-D travel time and flow over 1.5 hours of simulation period, were adopted as the preceding time steps in Eqs. (3) and (4).

(2) Calibration and Validation

Inflow volumes with different random seed in FRESIM yield different traffic patterns. Since each simulation run produced twelve data sets for each input pattern, six different random seeds eventually provided 864 data sets in total. These are enough to train the ANN models of both state and measurement equations because the number of synapse weights of the ANN models is 216 and 297, respectively.

Two data patterns of "Light" and "Heavy" were selected out of twelve in order to validate the effect of the number of measurement points for different traffic situations. The "Light" situation is the third pattern whose inflow volumes at O1 are distributed between 1,040 and 1,310 vph. As will be shown later, the O-D travel time significantly increased due to the lane closure, while the O-D flows were almost stable because the inflow volumes were not so large. The "Heavy" situation is the tenth pattern whose inflow volumes varied from 3,190 to 3,460 vph. In this condition, as will be seen below, the O-D travel times steadily increased, while the O-D flows fluctuated due to the difference in diverging rates between normal and lane-closure conditions.

(3) Procedure

The numerical analysis was carried out to see how precisely a NKF model estimates O-D travel time and flow on the freeway with the different number of measurement points. The effect of the number of measurement points on the estimation precision was evaluated for both "Light" and "Heavy" traffic conditions, assuming three cases with different sets of measurement points; Cases 1, 2 and 3, as shown in Tab. 2. Case 1 employed only three points; two points ① and ④ on a mainline, and one at the off-ramp D1. In Case 2, two more points of ② and ⑤ were added on the mainline, and outflow volumes were measured at both D1 and D2. The last case used all detectors of ① to ⑥ installed on the mainline and three off-ramps of D1, D2 and D3, as depicted in Fig. 6.

Tab. 2. Three sets of measurement points

Measurement Points	link volumes Spot speeds	Off-ramp volumes
Case 1	①, ④	D1
Case 2	①, ②, ④, ⑤	D1, D2
Case 3	①-⑥	D1, D2, D3

(4) Experimental Results

(a) Light condition

Fig. 9 exhibits the estimates of O-D travel time for O-D pair No. 3 (NW-BN) for three cases. Case 1 significantly over-estimated the target O-D travel time after 55 minutes passed. Although Case 2 resulted in better estimated in compaison to Case 1, but the fluctuation after 55 minutes is still large. In Case 3, the fluctuations were reduced significantly and the estimate followed the target O-D travel time very well over the whole simulation period.

Similar results were obtained for O-D flow estimates of the same O-D pair No. 3. As depicted in Fig. 10, Case 1 was not enough to represent the target O-D flow, especially the difference is quite large after 70 minutes of simulation run. In Case 2, the NKF yielded significant over- and under-estimation states with large fluctuation for the whole time period. Case 3 decreased the fluctuation very well. Particularly, it followed the target quite well before the travel time starts to decrease at around 65 minutes. Even Case 3 over-reacts to the reduction of travel time from 70 to 90 minutes although it recovers the reduction at the end of simulation.

Figs. 11 and 12 present RMS errors of O-D travel time and flow estimates for three cases. In O-D travel time, Case 3 yielded the best result for all O-D pairs as a whole. More importantly, the errors decrease with the number of measurement points increasing except for Case 1 of O-D pair No.1 in Fig. 11. This is clearly seen in the estimation of O-D flow in Fig. 12. That is, it suggests that the use of more detectors brought the improvement in the estimates. The ratios of the RMS errors in Case 3 to the average O-D travel times were 19.0, 40.0 and 15.9 % for O-D pairs No. 1, 2 and 3, respectively. For O-D flow estimations, the ratios were 16.7, 18.6 and 18.6 %, respectively. The ratios are still large for actual implementations of the O-D travel time and flow

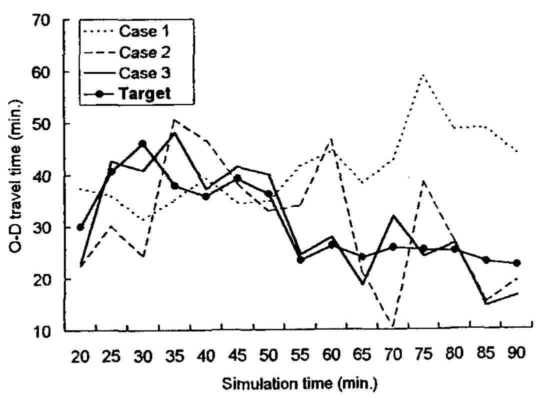

Fig. 9. Comparison of O-D travel time estimates (Light)

