Using mobile vehicle probes to estimate network-wide traffic conditions

Vikash V. Gayah *

Department of Civil and Environmental Engineering,

The Pennsylvania State University, University Park, PA, USA

Vinayak V. Dixit

School of Civil and Environmental Engineering

University of New South Wales, Sydney, Australia

* Email: gayah@engr.psu.edu

Recently, several network-wide traffic control strategies have been developed to improve traffic operations on urban street networks. These strategies include: optimal metering of vehicle entry [1, 2]; optimal pricing of vehicle entry [3]; optimal operation and pricing of cars and transit [4]; and, optimal allocation of space to cars and transit [5]. These strategies make use of macroscopic relationships that have been shown to exist on urban street networks—specifically relationships between average vehicle flow, average vehicle density and the average rate at which trips are completed [1, 6, 7]. While these urban-scale control strategies tend to be elegant and simple to apply in theory, they often take for granted that network-wide traffic conditions (e.g., the density of vehicles across all streets within the network) can be measured accurately in real time.

This is not a trivial issue: measuring traffic conditions across even a small street network typically requires a tremendous amount of data, and these data are not available in many cities. Even when these data are available, the accuracy of the estimations is in doubt. Fixed inductive loop detectors, the most common method used to collect traffic data, are problematic in urban areas. This is because these detectors are usually placed near intersections and the presence of queues that form at these intersections can result in incorrect density estimates [8]. Other fixed detectors, such as cameras, are unable to cover the entire network without significant expense. And the time required to process this type of visual data makes real-time estimation doubtful.

However, the proliferation of GPS sensors have made it possible for individual vehicles to serve as mobile probes to measure traffic conditions. The probe vehicles can easily cover all areas of the network, and will accurately reflect driver behavior and origindestination patterns in the network since the GPS devices are placed within vehicles driven by regular drivers. The data obtained can also be aggregated and analyzed in real time to estimate traffic conditions. By combining this mobile probe data with macroscopic traffic relationships, network-wide traffic conditions can be estimated. Figure 1 shows a typical plot of average network flow vs. average network density (more commonly known as the Macroscopic Fundamental Diagram, or MFD). Note that each value of network density is associated with a unique value of average travel speed. Thus, we can estimate network densities by first using mobile probe vehicles to get an estimate of average travel speed within the network, and then looking up the corresponding network density on the MFD.

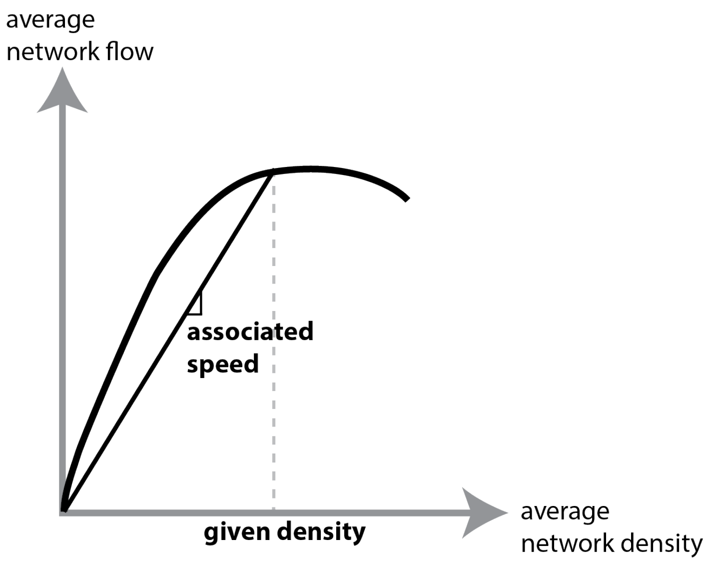


Figure 1. Typical MFD showing average vehicle speed associated with a given network density

To test this methodology, data from a calibrated micro-simulation of the downtown Orlando street network was used [9, 10]. Figure 2a presents the plot of average network flow vs. average network density measured at 5-minute intervals during peak hour conditions within the network. Note that this figure only shows data obtained during the loading period (beginning of the rush) as previous work has shown that urban street networks behave more chaotically and less predictably during the end of the rush [11]. This asymmetric network behavior is caused by natural instabilities in the network when congested [12, 13]. Therefore, in this work density estimates are only obtained during this loading period. Figure 2b presents the corresponding relationship between average network density and average travel speed obtained from the MFD. The fitted curve displayed in Figure 2b was used to map travel speeds to network densities, and fits the observed data very well.

