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Significance of sensor location in real-time traffic state estimation

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Abstract

Short-term congestion caused due to traffic incidents or other road environment factors significantly reduces traffic flow capacity of a link which forms a major part of travel time delays. Accurate and reliable estimate of real-time traffic state is essential for optimizing network performance during unpredictable events. Inaccurate estimate of current traffic state produces unreliable travel-time estimations which lead to ineffective traffic management strategies during traffic incident.
This study highlights the accuracy and reliability of traffic state estimate when a traffic flow prediction model is not provided with information about duration and impact of the incident on traffic flow capacity of the link. Cell Transmission Model (CTM) is used for prediction of traffic state and measurements from the sensor are combined in Extended Kalman Filter (EKF) to minimize square of error between predicted and measured traffic state. A simple link is used to highlight the difference between actual traffic state and estimated traffic state using a naive prediction model for real-time traffic state estimation. Analysis of simulation results shows that estimate of traffic state is reliable and accurate for cells upstream of the measurement sensor when incident occurred downstream of measurement sensor. Whereas when incident location is upstream of measurement sensor, the estimated traffic state for downstream cells of measurement sensor is more close to actual traffic condition.

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Keywords: traffic estate estimation; sensor location; traffic flow parameters; cell transmission model; extended kalman filter

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1. Introduction

Real-time traffic state estimation has been an emerging field since last few decades in traffic flow modeling to obtain reliable and accurate traffic state of road networks. Traditionally, traffic flow models have been used to predict traffic state on segments of freeway or urban networks. Predictions from traffic flow models can be accurate depiction of existing traffic state if accurate traffic demand is known and there is no unpredictable variation in traffic flow capacity of links in the road network. Increase in number of traffic sensors along major freeways and urban roads and availability of real-time traffic measurements have facilitated utilization of measured traffic variables to improve overall estimate of traffic state. Despite increase in number of measurement sensorsinstalled along the network, these sensors still do not cover every part of the network and cannot provide a complete picture of existing traffic state with higher spatial resolution. In traffic state estimation prediction from traffic flow models, which can be of higher spatial resolution is combined with real-time measurements to get a final estimate with higher spatial and temporal resolution.Thus, real-time traffic state estimation refers to estimation of traffic flow variables (traffic flow, density) for a segment of road or network with an adequate time and space resolution based on limited available measurements from traffic sensors [1].

Many research studies have been carried out to improve estimation of traffic state by using different estimation algorithms and different traffic flow models. Wang and Papageorgiou [2] presented a comprehensive methodology of estimating traffic state using real-time traffic data from sensors and prediction of traffic state from a second order traffic flow model. In this estimation model, parameters of second order traffic flow models presented by Papageorgiou et al. [3] such as free-flow speed and critical density were converted into stochastic variables by using random-walk equations and estimated for each time-step. Ngoduy [4] proposed a framework that utilizes particle filtering algorithm with second order traffic flow model to estimate traffic for a section of freeway. Ngoduy [5,6] utilized unscented Kalman filter algorithm with macroscopic traffic flow model for freeway traffic state estimation.Munozet al. [7, 8] transformed CTM into a linear model by introducing Switch Mode Model (SMM). CTM-based SMM was derived based on five different traffic modes to avoid non-linearity caused due to nature of fundamental traffic flow diagram in CTM. At any given time-step, one of the five modes is selected for the whole link to estimate traffic density based on the measurement of densities at upstream and downstream cells of the link.

Hong and Fukuda [9] studied effect of sensor location when there are constrains on the number of sensors which can be installed over a network. They used CTM with ensemble Kalman filter (EnKF) to study the impact of various sensor location configurations on estimation of travel speed. Hong and Fukuda [9] concluded that sensors located at large distances from each other without location optimization lead to overestimation of travel speed, whereas sensor numbers can be reduced if their locations are optimal to achieve a better estimate of travel speed.Vitiet al. [10] proposed a framework to optimize sensor locations in road network which minimizes relative error in travel timeprediction. Many other studies have focused on optimization of sensor location to find the minimum number of traffic sensors to cover a road network [11,12, and 13].

This research is focused on highlighting the significance of sensor location in estimating traffic state when there is a sudden drop in capacity of a link and this drop in capacity is not automatically detected and quantified by the traffic controller. Traffic state estimation algorithms with real-time estimation of traffic flow parameters have capability to identify and quantify the sudden change in road capacity due to traffic incident or severe climate conditions. This research compares estimation results from two difference scenarios to highlight the significance of incident location with respect to the measurement sensor. A simple link of 7 km in length with one measurement sensor was selected for simulation. EKF is used for estimation of traffic state based on prediction from CTM and measurement from the sensor.

