A Pilot Study into the Impacts of Lane Change Maneuvers on Congested Freeway Segment Delays

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ABSTRACT

Freeway traffic congestion and associated delays have become a serious problem over much of the world. Considerable effort has been made to study different factors that could cause traffic delays. Among these factors it is suspected that Lane Change Maneuvers (LCMs) could be one source of traffic delay. Little empirical research has been done on this topic although the lane changing process is very common on multilane roadway segments. This fact arises from two main difficulties: first, it is difficult to differentiate the changes in delay caused by LCMs from that of the preexisting delay caused by a queue. Second, it is difficult to quantify LCMs since it requires both spatial and temporal coverage. This paper presents the concept of delay caused by LCMs and proposes a method to estimate it within a given lane relative to the situation in which no LCMs had taken place. This estimation method enables us to investigate the impact of LCMs on traffic delays based on vehicle trajectory data, which record the time and location of each vehicle at each instant. The preliminary study shows the effectiveness of the proposed method to estimate delays caused by LCMs and reveals how LCMs impact delays on congested freeway segments.

INTRODUCTION

Freeway traffic congestion and associated delays have become a serious problem over much of the world. Considerable effort has been made to study different factors that cause traffic delays. Among these factors it is suspected that Lane Change Maneuvers (LCMs) could be one source of traffic delays.

To understand this conjecture, first consider a single LCM during congestion. For a vehicle that changes from origin lane A to destination lane B, it exits the former and enters the latter. Intuitively, "during very high flow or queued conditions, each entering vehicle would delay the following driver and these delays would propagate upstream" (1). The extent of this influence depends on how fast the resulting disturbance propagates and whether it will dissipate before the end of the queue. On the other hand, each exiting vehicle should make it possible for the following drivers in the origin lane to accelerate and reduce their delays. This disturbance would also propagate upstream. So each LCM is expected to induce two contrary effects, causing delay in the lane the vehicle enters and reducing delay in the lane the vehicle leaves. However, the addition in delay caused by an entering vehicle might be greater than the savings in delay by an exiting vehicle in congested traffic conditions. On congested freeway segments, if vehicle i forces its way into lane B from lane A, the vehicle that will be following vehicle i in lane B has to decelerate immediately to avoid collision, the deceleration is mandatory. The following vehicle in lane A does not necessary have to accelerate immediately and take the advantage of the larger gap left by vehicle i, the acceleration is discretionary. In addition to this imbalance in the effects of entering and exiting vehicle on traffic delay, there are also likely transient effects arising from the fact that the vehicle will simultaneously occupy two lanes during the process of changing lanes, momentarily decreasing the capacity of the link. This latter feature becomes particularly important near bottlenecks where it might reduce the already limited throughput.

Although the lane changing process is very common on multilane roadway segments, little research has been done on the possible delays caused by LCMs. Previous research on LCMs either developed models to study the interrelations between the traffic conditions and the frequency (or fraction) of vehicles changing lanes (2-7), or specified lane changing rules and applied these rules in traffic simulation (8-14). The published research is lacking in empirical studies investigating the concept of delays caused by LCMs explicitly, due to two main difficulties. First, it is difficult to differentiate the changes in delay caused by LCMs from that of the preexisting delay caused by a queue. Second, it is difficult to quantify LCMs since it requires both spatial and temporal coverage.

This paper presents the concept of delay caused by LCMs and proposes a method to estimate it within a given lane. The basic idea is to estimate delay caused by LCMs as the difference of the measured travel time and the estimated travel time assuming that there had been no LCMs. Vehicle trajectory data are employed in this paper. Since the location of each vehicle at each second is known from the trajectory data, it is trivial to calculate the measured travel time and to quantify LCMs, i.e., to find the time and location of each LCM. This preliminary study shows the effectiveness of the proposed method to estimate delays caused by LCMs. It also reveals how LCMs would impact delays on congested freeway segments. Although there are some limitations in this pilot study, the results motivate further research on the effects of LCMs and help the understanding of the factors contributing to delay, which could be used in evaluating the necessity of lane management strategies in areas of frequent LCMs, such as weaving sections. Such study also has the potential to be used to quantify LCMs since it models the relationship between LCMs and changes in delay caused by LCMs.