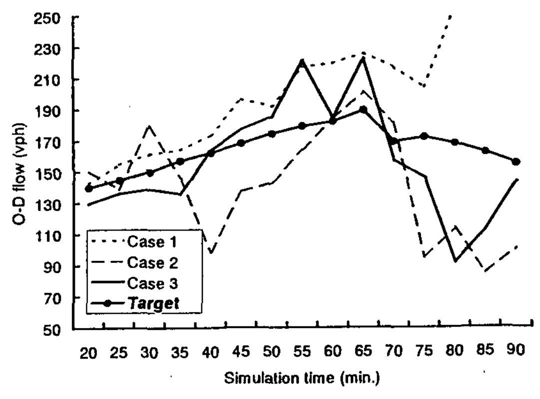

Fig. 10. Comparison of O-D flow estimates (Light)

estimations in a real world. The estimation model by a NKF should be improved by learning more number of field data on extensive traffic situations.

(b) Heavy condition

Fig. 13 shows the variations of O-D travel time for O-D pair No. 3 estimated for "Heavy" condition with comparison among three cases. The estimates by Case 1 significantly fluctuated and estimated poorly and even resulted in almost zero O-D travel time at around 65 minutes. Case 2 reduced the fluctuations in comparison to Case 1 and followed the target O-D travel time until 75

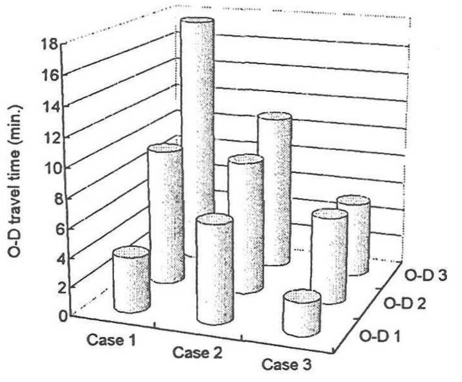

Fig. 11. RMS errors of O-D travel time estimations (Light)

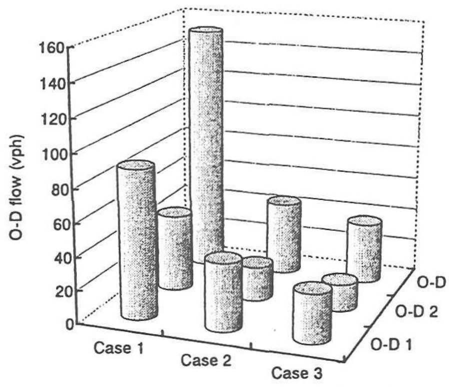

Fig. 12. RMS errors of O-D flow estimations (Light)

minutes of the simulation time. From 80 to 90 minutes, however, the estimate caused a large under-estimation state. There is a little improvement in Case 3 compared with Case 2. The fluctuation in the middle part and the under-estimation state were slightly reduced in Case 3.

Fig. 14 depicts the comparison of O-D flow estimates for O-D pair No.3 among three cases. In Case 1, the estimates heavily fluctuated and still far from the target. The fluctuations were a little bit reduced in Case 2. But, the estimates by Case 2 are still different from the target. It yielded under-estimations over the whole simulation time. On the contrary, Case 3 provided better goodness-of-fit between the estimated and target O-D flow. It follows the target very well, especially until 65 minutes, although the discrepancy is enlarged at the end of the simulation time from 80 to 90 minutes. RMS errors of O-D travel time and flow

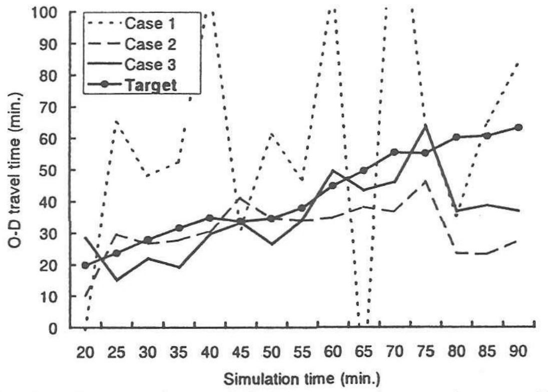

Fig. 13. Comparison of O-D travel time estimates (Heavy)

