Journal of Transportation Technologies, 2022, 12, 533-543
https://www.scirp.org/journal/jtts
ISSN Online: 2160-0481
ISSN Print: 2160-0473

Real-Time Traffic State and Boundary Flux Estimation with Distributed Speed Detecting Networks

Yichi Zhang, Heng Deng*

Faculty of Information Technology, Beijing University of Technology, Beijing, China
Email: zhangycyz@emails.bjut.edu.cn, *dengheng@bjut.edu.cn

How to cite this paper: Zhang, Y.C. and Deng, H. (2022) Real-Time Traffic State and Boundary Flux Estimation with Distributed Speed Detecting Networks. *Journal of Transportation Technologies*, **12**, 533-543.
https://doi.org/10.4236/jtts.2022.124031

Received: July 7, 2022
Accepted: July 29, 2022
Published: August 1, 2022

Abstract

The rapid development of 5G mobile communication and portable traffic detection technologies enhances highway transportation systems in detail and at a vehicle level. Besides the advantage of no disturbance to the regular traffic operation, these ubiquitous sensing technologies have the potential for unprecedented data collection at any temporal and spatial position. While as a typical distributed parameter system, the freeway traffic dynamics are determined by the current system states and the boundary traffic demand-supply. Using the three-step extended Kalman filtering, this paper simultaneously estimates the real-time traffic state and the boundary flux of freeway traffic with the distributed speed detector networks organized at any location of interest. In order to assess the effectiveness of the proposed approach, a freeway segment from Interstate 80 East (I-80E) in Alameda, Emeryville, and Northern California is selected. Experimental results show that the proposed method has the potential of using only speed detecting data to monitor the state of urban freeway transportation systems without access to the traditional measurement data, such as the boundary flows.

Keywords

Traffic State, Boundary Flux, Estimation, Extended Kalman Filtering, Distributed Speed Detecting Networks

1. Introduction

Real-time knowledge about traffic conditions of urban road transportation systems is critical for traffic management and control. There are many well-established technologies for collecting vehicle speed and flux data, including loop detectors and Automatic Vehicle Identification (AVI) sensors [1]. However, equipped segments in the network are typically low and not representative of the urban network as a whole, which leaves the traffic conditions in most of the network unknown. Recently, the novel ubiquitous sensing technologies have the potential of unprecedented data collection at any spatial position of the large-scale road transportation networks. For example, dedicated probe vehicles or simple portable radar speed detect guns embedded with wireless communication constitute a wireless sensing network for vehicle mean speed measurement [2].

Road traffic condition estimation includes traveling time estimate and traffic parameter estimate for any origin-destination pair of the networks. The literature on travel time estimation and forecasting using the speed and position of probe vehicles has grown in recent years as technology has become more available [3]. Hunter *et al.* [4] present a probabilistic model of travel times in the arterial network based on low-frequency taxi GPS probes. Development of the approach more clearly aimed toward travel time forecasting is presented in Hofleitner *et al.* [5]. Jenelius and Koutsopoulos [6] further consider the effect of explanatory variables on travel times using probe vehicle data.

The filtering approach is mostly used for traffic parameter estimates by predicting the macroscopic traffic flow models [7]. Wang *et al.* [8] propose an extended Kalman filtering (EKF) to estimate the real-time traffic density and vehicle speed of a freeway link with a stochastic version of METANET model. In [9], a solution to freeway traffic estimation in Beijing is proposed using a particle filter, based on macroscopic traffic flow model, which estimates both traffic density and speed. Sun *et al.* [10] present a solution to traffic density estimate with the sequential Monte Carlo algorithm, which is the so-called mixture Kalman filtering. Although the previous works demonstrate the possibility of extracting traffic parameters, the proposed methods are based on the general assumption that the boundary fluxes of the traffic networks are accessible or measurable.