This paper is organized as follows. First, a method to estimate delay caused by LCMs and a method to study the impact of LCMs on delays are introduced. Next, the two methodologies are applied based on a set of trajectory data collected from California. Finally, the paper closes with a discussion of the findings, limitations, and future research.

METHODOLOGY

The first task to study delay caused by LCMs is to quantify it. It is proposed that this delay be computed as the difference of the measured and estimated travel time. The measured travel time can be easily obtained from trajectory data or Vehicle Reidentification Algorithms, which match the observations of a given vehicle from two locations in space, e.g., (15-20). In this paper the estimated travel time should reflect conditions in the lane if there had been no LCMs, this approach can employ the travel time estimation algorithm proposed by Coifman (21). This algorithm was initially proposed to estimate the expected travel time from a dual loop detector and is briefly described in the first subsection below. However, as will be shown in the second subsection, such estimation algorithm can also serve to estimate the expected travel time had there been no LCMs. The third subsection presents the method to study the impacts of LCMs on delays.

Travel Time Estimation Algorithm

The travel time estimation algorithm (21) assumes that during congestion signals and waves propagate upstream at some constant velocity (u_c) and remain unchanged over the entire segment; every vehicle that passes a detector station reflects the continually evolving traffic state. Although the constant wave velocity assumption is not perfect, this assumption has been supported by several studies (22-30), both theoretical and empirical.

Vehicle speeds and arrival times are recorded at the detector station and can be represented in a time-space plot. A chord in the time-space plane is defined to be the straight line passing the location of the detector at the instant the vehicle passes with a slope equal to the vehicle's measured speed. The hypothetical example in Figure 1 shows the chords for vehicle i to $i+5$ at the detector station during congestion. A chord provides a rough approximation of vehicle trajectory for a short distance downstream of the detector station. During congested conditions the model assumes the change in traffic state between two vehicles is small and the evolving state can be approximated by the discrete observations when vehicles pass. Given u_c, the interfaces between the discrete states are parallel signals (dashed lines in Figure 1) reaching the detector station each time a vehicle passes and all vehicles encountering a signal will make the same traffic state transition. Since the chord of vehicle i intersects the signal that later reaches the detector at instant t_i^{i+1}, vehicle i changes its speed to that dictated by the signal, as detected at the station when vehicle $i+1$ passes. Vehicle i will travel at this speed until it reaches another observed signal. Iterating this procedure, the estimated trajectory of vehicle i can be constructed as the bold line in Figure 1. The estimated travel time between the detector station and any specific location D would be the difference of the passage times at two locations based on the estimated trajectory. Using this algorithm, each vehicle is assumed to follow the same trajectory as the vehicle ahead of it, shifted in space and time, which coincides with the model proposed by Newell (22).

This method can also be applied upstream of a detector station, with the speed of vehicle i updated by the detected speeds of vehicles preceding (instead of following) vehicle i. So, the travel time between two stations can be estimated from either end: using the observed data at

the downstream station to estimate conditions on the link upstream of that station, $TT_{est}^{d/s}$, or using the observed data from the upstream station for conditions on the link downstream of that station, $TT_{est}^{u/s}$. Both estimates are for the same link, but come from separate data at one end or the other, allowing for a comparison to catch detector errors. In this study $TT_{est}^{d/s}$ is employed for reasons discussed in the Pilot Study Based on Field Data section below. The identification of detector errors is addressed in detail in (21).

Method to estimate delays caused by LCMs

To understand how the travel time estimation algorithm produces an estimate assuming there are no LCMs, first consider how LCMs influence vehicle travel times. The hypothetical example in Figure 2(a) shows the trajectories of seven vehicles in the same lane during congestion. To simplify the problem, all vehicles are assumed to travel with speed $V1$ most of the time. There are detector stations on either end of the subject link, labeled upstream and downstream. All vehicles pass both stations in the lane except vehicle a3, which enters the subject lane between the two stations from another lane. Under congested traffic conditions vehicle a4 has to decelerate from $V1$ to $V2$ to accommodate the entrance of a3 ahead. The transition between traffic states of $V1$ and $V2$ induces a signal propagating upstream. After a3 finishes the LCM and there is acceptable headway between a3 and a4, the latter vehicle resumes car following and accelerates to travel with an average speed $V1$ to match the vehicle ahead of it. This transition generates another signal propagating upstream, parallel to the previous one.