The paper consists of six sections. Section 2 elaborates CTM for prediction of traffic state; section 3 defines state-space model of CTM for estimation of traffic state; section 4 explains EKF adopted for CTM; section 5 describes simulation scenario and discussion on important simulation results and section 6 concludes findings of the research paper.

2. Prediction and measurement of traffic flow

2.1 Prediction of traffic state using CTM

In this research, modified CTM proposed by Munoz et al. [7] is used, as this modification in CTM proposed by Daganzo[14] allows use of variable cell lengths. The modified CTM is used as prediction model and EKF as recursive optimization algorithm. CTM being first order traffic flow model has lesser number of output variables compare to other higher order models, thus it is more suitable for real-time traffic estimation problems due to its better computing efficiency.

The modified CTM uses density of a cell as output variable instead of occupancy and a slightly different traffic flow equation than Daganzo[14]. The link is divided into 'i' homogeneous segments where $i=1, 2, 3,$....and length of each segment represented by 'l' measured in km. With free flow speed 'v_f' measured in km/hr, a car takes time 't' to traverse a cell, if the cell is in free flow condition. The simulation horizon is divided into discrete time step $k=1, 2, 3,$.....with duration of each time-step 't'. CTM predicts traffic density 'ρ_i' for future time-step $(k+1)$ based on equation (1).

$$\rho_i(k+1) = \rho_i(k) + \frac{t}{l}\{q_i(k) - q_{i+1}(k)\} \tag{1}$$

Where 'q_i' is inflow to cell 'i' from cell 'i-1' and it is based on fundamental traffic flow diagram shown in Fig. 1.

$$q_i(k) = \min\{d_{i-1}(k), s_i(k)\} \tag{2}$$

Where 'd_{i-1}' is traffic demand generated for cell 'i' from cell 'i-1' and 's_i' is capacity supplied from receiving cell 'i' and they are given by:

$$d_{i-1}(k) = min\{\rho_{i-1}v_f(k), c_{i-1}(k)\} \tag{3}$$

$$s_i(k) = min\left\{w\left(\rho_i^J(k) - \rho_i(k)\right), c_i(k)\right\} \tag{4}$$

Where 'c_i' is traffic flow capacity of cell 'i', ρ_i^J is jam-density of cell 'i' and 'w' is backward wave speed.

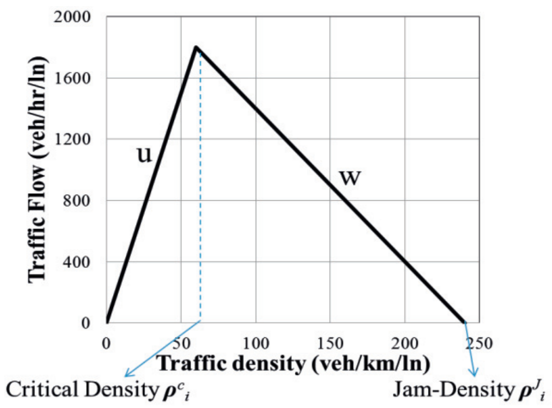


Fig. 1. Fundamental traffic flow diagram

2.2 Measurement of traffic density

The proposed model assumes that traffic density is measured at the sensor at each time-step and it is communicated to the controller for estimation of traffic state. The measured traffic density is related to the predicted density by the following relation:

$$m_i^{\rho}(k) = \rho_i(k) + \emptyset_i(k) \tag{5}$$

Where m_i^{ρ} is measured traffic density from sensor and $\emptyset_i$ is related noise in measurement of traffic density.

3. State-Space Model

For simplifying presentation of variablesto be estimated, 'ρ_i'for all cells in the link is defined in a vector$\boldsymbol{x}$.
Traffic density prediction: $\boldsymbol{x} = [\rho_1 \rho_2 \rho_3 \ \ .... \ \ \rho_N]$ (6)
Noise in prediction of traffic density: $\boldsymbol{\varepsilon} = \left[\varepsilon_1^{\rho} \varepsilon_2^{\rho} \ .... \varepsilon_N^{\rho}\right]$ (7)
Cell transmission model can be written as differentiable function *f* of traffic state at pervious time-step:

$$\boldsymbol{x}(k+1) = f[\boldsymbol{x}(k), \boldsymbol{\varepsilon}(k)] \tag{8}$$