The methodology proposed in this paper extends previous work on traffic parameter estimation with distributed speed detecting networks by considering the simultaneous traffic density and boundary flux estimation. The observations come from loop or portable speed detectors reporting the mean vehicle speed and detector position in the traffic networks. Portable means that the speed for all segments of the transportation network may be achieved by moving or placing the detecting devices at any observation positions. The proposed methodology is based on three-step extended Kalman filtering that jointed estimates state and input in a situation where the boundary traffic fluxes are not measurable. Since measuring the border fluxes is not easily accessible to each interested portion of the large-scale networks, it could become a crucial factor in experimental tests.

This paper is organized as follows. The Godunov scheme for the discretization of the macroscopic traffic flow model, observation model using distributed speed detecting networks, and simultaneous state and input estimate are given in Sections 2.1, 2.2, and 2.3, respectively. In Section 3, two experiment scenarios with the empirical traffic data are simulated to illustrate the effectiveness of this approach. Finally, Section 4 concludes the paper.

2. Methodology

2.1. Godunov Scheme for LWR Traffic Flow Model

The first-order macroscopic (Lighthill-Whitham-Richards, LWR) traffic flow model [11] [12] formulates the relationship between the traffic density $\rho(x,t)$ and the traffic flow $q(x,t)$ at the position x and at the time t by the conservation law

$$\frac{\partial\rho}{\partial t}+\frac{\partial q}{\partial x}=0. \tag{1}$$

Using the space mean speed measurement and the hydrodynamic of the flow-speed relation

$$v=\frac{q}{\rho}, \tag{2}$$

Equations (1) and (2) form a closed system since there are two Equations with two unknown functions.

Based on the Smulders fundamental diagram [13], a static speed-density relationship is given by the following piecewise function

$$v=\begin{cases}\dfrac{v_c-v_f}{\rho_c}\rho+v_f, & \rho\le\rho_c\\[2ex] \dfrac{\rho_c v_c}{\rho_J-\rho_c}\left(\dfrac{\rho_J}{\rho}-1\right), & \rho>\rho_c\end{cases} \tag{3}$$

which contains four parameters that are specific to freeway link: free flow speed v_f, critical speed v_c, critical density ρ_c and jam density ρ_J. These parameters also define the capacity of the freeway link $q_{\max}=v_c\rho_c$. Figure 1 shows the shape of this fundamental diagram.

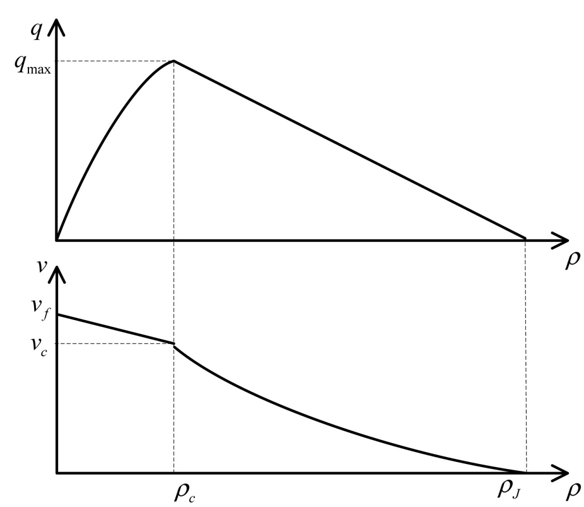

Figure 1. Flow-density and speed-density curves with Smulders fundamental diagram.