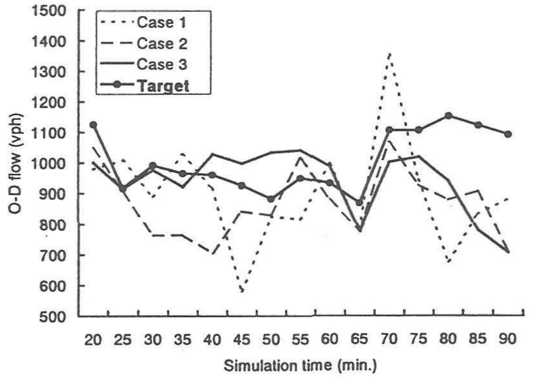

Fig. 14. Comparison of O-D flow estimates (Heavy)

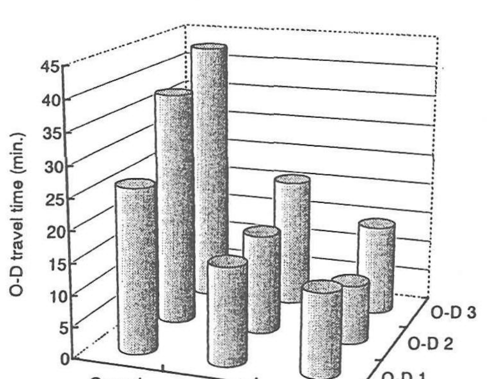

Fig. 15. RMS errors of O-D travel time estimations (Heavy)

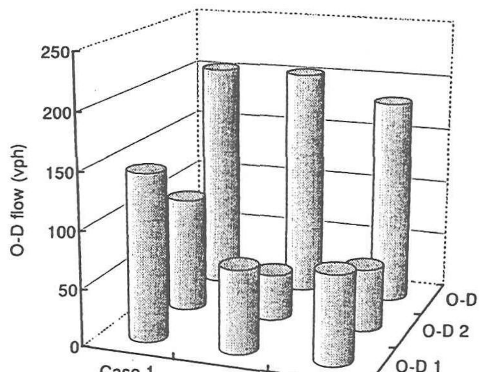

Fig. 16. RMS errors of O-D flow estimations (Heavy)

estimations under "Heavy" condition were both given in Figs. 15 and 16, respectively. Fig. 15 shows that similar to the "Light" condition, more number of detectors contributed in improving the estimation precision of O-D travel time for all O-D pairs. However, this was not always the case in O-D flow estimates. Case 3 did not give the best estimates for O-D pairs 1 and 2 although the difference is small between Case 2 and Case 3 and much better than those of Case 1. This will be discussed in the following section. The ratios of the RMS errors in Case 3 to the average O-D travel time and flow were also computed, respectively. They were: 38.0, 23.6 and 28.9 % for O-D pairs No. 1, 2 and 3 in O-D travel time estimations, and 24.3, 31.5 and 18.1 % in O-D flow estimations, respectively. However, these values are still far from the actual implementations of O-D travel time and flow. Similar to "Low" condition, the ratios should be reduced by improving NKF models. RMS errors of O-D travel time and flow estimations under "Heavy" condition were both given in Figs. 15 and 16, respectively. Fig. 15 shows that similar to the "Light" condition, higher number of detectors contributed in improving the estimation precision of O-D travel time for all O-D pairs. However, this was not always the case in O-D flow estimates. The RMS errors for O-D pair No. 3 did not decrease significantly with the increase in the number of measurement points as expected. Also, Case 3 did not give the best estimates for O-D pairs 1 and 2 although the difference is small between Case 2 and Case 3 and much better than those of Case 1. These two findings will be discussed in the following section.

(5) Discussion

The numerical analysis showed that O-D travel time and flow estimates were improved in most cases as more number of detectors were used for the estimations. In addition, the use of more detectors helped to make a NKF stable because ANN models were trained using bigger data set covering extensive traffic conditions. However, addition of more detectors resulted in larger estimation errors in the following two cases:

- For two O-D pairs No. 1 and 2 in Fig. 11, Case 2 yielded larger errors of O-D travel time estimates than Case 1 under "Light" condition.
- Case 3 in O-D flow estimations under Heavy condition gave larger errors than Case 2 for O-D pairs No. 1 and 2, as depicted in Fig. 16.