Similarly, measurements obtained from traffic sensors can also be written in a linear differentiable function *g* as follows:

$$\boldsymbol{y}(k) = g[\boldsymbol{x}(k), \boldsymbol{\varphi}(k)] \tag{9}$$

4. Extended Kalman filter for urban traffic state estimation:

Wang and Papageorgiou presented a comprehensive methodology of estimating traffic state using real-time traffic data from sensors and prediction of traffic state from a second order traffic flow model [2]. Extended Kalman filter (EKF), which is a variation of Kalman filter, combines prediction from traffic flow model and measurement from sensors to obtain suboptimal estimate of traffic state which minimizes square of error between measurement from the sensors and prediction from traffic flow model. The final estimate obtained using EKF has less unreliability than prediction or measurement alone.

For traffic density estimation of a road link, framework described by Wang and Papageorgiou [2]is adapted for CTM. The objective of EKF at each time-step 'k' is to find a state estimate which minimizes covariance of estimation error using all available measurements till time-step 'k'.

$$E\{[\boldsymbol{x}(k+1) - \widehat{\boldsymbol{x}}(k+1/k)]^T . [\boldsymbol{x}(k+1) - \widehat{\boldsymbol{x}}(k+1/k)]\} \tag{10}$$

For any estimation problem using Kalman filter or EKF following three conditions must satisfy.

i) Noises in measurement $\boldsymbol{\varphi}(k)$ and in prediction process $\boldsymbol{\varepsilon}(k)$ are zero-mean Gaussian white random processes. For any $k > 0$ and $l > 0$,

$$E[\boldsymbol{\varepsilon}(k)] = \boldsymbol{0};$$
$$E[\boldsymbol{\varphi}(k)] = \boldsymbol{0};$$
$$E[\boldsymbol{\varepsilon}(k)\boldsymbol{\varepsilon}^T(l)] = \begin{cases} \boldsymbol{Q} \ if \ k = l, \\ \boldsymbol{0} \ otherwise \end{cases}$$
$$E[\boldsymbol{\varphi}(k)\boldsymbol{\varphi}^T(l)] = \begin{cases} \boldsymbol{R} \ if \ k = l, \\ \boldsymbol{0} \ otherwise \end{cases}$$
$$E[\boldsymbol{\varepsilon}(k)\boldsymbol{\varphi}^T(l)] = \begin{cases} \boldsymbol{M} \ if \ k = l, \\ \boldsymbol{0} \ otherwise \end{cases}$$

Where $\boldsymbol{Q}$ and $\boldsymbol{R}$ are known symmetric matrices representing variance of noise in prediction model and measurement, respectively.

ii) Initial state $\boldsymbol{x(0)}$ is a Gaussian random with known mean and covariance matrix.

$$\widehat{\boldsymbol{x}}_0 = E[\boldsymbol{x}(0)]$$
$$\boldsymbol{P}_0 = E\{[\boldsymbol{x}(0) - \widehat{\boldsymbol{x}}_0] \,.\, [\boldsymbol{x}(0) - \widehat{\boldsymbol{x}}_0]\}$$

iii) Initial state $\mathbf{x}(0)$ is not correlated with model prediction or measurement noise at any time instant.

The recursive equation of EKF is given by:

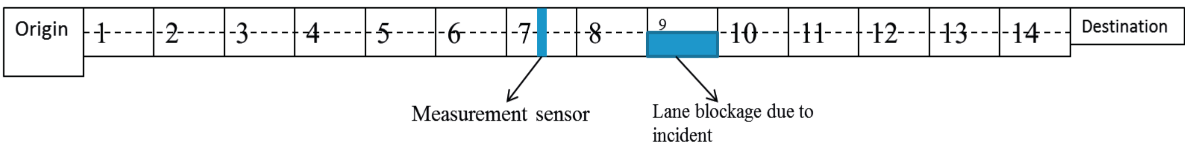
$$\widehat{\boldsymbol{x}}(k+1/k) = f[\widehat{\boldsymbol{x}}(k/k-1)\,,\mathbf{0}] + \boldsymbol{K}(k)[\boldsymbol{y}(k) - g(\widehat{\boldsymbol{x}}(k/k-1)\,,\mathbf{0})] \tag{11}$$

Where **K** is Kalman Gain Matrix and it is estimated at each time-step:

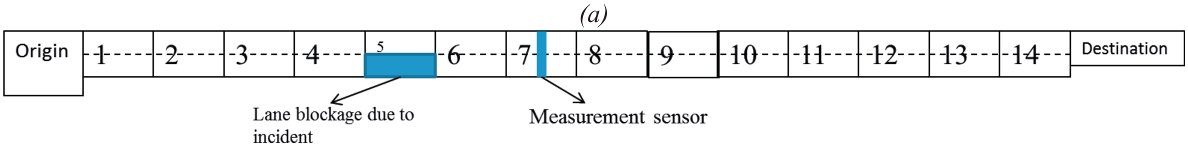
$$\boldsymbol{K}(k) = [\boldsymbol{A}(k)\boldsymbol{P}(k/k-1)\boldsymbol{B}^T(k) + \boldsymbol{\Delta}(k)\boldsymbol{M}(k)\boldsymbol{\Pi}(k)].[\boldsymbol{B}(k)\boldsymbol{P}(k/k-1)\boldsymbol{B}^T(k) + \boldsymbol{\Pi}(k)\boldsymbol{R}(k)\boldsymbol{\Pi}(k)]^{-1} \tag{12}$$
$$\boldsymbol{P}(k+1/k) = [\boldsymbol{A}(k) - K(k)\boldsymbol{B}(k)].\boldsymbol{P}(k/k-1)\,\boldsymbol{A}^T(k) + \boldsymbol{\Delta}(k)\boldsymbol{Q}(k)\boldsymbol{\Delta}(k) - \boldsymbol{K}(k)\,\boldsymbol{\Pi}(k)\boldsymbol{M}^T(k)\boldsymbol{\Delta}^T(k) \tag{13}$$
$$\boldsymbol{A}(k) = \frac{\partial f}{\partial x}(\widehat{\boldsymbol{x}}(k/k-1)\,,\mathbf{0}); \tag{14}$$
$$\boldsymbol{B}(k) = \frac{\partial g}{\partial x}(\widehat{\boldsymbol{x}}(k/k-1)\,,\mathbf{0}); \tag{15}$$
$$\boldsymbol{\Delta}(k) = \frac{\partial f}{\partial \varepsilon}(\widehat{\boldsymbol{x}}(k/k-1)\,,\mathbf{0}); \tag{16}$$
$$\boldsymbol{\Pi}(k) = \frac{\partial g}{\partial \varphi}(\widehat{\boldsymbol{x}}(k/k-1)\,,\mathbf{0}); \tag{17}$$

5. Simulation scenario and results

The proposed estimation model for estimating real-time traffic state was applied on two different scenarios on a road link to evaluate the significance of sensor location on estimated traffic state. A 7 km long segment of a road is selected for analysis which has one measurement sensor in it. The position of sensor is fixed and it is located at distance of 3.5 km from starting point of the segment. The segment of road has two lanes and one of its lanes is affected due toan incident which causes drop in capacity. It is assumed that the estimation model does not have capability of tracking this drop in capacity and prediction model is using normal values of traffic flow parameters during the incident. The location of incident is changed with respect to the sensor and its impact on estimated traffic state is analyzed. Fig. 2 describes both the scenarios created to estimate traffic state and assess impact of incident location on estimated traffic state.



(a)



(b)

Fig. 2(a)Scenario forestimation when incident location is downstream of sensor location (b) link with incident location upstream of the measurement sensor

5.1 Incident location downstream of measurement sensor

This scenario is design to model traffic flow and obtain estimate of traffic state when the incident is occurred downstream of incident location. To model traffic flow using CTM, the link is divided into 14 cells, each of length 500 m and two dummy cells to generate traffic demand and absorb outgoing flow from the link. A vehicle traverses each cell in 30 seconds with a speed of 60 km/hr if downstream traffic is in free flow condition. The simulation horizon of 3 hours is divided into 360 time-steps, each of 30 seconds. Other parameters of CTM are defined based on Fig. 1 with critical density of each cell as 60 veh/km, jam-density of 240 veh/km, traffic flow capacity of 3600 veh/hr and backward wave speed of 20 km/hr. Traffic demand for the link is measured from a upstream sensor and it is same for both the scenarios.