Numerical solutions of Equations (1) and (2) could be obtained using the Godunov scheme, whereby each segment of the freeway link is discretized into cells with length $L_i, i = 1, \cdots, N$ and time is discretized into the interval with length Δt. From the Courant-Friedrichs-Lewy condition, the numerical solution is stable as the length of each cell satisfies

$$L_i \le v_f \Delta t. \tag{4}$$

Given this discretization, the conservation Equation can be rewritten in the form

$$\rho_i(k+1) = \rho_i(k) + \frac{\Delta t}{L_i}\left(q_i^{in}(k) - q_i^{out}(k)\right), \tag{5}$$

where $\rho_i(k)$ is the vehicle density of cell *i* at time index *k*, $q_i^{in}(k), q_i^{out}(k)$ are vehicle flows entering and leaving cell *i* during the time interval $[k\Delta t, (k+1)\Delta t]$, respectively. For the adjacent cells, the driving-out flux of the upstream cell is equal to the driving-in flux of the downstream cell

$$q_i^{out}(k) = q_{i+1}^{in}(k), i = 1, \cdots, N-1. \tag{6}$$

Fluxes $q_i^{in}(k)$ between cell borders are determined by comparing the available supply $S_i(k)$ and the prevailing demand $D_{i-1}(k)$, that is

$$q_i^{in}(k) = \min\{D_{i-1}(k), S_i(k)\}. \tag{7}$$

These demand and supply functions are defined as

$$\begin{aligned} D_i(k) &= v(\rho_i)\rho_i, \quad S_i(k) = q_{\max}, \quad \rho_i(k) \le \rho_c \\ D_i(k) &= q_{\max}, \quad S_i(k) = v(\rho_i)\rho_i, \quad \rho_i(k) > \rho_c \end{aligned} \tag{8}$$

Therefore, the nonlinear state-space form of the traffic dynamics in the freeway segment can be rewritten as

$$\rho(k+1) = F(\rho(k)) + Gd(k) \tag{9}$$

where $\rho^{\mathrm{T}} = [\rho_1, \cdots, \rho_N]$ and $d^{\mathrm{T}}(k) = [q_1^{in}(k), q_N^{out}(k)]$ are the unknown boundary driving-in and driving-out fluxes of this freeway segment, respectively.

2.2. Speed Detecting Networks

We are interested in estimating the state of the freeway traffic link using the distributed speed detector networks with communication inside to transmit mean speed information among them. Distributed detectors with a wireless communication network constitute a mobile wireless sensing network for vehicle mean speed measurement. The mean speed measurement may be achieved at any interested measurement positions of the freeway link, while the observation data is time-synchronized.

Using the speed-density Equation (3), each measurement $v_j(k), j \in \{1, \cdots, M\}$ can be described as a function of the current vehicle density $\rho_j(k)$ of the cell *j*, where $M \in \mathbb{Z}_+$ is the number of detectors and $M \le N$. Given the collective speed information $y(k) = [v_1, \cdots, v_M]^{\mathrm{T}}$ in the detecting network, the observation equation can be expressed as a nonlinear model

$$y(k) = H(\rho(k)) + v(k), \tag{10}$$

where $v(k)$ is assumed zero-mean Gaussian measurement noise with a covariance matrix $R(k)$.

2.3. Simultaneous State and Input Estimation

The classical EKF method requires deterministic inputs in the model, which sometimes may not be the case in reality. For example, the boundary fluxes of a freeway segment mainly depend on the supply-demand relationship. That could be unknown signals with an arbitrary type and magnitude, so it is not acceptable to assume them to be stationary and zero-mean random noise.

In this regard, joint estimation of states and unknown inputs for nonlinear systems becomes a meaningful task, which is often addressed as a constrained optimization problem [14] [15]. We consider a recursive three-step filter of the form

$$\rho(k+1|k) = F(\rho(k|k)) \tag{11}$$

$$\hat{d}(k) = M(k)\big(y(k) - C(k)\rho(k+1|k)\big) \tag{12}$$

$$\bar{\rho}(k+1|k+1) = \rho(k+1|k) + G\hat{d}(k) \tag{13}$$

$$\rho(k+1|k+1) = \bar{\rho}(k+1|k+1) + K(k)\big(y(k) - C(k)\bar{\rho}(k+1|k+1)\big) \tag{14}$$

where

$$C(k) = \left.\frac{\partial H}{\partial \rho}\right|_{\rho(k+1|k)}, G^{\mathrm{T}} = \begin{bmatrix} 0 & 0 & \cdots & 1 \\ 1 & 0 & \cdots & 0 \end{bmatrix} \tag{15}$$

$M(k), K(k)$ can be determined from optimization.