If there were no LCMs, all vehicles (except a3) would traverse two stations within time $t1$ as illustrated in Figure 2(a). As a result of the LCM of a3, vehicles a4, a5 and a6 will travel with speed $V2$ for some distance while between the two stations. The travel time for vehicle a4 is extended to $t2$ as shown in Figure 2(a), i.e., it encounters a delay of $t2 - t1$ caused by the LCM, in which $t2$ is the measured travel time of vehicle a4 and $t1$ is the estimated travel time assuming there were no LCMs. The sum of delays for a4, a5 and a6 would be the total delay within the link caused by the LCM of a3. A similar example for an exiting vehicle is shown in Figure 2(b), where the expected travel time should be longer than the measured travel time, indicating that an exiting vehicle allows its following vehicle traverse the link faster than otherwise expected.

In both examples the estimated travel time based on the observed data at the downstream station, $TT_{est}^{d/s}$, produces an estimate of travel time without the influence of LCMs, $t1$, for all seven vehicles since the disturbance of the LCM of a3 propagates upstream and was not observable at the downstream station. On the other hand, the estimated travel time based on the observed data at the upstream station, $TT_{est}^{u/s}$, is an estimate including the influence of LCMs, $t2$, for all seven vehicles. In either case, the travel time is estimated correctly for some vehicles and incorrectly for others.

To formulize the above analysis, the delay caused by LCMs for each vehicle can be estimated as follows:

$$Delay_{LCM} = TT_{measured} - TT_{est}^{d/s} \tag{1}$$

Where, $Delay_{LCM}$ is delay attributed to LCMs, and $TT_{measured}$ is the measured travel time.

In reality, the trajectories in Figure 2(a) and 2(b) would not be straight lines and they are not necessarily parallel. Likewise, the detected speeds at the downstream station would not all be identical. It is not clear how long the disturbance generated by the LCM could propagate and how it is related to the traffic conditions such as density. The approach assumes that a LCM occurs at a point but the following vehicle's accommodation occurs over some distance, e.g., a4 traveling at V2 in Figure 2(a). When a LCM occurs just downstream of a detector it is possible that most of the accommodation actually occurs upstream of the detector, placing the event in one link and the impact in another. There could also be detection errors at the detector stations. All of these factors add errors to Equation 1. Thus, it is of interest to verify the assumption that $TT_{est}^{d/s}$ captures conditions without the influence of LCMs.

Method to study the impact of LCMs on delays

Consider the hypothetical example in Figure 3. The freeway is congested between two detector stations, denoted upstream and downstream. Five vehicles pass both stations and are represented with bold lines labeled from a1 to a5 in Figure 3. Their travel times are available based on trajectory data. The lane changing vehicles are labeled with b1 to b4. The speed of the backward moving signals is assumed to be constant at u_c and an upstream moving signal passing through vehicle a5 as it crosses the upstream detector is represented by a dashed line. Thus, $TT_{est}^{d/s}$ employs the traffic state along line segment AB to estimate travel time along AC assuming no LCMs take place within triangle ABC while $TT_{measured}$ reflects conditions experienced by a vehicle traveling along trajectory AC to measure travel time directly and as a result capturing the effects of any LCMs downstream of AC.

Vehicle a5 passes the upstream station at time t_2 and the downstream station at time t_4. During this period, it passes through the signals emanating from LCMs ahead of it. In the absence of any LCM, all signals that influence the progression of a5 through the link would pass the downstream station after t_5, the downstream station passage time of the signal that eventually meets a5 as the vehicle passes the upstream station at t_2. LCM signals emanating to the left of the line BC in Figure 3, such as that from vehicle b1, are not expected to influence the travel time of a5 between the two stations since such signals reach vehicle a5 outside of the two stations. Signals emanating from LCMs downstream of both stations in Figure 3, such as the LCM signal from vehicle b2, would influence the travel time of a5 between the two stations but this signal would pass both stations. Both $TT_{est}^{d/s}$ and $TT_{measured}$ would include the influence from vehicle b2 and the difference on the right side of Equation 1 is not expected to contain such influence. LCM signals emanating within the triangle ABC in Figure 3, such as that from vehicle b3, would influence the travel time of a5 between the two stations but not the estimated travel time based on downstream station. So the LCM of vehicle b3 contributes to the delay of vehicle a5 between the two stations as measured by Equation 1, and in general the delay of vehicle a5 will change in response to LCMs in the triangular time space region ABC (obviously, such delay is likely related to other traffic features as well).