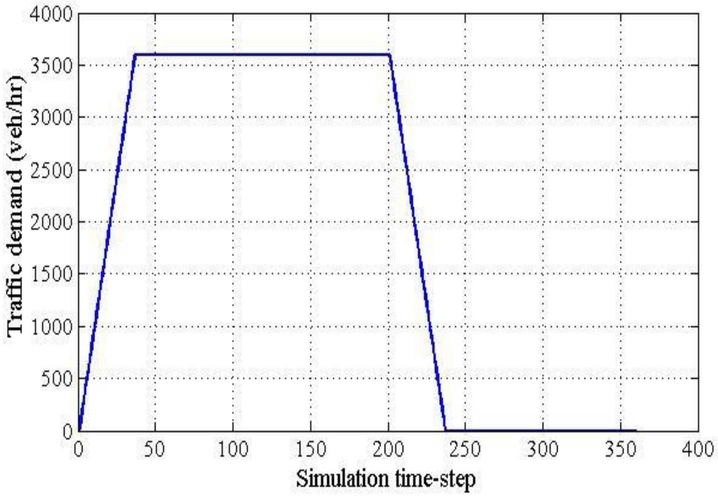


Fig.3. Demand profile for the link

Traffic incident is occurred at a distance of 4.5 km from starting point of the link during simulation time-step 120 and it lasts for one hour till simulation time-step 240. This incident caused one of the lanes to remain block in cell-9 for one hour. The location of sensor is fixed in both scenarios and it is installed at a distance of 3.5 km from starting point of the link in cell-7. If the controller does not have automatic incident detection facility and incident is not detected then the estimate of traffic deviates from on ground prevailing traffic condition. Fig.4 compares estimate of traffic state using KCTM for various cells in the link with simulated reality. The simulated reality represents actual traffic state on the link, produced using traffic demand and CTM with information provided regarding drop in capacity due the incident. Whereas estimated traffic state using KCTM is based on a prediction model which is not provided with any information about drop in traffic flow capacity.

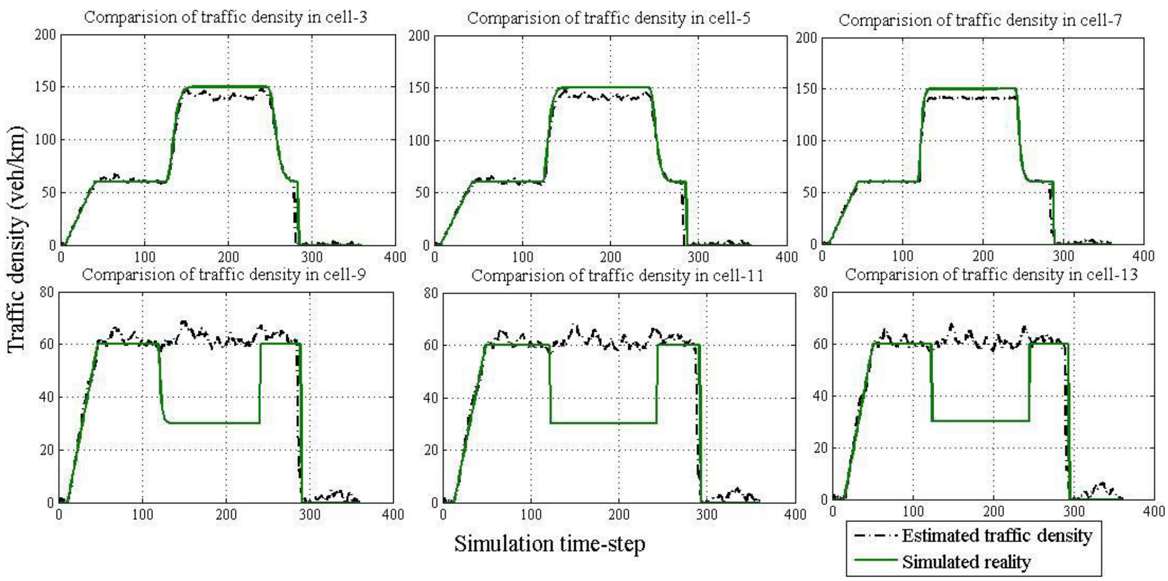


Fig.4. Comparison of estimated traffic density in cells 3, 5, 7, 9, 11 and 13with simulated reality

When the location of accident is downstream of sensor location, it can be observed from estimated traffic density in cell-3, cell-5 and cell-7 that KCTM estimate is significantly close to the simulated reality. Estimated traffic density in all other cells upstream of the sensor location is also representing the prevailing traffic state and the estimate is very close to the simulated reality. However, for cell-9, cell-11 and cell-13 the estimated traffic state using KCTM is deviating from actual traffic state when the link is affected with the incident. Similarly, all other cells downstream of accident location are showing deviation from prevailing traffic state during traffic incident. This analysis shows that if the incident location is upstream of the sensor location, then estimated traffic state for all the cells upstream of the sensor location is very good depiction of prevailing traffic state. However, estimated traffic state for all the cells downstream of the incident location deviates significantly from actual traffic condition during incident interval.