The first step (11), which we call the time update, yields an estimate of the traffic density $\rho(k+1|k)$, given measurements up to time *k*. The second step (12) yields the boundary flux estimate as the unknown input $\hat{d}(k)$. Finally, in the third step (14), the so-called measurement update yields an estimate $\rho(k+1|k+1)$ with the given measurement up to time $k+1$ and an input estimate $\hat{d}(k)$ in the second step.

The linearization matrix $A(k)$ of the dynamic traffic model (9) is used to correct the estimate

$$A(k) = \left.\frac{\partial F}{\partial \rho}\right|_{\rho(k|k)} \tag{16}$$

The estimate gain matrices $M(k)$ and $K(k)$ can be calculated using the error variance-covariance equations as follows

$$P(k+1|k) = A(k)P(k|k)A^{\mathrm{T}}(k) + Q(k) \tag{17}$$

$$M(k) = \big(D^{\mathrm{T}}(k)\tilde{R}(k)D(k)\big)^{-1} D^{\mathrm{T}}(k)\tilde{R}^{-1}(k) \tag{18}$$

$$K(k) = P(k+1|k)C(k)\tilde{R}^{-1}(k) \tag{19}$$

$$\tilde{R}(k) = C(k)P(k+1|k)C^{\mathrm{T}}(k) + R(k) \tag{20}$$

$$P(k+1|k+1) = (1 - M(k)C(k))P(k+1|k) \tag{21}$$

where $Q(k)$ is the process error covariance matrix.

3. Empirical Studies

In our experiment, the interested freeway link is a section of Interstate 80 East, approximately two miles in length with two off-ramps in Alameda, Northern California, as shown in Figure 2.

This section is instrumented with loop inductance detectors, which are embedded in the pavement along the mainline, HOV lane, and off-ramps. The blue points along the freeway link denote where loop detectors are installed. Each loop detector gives volume, speed, and occupancy measurements every 30 seconds. In the empirical studies, the utilized traffic data of 6 hours (7:00 am - 1:00 pm) which including the morning rush-hour congestion on Oct. 20 2013, are collected from PeMS [16].

The freeway link is partitioned into three cells with lengths ranging from 0.7, 0.59, to 0.63 miles. The fundamental diagrams are roughly calibrated using the linear regression method that uses one week of historical data of all detectors in this segment. The historical densities are computed for each cell using the occupancy divided by the g-factor, where the g-factor is the effective vehicle length for the detector. The four parameters of the Smulders fundamental diagram are validated as the free-flow speed $v_f = 70$ mile/h, the critical density $\rho_c = 80$ veh/mile, the jam density $\rho_J = 320$ veh/mile, and the capacity volume $q_{\max} = 4230$ veh/h, respectively, as shown in Figure 3.

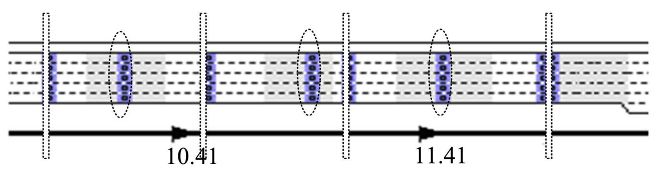

Figure 2. A freeway link of I80-E is divided into three cells and its speed detectors configuration.