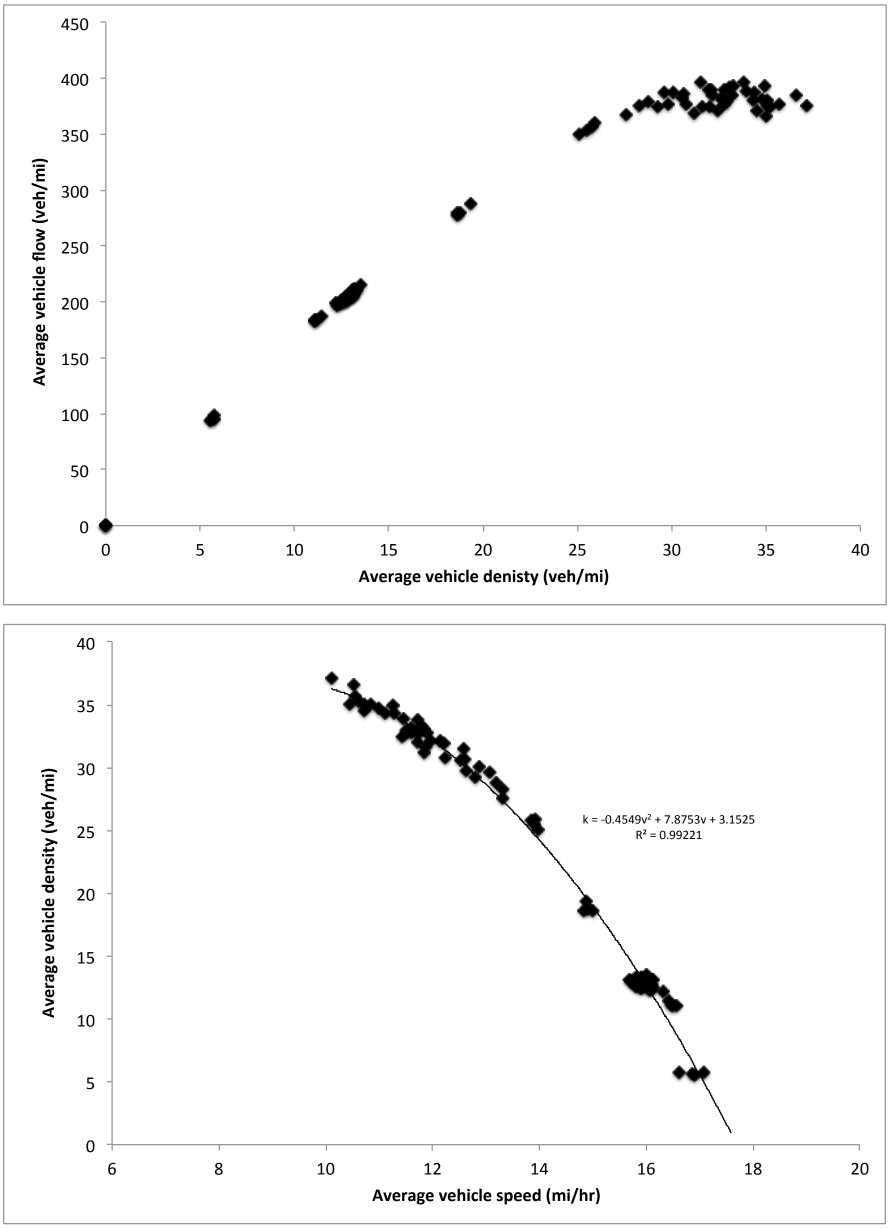
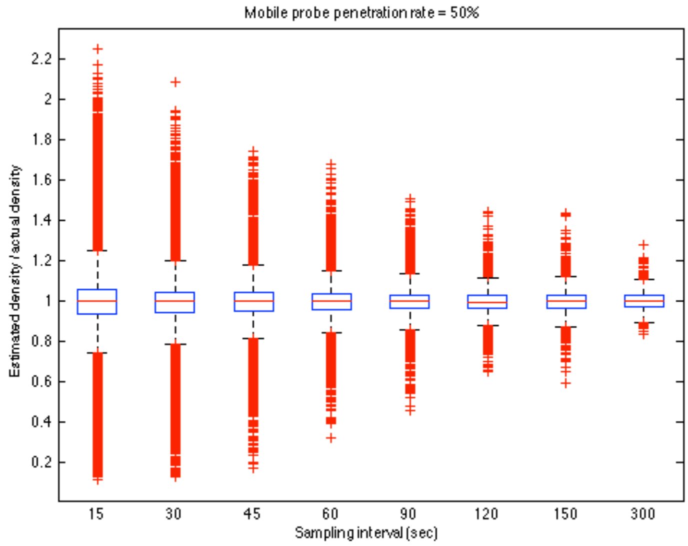