To study the impact of LCMs on delays, the dependent variable is chosen to be the estimated delay caused by LCMs for each through vehicle based on Equation 1, and the explanatory variables include the number of LCMs in the triangular time space region ABC along with variables describing the traffic conditions. Some examples of the explanatory variables are the number of entering vehicles N_{EN}, the number of exiting vehicles N_{EX}, the net inflow

(defined to be N_{EN} minus N_{EX}), density (31), speed, headway and flow at the upstream and downstream stations. The effect of the number of entering and exiting vehicles has already been discussed above. As for the other possible explanatory variables, it is expected that as density increases, the impact of a LCM on delay is diminished since the reactions of the non-lane-changing drivers to LCMs is damped. Similarly, lower speeds have the same effect on delays for the same reason.

PILOT STUDY BASED ON FIELD DATA

A pilot study was conducted using the above methods with vehicle trajectory data collected by Turner-Fairbank Highway Research Center (TFHRC) in June, 1983 from I-405 South Bound at Santa Monica Blvd., Los Angeles, CA (32). A schematic of the site is shown in Figure 4. The site was filmed from an aircraft flying clockwise at a slow speed. Data were reduced at one frame per second for one hour of the film. Each record contains the information of a vehicle at an instant, which includes vehicle ID, speed, lateral and longitudinal position, and lane number. Traffic was free flow for the first several minutes after which a surge in ramp volume caused the average speed in lane 1 to drop to about 20 mph and this state continued for the remainder of the dataset. Queuing in lane 1 extended upstream of the section approximately 30 minutes into the film and no incidents affected flow in the section. The second half hour data on lane 1 were selected for the pilot study since the study is focused on LCMs in congested traffic conditions.

The travel time estimation algorithm requires the observations of time and speed at which vehicles pass the downstream station. Such data can be collected by traditional detection devices like loop detectors but cannot be directly obtained from trajectory data. So for this dataset it is necessary to specify the locations of hypothetical upstream and downstream detector stations and then interpolate the trajectory data to derive vehicle passage times and speeds at these locations. Theoretically, these stations can be placed at any location along the 1616 ft segment. To avoid the direct influence from the on-ramp and simplify the problem in this pilot study, the hypothetical upstream and downstream stations are placed at 200 ft and 800 ft respectively. Based on the trajectory from a vehicle, the passage time at the upstream station, tA, is the linear interpolation of the time of the observations just before and after the vehicle crosses the upstream station. The quotient of distance and time between these two observations is taken as vA, the vehicle speed at the upstream station. The passage time tB and speed vB at the downstream station are similarly defined. The simulated downstream detector data are used to calculate $TT_{est}^{d/s}$ between the upstream and downstream stations, i.e., the travel time without the influence of LCMs between the stations. These estimated travel times are then used together with the measured travel times to calculate delays caused by LCMs based on Equation 1. As stated earlier, the wave velocity is assumed constant and a value of 10 mph is adopted in this study after calculating the wave velocity based on several different methods, including studying the generalized flow-density relationship (31), studying the propagation of stop waves, Newell's simplified car following model (22), cross correlation analysis (33), and cross spectral analysis (33). The minimum and maximum across the five estimates are 8.7 mph and 10.8 mph, respectively.

This pilot study recognized the following dependent variable and subsequently explanatory variables relative to the notation in Figure 3:

$Delay_{LCM}$ = estimated delay caused by LCMs defined in Equation 1 (seconds),

N_{EN} = number of entering vehicles in time space region ABC (vehicle),

N_{EX} = number of exiting vehicles in time space region ABC (vehicle),

V_{dn}^{a} = arithmetic mean speed (time mean speed) at downstream station over time interval AB (mile/hour),

V_{dn}^{h} = harmonic mean speed (space mean speed) at downstream station over time interval AB (mile/hour), and

K_{dn} = density at downstream station (veh/mile) defined as Q_{dn} / V_{dn}^{h}, where Q_{dn} (veh/hour) is flow at downstream station over time interval AB.

The corresponding upstream measures are not used because their measurement region only touches ABC at a point in the time space plane.