In "Light" condition, congested traffic flows generated near the detector ⑥ were propagated slowly because traffic was not very heavy. There were some time lags that the congested flows were propagated near the detectors such as ④ or ③, which have influence on the O-D travel times for O-D pairs No. 1 and 2. This caused the O-D travel times for O-D pairs No. 1 and 2 almost stable during whole simulation time. In Case 2, only the detector ⑤ measured congested flows out of four mainline detectors ①,②, ④ and ⑤. In this case, the NKF gets unstable because ANN models do not have much data learning process under congested traffic flow states. Since the change of traffic conditions near the detector ⑤ was very significant, the detector outputs of ⑤ may not be suitable to explain the stable O-D travel times for the O-D pair No. 1 and 2. This caused the errors in Case 2 larger than that in Case 1 for O-D pairs No. 1 and 2.

The larger errors of O-D flow estimations in Case 3 under "Heavy" condition (Fig. 16) were mainly caused by over-estimations for O-D pairs No. 1 and 2 and under-estimation for pair No. 3 at the end of simulation time. After a lane was cleared at the lane closure point, the traffic states near the detectors ⑤ or ⑥ were changed from severe congested flow to free flow states at a high speed. The changes were detected at the end of simulation time in Case 3. Since the changes were quite significant, and both detectors were closely located in 800 meters, the changes of traffic conditions measured by ⑤ and ⑥ have significantly influenced on the O-D flow estimations by Case 3. As mentioned in Chapter 3, a NKF sometimes gives fluctuated estimates. Two similar detector outputs by the detectors ⑤ and ⑥ made the NKF more sensitive in the O-D flow estimations.

6. Conclusion

The neural Kalman filtering method, in which artificial neural network (ANN) was integrated into the conventional Kalman filter, was developed. The method is characterized by the superiority in representing non-linear and unsteady phenomena of some dynamic variables. Also, it is based on a feedback technique which fully utilizes traffic detector data installed on freeways. Following the development of fundamental structures in the previous studies, this method has been applied to the estimation of O-D travel time and flow on a long freeway. The model was further enhanced in order to consider the mutual interaction between O-D travel time and flow in this study. The NKF model was modified so as to estimate both O-D travel time and flow simultaneously and then it was investigated how effective the simultaneous estimations were on the estimation precision. Moreover, in terms of the feedback process, the influence of the number of measurement points on the estimation precision was investigated. Major findings are summarized as follows:

- The simultaneous estimation was found effective not only in improving the estimation precision but also in decreasing the fluctuations that occurred unexpectedly. The RMS errors were reduced by the simultaneous method for all three O-D pairs analyzed here.
- With higher number of traffic detectors in operation there were lesser fluctuations in O-D travel time and the RMS errors were smaller. Estimation precision for O-D travel time was found to be better than for O-D flow.

Those findings are still conditional and limited because the traffic data used for analyses came from the simulation imitating the expressway system of Bangkok.

Different from western countries, traffic detectors are densely installed and the traffic data measured are reliable enough in Japan. In this respect, the neural Kalman filter has a good potential of establishing a new feedback method. Further enhancements and applications to the real road network are required for actual implementations of O-D travel time and flow estimations.

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An Application of a Neural-Kalman Filter for Dynamic Estimations of O-D Travel Time and Flow with the Different Number of Traffic Detectors

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A Neural-Kalman filter method, which was originally developed by the authors, was further updated with the addition of simultaneous estimation capability of O-D travel time and flow. Numerical experiments exhibited that the consideration of mutual interaction between them contributed in improving the estimation precision for all three O-D pairs tested. Moreover, considering the fact that this new method is based on a feedback technique, it was investigated if the estimation error would decrease with the increase in the size of the measurement data. Analyses by changing the number of traffic detectors showed that the higher number of traffic detectors gave the better the estimates for the O-D travel time and flow for all three O-D pairs tested.

感知器の数を変化させた場合におけるニューロカルマン法の動的O-D旅行時間及び交通量の同時推定への応用

鈴木宏典, 中辻隆, ヨッポン・タナボリブン, 高橋清

筆者らによって提案されてきたニューロカルマン法を、高速道路上の任意の入口・出口間を通過する交通量及びその所要時間を同時に推定するためのモデルとして拡張した。タイ・バンコク首都圏の高速道路を対象として数値計算を行った結果、交通量と所要時間を同時に推定することによって両者の推定精度が著しく向上することを検証した。さらに、ニューロカルマン法は高速道路上に設置された交通感知器による観測値をフィードバックして交通量や所要時間を推定する方法に基づくことから、感知器の数が両者の推定値に与える影響を新たな数値計算により検討した。この結果、感知器の数を増加させた場合、交通量及び所要時間ともにより精度の良い推定値が得られることを定量的に示した。