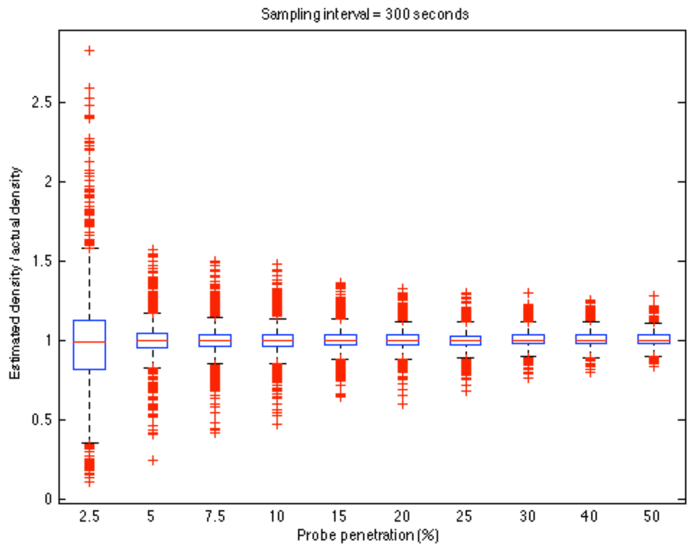
Figure 2. Relationship between: a) average network flow and average network density; and, b) average network density and average travel speed in the Orlando downtown network

Estimates of network density were obtained using several different mobile probe penetration rates and data sampling intervals. Penetration rate refers to the proportion of vehicles that are equipped with GPS devices and are able to yield real time travel information. Sampling interval refers to the length of time over which average speed, and thus network density, is calculated across the network. Higher sampling intervals means that network conditions are estimated fewer times during a given time period.

The estimated network density, $\hat{k}$, is calculated using average travel speed estimates and the equation shown in Figure 2b, and then compared to the actual network density, k. The value $\hat{k}/k$ is computed to measure the accuracy of the estimation. Figure 3 presents box-plots of the $\hat{k}/k$ values obtained during the entire loading period over many simulation runs for various combinations of mobile probe penetration rates and sampling intervals. Note that the results do not look very promising. Even for the highest penetration rates and sampling intervals, the data shows that density estimates are not very accurate.



a)

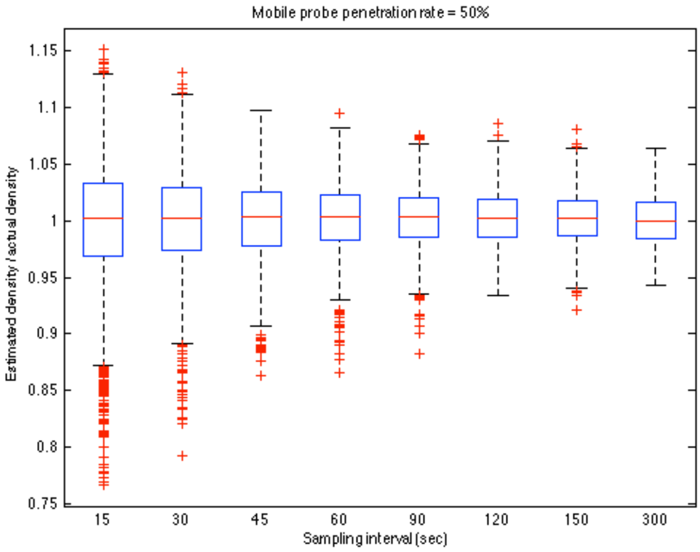


b)

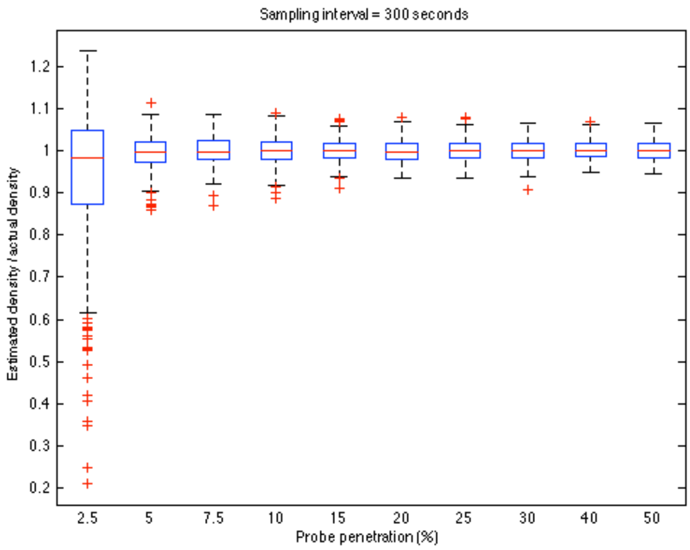
Figure 3. Box-plots showing accuracy of estimations during the entire loading period for: a) mobile vehicle probe penetration rate of 50%; and, b) sampling interval of 300 seconds.