Figure 5 shows the scatter plots of the dependent variable $Delay_{LCM}$ and LCM related explanatory variables, N_{EN} and N_{EX}. Figure 5(a) indicates that the estimated travel time tends to be greater than the measured travel time in these data; that is, $Delay_{LCM}$ tends to be negative. Since $Delay_{LCM}$ is the estimated delay caused by LCMs and there are more exiting vehicles than entering vehicles on the subject section, as can be seen from the negative net inflows in Figure 5(b), this result concurs with the expectation that exiting vehicles would reduce delays. Similarly in Figure 5(b), 81% of the data points lie in the quadrant corresponding to negative delay and negative net inflow, indicating that when net inflow is negative, the estimated delay caused by LCMs tends to be negative. Figures 5(c) and 5(d) illustrate that $Delay_{LCM}$ tends to increase with N_{EN} and decrease with N_{EX}, as indicated by the estimated simple regression lines where delay is regressed against N_{EN} and N_{EX}, respectively. All of these observations lend credence to the effectiveness of the estimation method of delay caused by LCMs defined in Equation 1.

As a first attempt in the study of the impact of LCMs on traffic delays, basic linear regression models are estimated to capture the relationship between delay and the various explanatory variables discussed in the methodology section. More sophisticated models are left for future research.

The residual plots of the simple linear regression models, whereby one explanatory variable is considered at a time, were examined first. The results show that no transformations of N_{EN}, N_{EX} and density variables are necessary. However, the reciprocal transformation of the speed variable is more reflective of the raw data and yields a higher correlation with delay. The correlations among the explanatory variables were also computed and analyzed. As expected, density and the reciprocal of speed are highly correlated. Therefore, one of these variables is included in the model specification at a time since they relate to the same causal process as discussed in the previous section. As a result, three models are estimated. The first model only includes the primary explanatory variables N_{EN} and N_{EX}. The second and third models add density and the reciprocal of speed, respectively, measured at the downstream station, i.e., along AB in Figure 3, consistent with the use of $TT_{est}^{d/s}$. The estimation results of the three model specifications are shown in Table 1.

In all three models, both coefficients of N_{EN} and N_{EX} are significant at the 1% level, which shows that from the statistical regression point of view they do impact $Delay_{LCM}$ on the congested freeway segment. In addition, both coefficients have the expected signs in all three models, i.e., the positive coefficient of N_{EN} implies that each entering vehicle would cause delay and the negative coefficient of N_{EX} indicates each exiting vehicle would reduce delay. In Model 2 and 3, the coefficients of the additional explanatory variables are found to be significant at the 1% level and have the expected signs.

In all three models, the constant terms are significant. For Model 1, the significant constant indicates that when there is no LCM (i.e., $N_{EN} = N_{EX} = 0$), $Delay_{LCM}$ is significantly different from 0, which is not reasonable. However, for the other models, it can be shown that when there is no LCM, on average the constant term is cancelled out by the other terms in the model. Therefore, clearly N_{EN} and N_{EX} do not explain the process entirely.

Across different models, the coefficient of N_{EN} ranges from 1.44 to 2.19 seconds, and the coefficient of N_{EX} ranges from 0.6 to 1.0 seconds. These data give some idea of how much an entering vehicle would increase the delay and how much an exiting vehicle would decrease the delay in congested traffic conditions. In each of the models, hypothesis tests show that the coefficient of N_{EN} is significantly different in magnitude from that of N_{EX}, indicating that delay caused by an entering vehicle is greater than the savings in delay by an exiting vehicle in congested traffic conditions. Thus, it is not appropriate to use net inflow (i.e., $N_{EN} - N_{EX}$) as an alternate explanatory variable.

CONCLUSIONS

This paper presents the concept of delay caused by LCMs and proposes a method to estimate it. The estimation result is further applied to study the impact of LCMs on delays using trajectory data. Such study should help understand traffic delay for better congestion management and further the understanding of traffic dynamics into an important area where much remains unknown. A pilot study shows that the proposed study methods are feasible. Nevertheless, further research needs to be carried out to evaluate the impact of some of the simplifying assumptions made. Several linear regression models from this pilot study are presented and the results comply with the expectations. This paper provides an empirical start for the study of LCMs impacts on delay.