5.2 Incident location upstream of measurement sensor

This scenario is designed to model traffic flow and analyze the impact of incident on estimated traffic state when the incident location is upstream of measurement sensor. The incident has now occurred in cell 5, which is upstream of measurement sensor location of cell-7. The duration of incident, link demand and all other parameters are kept same as section 5.1. Fig.5 shows comparison of estimated traffic state in various cells of the link with simulated reality when incident location is upstream of the sensor location.

When incident location is upstream of sensor location, the estimate of traffic state for cell-3, cell 5 and other cells upstream of incident location is deviating significantly from actual traffic state. For cells downstream of the sensor location such as cells 9, 11 and 13 as shown in Fig.5, the estimate of traffic density using KCTM is comparatively better depiction of prevailing traffic stateduring traffic incident. Estimated traffic state in all cells of the link is describing prevailing traffic conditions very good for simulation period before traffic incident. However, during the incident traffic density estimate using KCTM is comparatively batter for cells downstream of the sensor location than the cells upstream of sensor location.

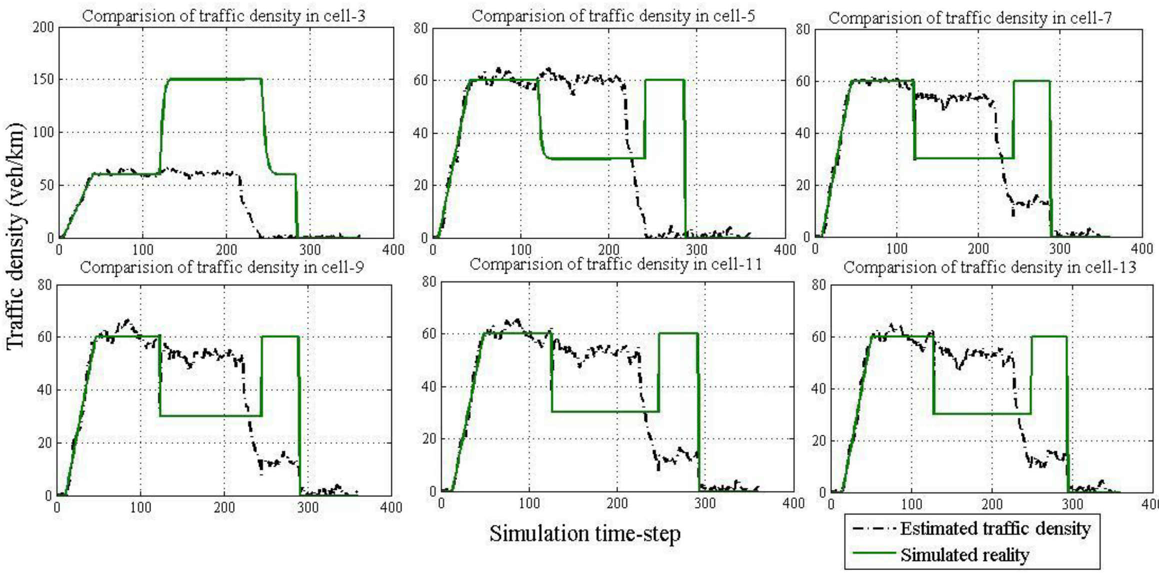


Fig.5. Comparison of estimated traffic density with simulated reality

6. Conclusion

This research study highlighted significance of sensor location when estimating traffic state using estimation algorithm such as EKF. The significance of measurement sensor with respect to the incident location was studied in detail. Two different scenarios with change in incident location were analyzed and their impact on estimated traffic state was studied. Based on analysis of simulation results, it can be concluded that location of traffic sensor with respect to the incident location is significant for reliability and accuracy of traffic state estimate. If incident location is downstream of the measurement sensor, then estimate of traffic state for all cells upstream of the sensor location is reliable, whereas estimated traffic state for cells downstream of sensor location deviates significantly from actual traffic condition. And if incident location is upstream of the measurement sensor, then estimate of traffic state downstream of sensor location is somehow close to actual traffic state, whereas for cell upstream of the sensor location estimated traffic state deviates significantly from actual traffic condition. The estimate of traffic state can be made more reliable by online estimation of traffic flow parameters such as traffic flow capacity, critical density and free-flow speed. Real-time estimation of traffic flow parameters allows estimation model to track any sudden drop in road capacity caused due to traffic incident or severe weather conditions.

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