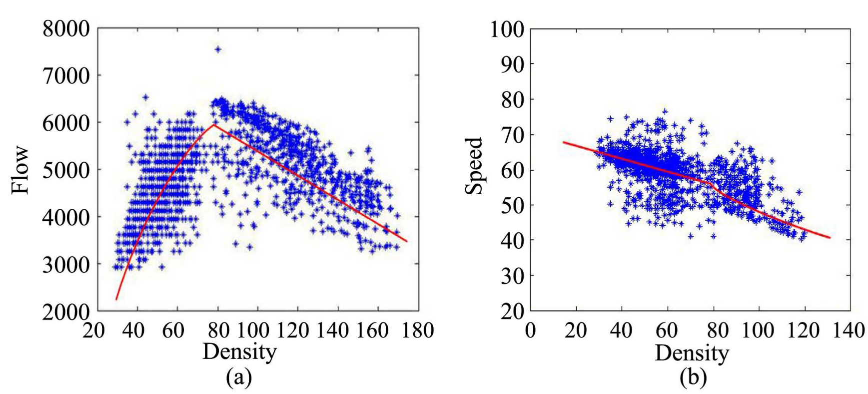

Figure 3. The fundamental diagrams of the freeway link are calibrated from the traffic flow data collected on Oct. 20, 2013. (a) Calibrated flow-density diagram; (b) calibrated speed-density diagram.

Since the speed measurements of each cell in this section are available, we can select some measurements to build our speed detecting networks. The observation information acquired from portable speed detectors, such as probe vehicles or radar speed guns usually has larger measurement noise than loop inductance detectors. We assume the noise covariance of observation in the model (9) is $R(k) = 0.05$ (measurement noise is about 0.7 mile/h).

Two experiment scenarios simultaneously estimate the traffic state and boundary flux of this freeway link with the empirical traffic data.

1) The first scenario is to jointly estimate the traffic densities and driving-out flux of a freeway link, *i.e.*, only the downstream boundary flow is unknown.

2) The second scenario is to estimate the traffic densities with both driving-in and driving-out fluxes, *i.e.*, the upstream and downstream boundary flows are not available simultaneously.

3.1. Experiment I

In this subsection, the synchronous mean speed measurement of cell 1 and cell 3 constitute speed detecting networks. Driving-in flux data of the upstream boundary of cell 1 is achieved from PeMS. It is assumed that the driving-out flux through the downstream boundary of cell 3 is not accessible. Therefore, in the state-space form of the traffic flow model (9)-(10), the system state vector is $\rho^{\mathrm{T}} = [\rho_1, \rho_2, \rho_3]$, the observation vector is $y(k) = [v_1, v_3]^{\mathrm{T}}$, and $q_3^{out}(k)$ is unknown input, $q_1^{in}(k)$ is the known input.

The estimated traffic densities are depicted against the historical data over the selected period in Figure 4. The measured and estimated driving-out fluxes through downstream boundary of cell 3 are depicted in Figure 5. The driving-in fluxes are measured directly. The corresponding mean absolute percent error (MAPE) (22) and root mean square error (RMSE) (23) between estimated and

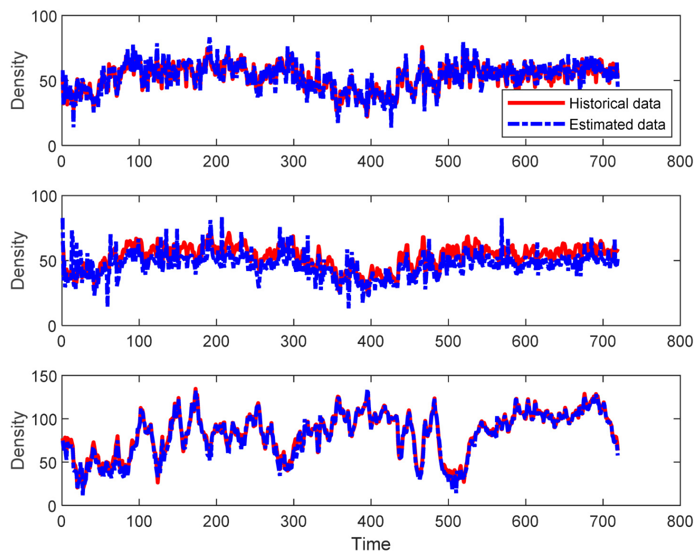

Figure 4. The estimated traffic densities (blue line) against the historical data (red line) with unknown driving-out flux.