There are some limitations of the work that should be addressed in the future, several of which are as follows. The proposed methodology has so far been tested only on half-hour of trajectory data from a single lane on a section just before an on-ramp. The observation data at the simulated upstream and downstream stations are interpolated from the vehicle trajectories, rather than collected from the field. In addition, the inhomogeneous geometric features of this section might have caused the low goodness-of-fit measure of the linear regression models. Identifying the impacts of inhomogeneous features is an important topic for further research and trajectory data collected from congested traffic conditions are necessary for further study.

Several assumptions and simplifications are made in this paper and some of them need further verification treatment. The wave velocity was assumed to be constant, a value of 10 mph was used in the pilot study. Although not shown in this paper, the value of the constant

wave velocity was proven to be an important confounding factor and its value should be determined carefully, as was done herein with five different methods. In addition, this study counts the number of LCMs in the triangular time space region as ABC shown in Figure 3. However, this triangular region is just a simplification since some LCMs outside of this region might also contribute to the delay. For example, vehicle b4 in Figure 3 will not influence the travel time of vehicle a5 between the two stations and will not contribute to the delay of vehicle a5 if it is assumed that a vehicle can change its speed instantly. However, in reality vehicle a5 will need some time to accommodate the lane change of vehicle b4 and such accommodation might occur between the two stations if vehicle b4 changes lane at a spot that is very close to line BC in Figure 3. Given that the numbers of entering and exiting vehicles are discrete variables, the treatment of such explanatory variables in statistically modeling delay relationships requires further attention.

One needs to both understand the operation of individual lanes and the combination of all lanes in a given direction, this paper is limited to the former. When considering the impacts across all lanes, on the one hand, it remains possible that some of the effects may cancel out and become imperceptible in aggregate delay. On the other hand, an aggregate change in delay could still be present and detectable due to the finding in this paper that the delay caused by a LCM into a lane is greater than the gain in travel time resulting from a LCM out of a lane. Moreover, because the accommodation occurs over long distances, the gain in one lane may be spatially or temporally separated from the loss in another. Although this imbalance may be small, it could prove to be one mechanism that causes delay and disturbances (e.g., the driver behind an entering vehicle may decelerate and then accelerate to accommodate the LCM, all following vehicles will be constrained by the fluctuations in this trajectory as the impacts propagate upstream). Likewise, a vehicle momentarily consumes more capacity while straddling two lanes than it would have had it remained in a single lane. From a capacity and delay standpoint one may argue that these phenomena are only important within a bottleneck, which may prove to be true, but the understanding of LCMs within a queue should also further understanding LCMs' impacts within a bottleneck where they can impact throughput. The understanding could also lead to establishing more precisely the influence area of a bottleneck, where it begins and ends. Away from bottlenecks the work potentially has implications on safety (e.g., accidents due to stop and go traffic) and car following theory. Finally, if LCMs away from a bottleneck cause a measurable change in delay for a given lane, it could provide a tool to quantify LCMs within a queue even if LCMs do not impact the net delay across all lanes, thereby providing previously unavailable details about the flow of vehicles within a queue.

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REFERENCES

[1] Coifman, B., Krishnamurthy, S., and Wang, X., "Lane Change Maneuvers Consuming Freeway Capacity", *Proc. of the Traffic and Granular Flow 2003 Conference*, October 3, 2003, Delft, Netherlands, pp. 3-14.

[2] Gazis D. C., Herman R., and Weiss G. H., Density oscillations between lanes of multilane highways. *Operations Res.*, Vol. 10, No.5, 1962, pp. 658-667.

[3] Munjal P.K. and Pipes L.A., Propagation of on-ramp density waves on non-uniform unidirectional two-lane freeways. *Transportation Research*, Vol. 5, 1971, pp. 241-255.

[4] Michalopoulos P., Beskos D., and Yamauchi Y., Multilane traffic flow dynamics: Some macroscopic considerations. *Transportation Research*, 18B, 1984, pp. 377-393.

[5] Worrall R. D., Bullen A. G., and Gur Y., An elementary stochastic model of lane-changing on a multilane highway. *Highway Res. Rec.*, 308, 1970, pp. 1-12.

[6] Sheu J-B., A stochastic modeling approach to dynamic prediction of section-wide inter-lane and intra-lane traffic variables using point detector data. *Transportation Research Part A*, Vol. 33A, 1999, pp. 79-100.