One reason for the large scatter in the box-plots is the extreme sensitivity of network density to travel speeds when average speeds are high; see Figure 2b. At high speeds, small errors in speed result in large errors in estimated density. Therefore, this methodology would not be as accurate when the network is operating in free flow as when the network is operating near congestion. Figure 4 confirms this by presenting a box-plot of the $\hat{k}/k$ values for traffic states near congestion. As shown in this figure, density estimates are much more accurate for congested states when compared to all states (free flow and congested). In fact, our results show that very accurate estimates can be obtained for congested or near congested traffic states for penetration rates greater than15 percent combined with sampling intervals greater than 90 seconds.

Accurate estimation of traffic states near congestion is beneficial since congested traffic states are the most critical to identify. The traffic control strategies previously mentioned [1, 2, 3, 4, 5] require accurate identification of congestion, and accurate estimation of the level of congestion in order to efficiently manage traffic. To implement these strategies traffic densities generally do not need to be estimated accurately when the network is in free flow. Thus, this methodology appears to be very promising. However, it is not without issues. Further research needs to be performed on estimating traffic conditions during the end of a rush period (as opposed to just the beginning as is done here). Nevertheless, this combination of mobile probe data and macroscopic traffic relationships does seem to be a feasible way to estimate network conditions in real time and make the implementation of efficient, real-time urban network control strategies a reality.



a)



b)

Figure 4. Box-plots showing accuracy of estimations of average vehicle densities near congestion for: a) mobile vehicle probe penetration rate of 50%; and, b) sampling interval of 300 seconds.

References

[1] Daganzo, C.F. (2007) Urban gridlock: Macroscopic modeling and mitigation approaches. Transportation Research Part B, Vol. 41, No. 1, pp. 49-62.

[2] Geroliminis, N. and Daganzo, C.F. (2007) Macroscopic modeling of traffic in cities. In *Proceedings of the 86th Annual Meeting of the Transportation Research Board.*

[3] Geroliminis, N. and Levinson, D. (2009) Cordon pricing consistent with the physics of overcrowding. In *Proceedings of the 18th International Symposium on Transportaiton and Traffic Theory*.

[4] Gonzales, E.J. and Daganzo, C.F. (2011) Morning commute with competing modes and distributed demand. *UC Berkeley Volvo Working Paper UCB-ITS-VWP-2011-2*.

[5] Daganzo, C.F., Gayah, V.V. and Gonzales, E.J. (2012) The potential of parsimonious models for understanding large scale transportation systems and answering big picture questions. *EURO Journal of Transportation and Logistics*, Vol. 1, No. 1-2, pp. 47-65.

[6] Daganzo, C.F. and Geroliminis, N. (2008) An analytical approximation for the macroscopic fundamental diagram of urban traffic. Transportation Research Part B, Vol. 42, No. 9, pp. 771-781.

[7] Geroliminis, N. and Daganzo, C.F. (2008) Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. Transportation Research Part B, Vol. 42, No. 9, pp. 759-770.

[8] Wu, X, Liu, H. and Geroliminis, N. (2011) An empirical analysis of the arterial fundamental diagram. *Transportation Research Part B*, Vol. 45, No., 1, pp. 255-266.

[9] Dixit, V.V., Crowe, J. and Radwan, E. (2009) Evaluation and microscopic simulation of the Orlando downtown network. Final report submitted to the City of Orlando, Department of Transportation.

[10] Dixit, V.V., Crowe, J. and Radwan, E. (2011) The calibration and validation of microsimulation using the two-fluid model. Proceedings of the 90th Annual Meeting of the Transportation Research Board, Paper No. 11-4006, Washington, D.C.

[11] Daganzo, C.F., Gayah, V.V. and Gonzales, E.J. (2011) Macroscopic relations of urban traffic variables: Bifurcations, multivaluedness and instability. Transportation Research Part B, Vol. 45, No. 1, pp. 278-288.

[12] Gayah, V.V. and Daganzo, C.F. (2011) Clockwise hysteresis loops in the macroscopic fundamental diagram: An effect of network instability. Transportation Research Part B, Vol. 45, No. 4, pp. 643-655.

[13] Gayah, V.V. and Daganzo, C.F. (2011) Exploring the effect of turning maneuvers and route choice on a simple network. *Transportation Research Record*, No. 2249, pp. 15-19.