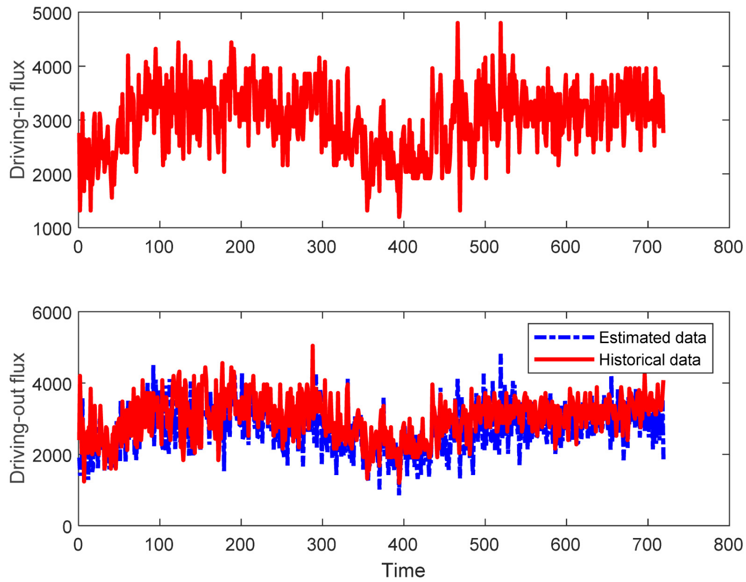

Figure 5. The estimated boundary flux (blue line) against the historical data (red line) with driving-in flux is known.

real traffic densities, and driving-out flux of the freeway link are reported in Table 1. Therefore, the simultaneous traffic state and boundary flux estimate of freeway link gives a pretty satisfactory result.

$$\text{MAPE} = \frac{1}{K_T}\sum_{k=1}^{K_T}\left|\frac{x(k\,|\,k)-x(k)}{x(k)}\right| \tag{22}$$

$$\text{RMSE} = \sqrt{\frac{1}{K_T-1}\sum_{k=1}^{K_T}\big(x(k\,|\,k)-x(k)\big)^2} \tag{23}$$

where $x(k\,|\,k)$ represents the estimated variable, $x(k)$ is the actual historical data, and K_T denotes the total number of time sample steps.

3.2. Experiment II

In this subsection, we assume that the driving-in flux and the driving-out flux are unknown inputs for the traffic flow model (9). The observation model includes the mean speed measurement of all three cells of the freeway link.

In this case, the state vector is $\rho^{\mathrm{T}} = [\rho_1, \rho_2, \rho_3]$, the observation vector is $y(k) = [v_1, v_2, v_3]^{\mathrm{T}}$, $q_1^{in}(k)$ and $q_3^{out}(k)$ are all unknown inputs of the state-space model (9). The estimated traffic densities and boundary fluxes are depicted against the historical data over the selected period in Figure 6 and Figure 7. The corresponding MAPE and RMSE of three cells and boundary fluxes are indicated in Table 2.

Compared with Experiment I, the MAPE and RMSE of the driving-out flux are much larger since the driving-in flux from the upstream boundary is unknown. Estimation error reduced from the driving-in flux directly effects the performance of traffic state estimate. In turn, increased state error will deteriorate the unknown input estimate.

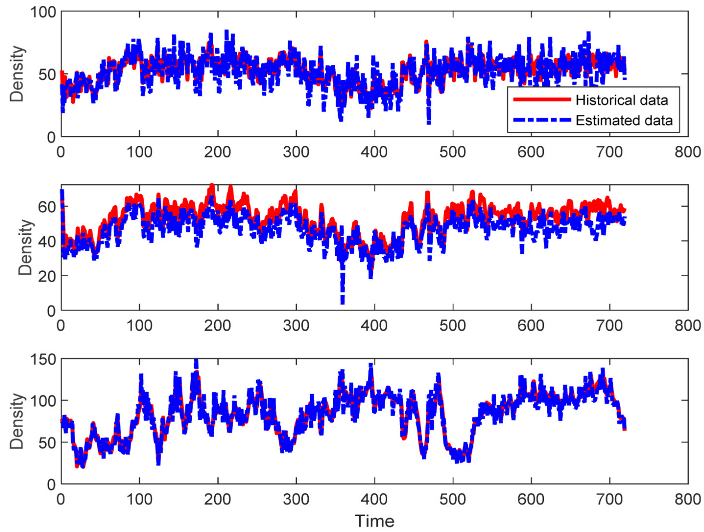

Figure 6. The estimated traffic densities (blue line) against the historical data (red line) with totally unknown boundary flux.

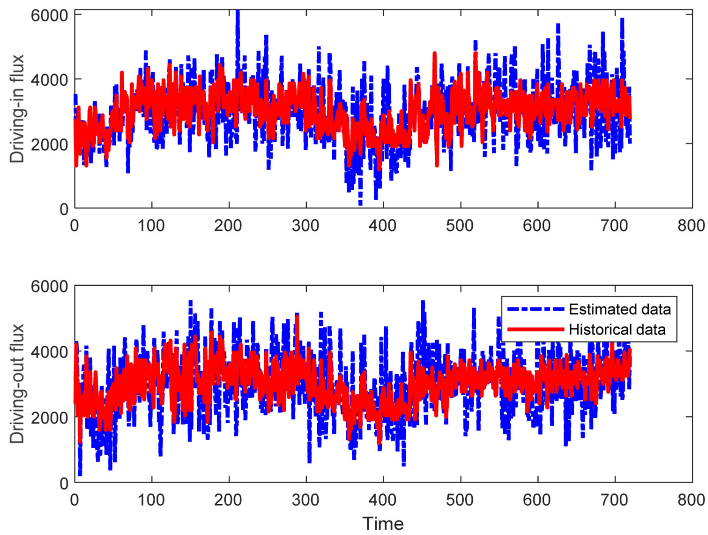

Figure 7. The estimated boundary flux (blue line) against the historical flux (red line) with both driving-in and driving-out are unknown.

Table 1. Performance evaluation of experiment I with unknown driving-out flux.

	Cell 1	Cell 2	Cell 3	Driving-out flux
MAPE	0.0818	0.1703	0.0359	0.1138
RMSE	5.6738	13.9007	7.1085	317.3517

Table 2. Performance evaluation of experiment II with unknown driving-in and driving-out fluxes.

	Cell 1	Cell 2	Cell 3	Driving-in flux	Driving-out flux
MAPE	0.1438	0.1077	0.0656	0.1559	0.1811
RMSE	9.1734	10.3364	11.6428	602.8	785.4582

4. Conclusion

Speed detecting in large-scale traffic networks is easy to access and measure with the development of ubiquitous sensing technologies. This paper presents three-step EFK filtering for traffic parameter estimates with unknown boundary flux data. The case studies highlight the potential of using only speed detecting data to monitor the state of urban freeway transportation systems without access to the traditional measurement data, such as the boundary flows. Therefore, this method has the ability to estimate traffic parameters for any interested segment of a transportation network in an urban setting. In the future, some date-driven approaches are researched to build the traffic dynamic model.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Zhang, L. and Qi, R. (2017) Real-Time Flux and Density Estimation of Freeway Traffic with Decentralized Speed Data. 2017 *Chinese Automation Congress* (CAC), Jinan, 20-22 October 2017, 1091-1095. https://doi.org/10.1109/CAC.2017.8242928

[2] Yeong, D.J., Velasco-Hernandez, G., Barry, J. and Walsh, J. (2021) Sensor and Sensor Fusion Technology in Autonomous Vehicles: A Review. *Sensors*, **21**, Article No. 2140. https://doi.org/10.3390/s21062140

[3] Zheng, F. and Van Zuylen, H. (2013) Urban Link Travel Time Estimation Based on Sparse Probe Vehicle Data. *Transportation Research Part C: Emerging Technologies*, **31**, 145-157. https://doi.org/10.1016/j.trc.2012.04.007

[4] Hunter, T., Das, T., Zaharia, M., Abbeel, P. and Bayen, A.M. (2013) Large-Scale Estimation in Cyberphysical Systems Using Streaming Data: A Case Study with Arterial Traffic Estimation. *IEEE Transactions on Automation Science and Engineering*, **10**, 884-898. https://doi.org/10.1109/TASE.2013.2274523

[5] Hofleitner, A., Herring, R., Abbeel, P. and Bayen, A. (2012) Learning the Dynamics of Arterial Traffic from Probe Data Using a Dynamic Bayesian Network. *IEEE Transactions on Intelligent Transportation Systems*, **13**, 1679-1693. https://doi.org/10.1109/TITS.2012.2200474

[6] Jenelius, E. and Koutsopoulos, H. N. (2013) Travel Time Estimation for Urban Road Networks Using Low Frequency Probe Vehicle Data. *Transportation Research Part B: Methodological*, **53**, 64-81. https://doi.org/10.1016/j.trb.2013.03.008

[7] Seo, T., Bayen, A.M., Kusakabe, T. and Asakura, Y. (2017) Traffic State Estimation on Highway: A Comprehensive Survey. *Annual Reviews in Control*, **43**, 128-151. https://doi.org/10.1016/j.arcontrol.2017.03.005

[8] Wang, Y., Papageorgiou, M., Messmer, A., Coppola, P., Tzimitsi, A. and Nuzzolo, A. (2009) An Adaptive Freeway Traffic State Estimator. *Automatica*, **45**, 10-24. https://doi.org/10.1016/j.automatica.2008.05.019

[9] Ren, S., Bi, J., Fung, Y.F., Li, X.I. and Ho, T.K. (2010) Freeway Traffic Estimation in Beijing Based on Particle Filter. 2010 6*th International Conference on Natural Computation*, Vol. 1, Yantai, 20-12 August 2010, 292-296. https://doi.org/10.1109/ICNC.2010.5583834

[10] Sun, X., Muñoz, L. and Horowitz, R. (2004) Mixture Kalman Filter Based Highway Congestion Mode and Vehicle Density Estimator and Its Application. *Proceedings of the* 2004 *American Control Conference*, Vol. 3, Boston, 30 June-2 July 2004, 2098-2103. https://doi.org/10.23919/ACC.2004.1383770

[11] Lighthill, M.J. and Whitham, G.B. (1955) On Kinematic Waves II. A Theory of Traffic Flow on Long Crowded Roads. *Proceedings of the Royal Society of London. Series A*: *Mathematical and Physical Sciences*, **229**, 317-345. https://doi.org/10.1098/rspa.1955.0089

[12] Richards, P.I. (1956) Shock Waves on the Highway. *Operations Research*, **4**, 42-51. https://doi.org/10.1287/opre.4.1.42

[13] Smulders, S. (1990) Control of Freeway Traffic Flow by Variable Speed Signs. *Transportation Research Part B*: *Methodological*, **24**, 111-132. https://doi.org/10.1016/0191-2615(90)90023-R

[14] Gillijns, S. and De Moor, B. (2007) Unbiased Minimum-Variance Input and State Estimation for Linear Discrete-Time Systems. *Automatica*, **43**, 111-116. https://doi.org/10.1016/j.automatica.2006.08.002

[15] Yang, J. N., Pan, S. and Huang, H. (2007) An Adaptive Extended Kalman Filter for Structural Damage Identifications II: Unknown Inputs. *Structural Control and Health Monitoring*, **14**, 497-521. https://doi.org/10.1002/stc.171

[16] The Freeway Performance Measurement System (PeMS).