[7] Sheu J-B. and Ritchie S.G., Stochastic modeling and real-time prediction of vehicular lane-changing behavior. *Transportation Research Part B*, Vol. 35B, 2001, pp. 695-716.

[8] Gipps P.G., A model for the structure of lane-changing decisions. *Transportation Research Part B*, Vol. 20B, No. 5, 1986, pp. 403-414.

[9] Yang Q. and Koutsopoulos H.N., A microscopic traffic simulator for evaluation of dynamic traffic management systems. *Transportation Research Part C*, Vol 4C, No. 3, 1996, pp. 113-129.

[10] Ahmed K.I., Ben-Akiva M., Koutsopoulos H.N. and Mishalani R.G., Models of freeway lane changing and gap acceptance behavior. *Proceedings of the 13th International Symposium on Transportation and Traffic Theory*, Lyon, France, 1996.

[11] Zhang Y., Owen L.E. and Clark J.E., Multiregime approach for microscopic traffic simulation. *Transportation Research Record, No. 1644*, 1998, pp. 103-115.

[12] Hidas P., Modelling lane changing and merging in microscopic traffic simulation. *Tranportation Search Part C*, Vol. 10C, 2002, pp. 351-371.

[13] Wei H., Meyer E., Lee J. and Feng C., Characterizing and modeling observed lane-changing behavior. *Transportation Research Record, No. 1710*, 2000, pp. 104-113.

[14] Toledo T., Koutsopoulos H.N. and Ben-Akiva M.E., Modeling integrated lane-changing behavior. *Transportation Research Record, No. 1857*, 2003, pp. 30-38.

[15] MacCarley, A.C., *Videobased Vehicle Signature Analysis and Tracking Phase1: Verification of Concept and Preliminary Testing.* California PATH Working Paper, UCB-ITS-PWP-98-10, 1998.

[16] Izumi, T., Takahashi, Y. and Kiryu, N., Travel time measurement using ultrasonic vehicle-identification equipment. *The Transactions of the Institute of Electrical Engineers of Japan*, Vol. 120D, 2000, pp. 651-657.

[17] Hellinga, B., Automated vehicle identification tag-matching algorithms for estimating vehicle travel times: comparative assessment. *Transportation Research Record, No. 1774*, 2001, pp. 106-114.

[18] Coifman, B., Vehicle reidentification and travel time measurement in real-time on freeways using the existing loop detector infrastructure, *Transportation Research Record, No. 1643*, 1998, pp. 181-191.

[19] Coifman, B. and Cassidy, M., Vehicle reidentification and travel time measurement on congested freeways. *Transportation Research Part A*, Vol. 36, Issue 10, 2002, pp. 899-917.

[20] Coifman, B., Identifying the onset of congestion rapidly with existing traffic detectors. *Transportation Research Part A*, Vol. 37, Issue 3, 2003, pp. 277-291.

[21] Coifman, B. Estimating travel times and vehicle trajectories on freeways using dual loop detectors. *Transportation Research Part A*, Vol. 36, No. 4, 2002, pp. 351-364.

[22] Newell, G.F., A simplified car-following theory: a lower order model, *Transportation Research Part B*, Vol. 36, 2002, pp. 195-205.

[23] Newell, G.F., A simplified theory of kinematic waves in highway traffic, part II: queuing at freeway bottlenecks, *Transportation Research Part B*, Vol. 27, 1993, pp. 289-303.

[24] Hall, F. L. and Gunter, M. A., 1986, Further analysis of the flow-concentration relationship. *Transportation Research Record, No. 1091*, pp. 1-9.

[25] Banks, J. H., Freeway speed-flow concentration relationships: more evidence and interpretations. *Transportation Research Record, No. 1225*, 1989, pp. 53-60.

[26] Cassidy, M.J., Bivariate relations in nearly stationary highway traffic. *Transportation Research Part B*, Vol. 32, 1998, pp. 49-59.

[27] Cassidy, M.J. and Mauch, M., An observed feature of long freeway traffic queues. *Transportation Research Part A*, Vol. 35, 2001, pp. 143-156.

[28] Mauch, M. and Cassidy, M.J., Freeway traffic oscillations: observations and predictions. *Proceedings of the 15th International Symposium on Transportation and Traffic Theory*, Elsevier, Amsterdam, 2002, pp. 653-674.

[29] Windover, J. and Cassidy, M., Some observed details of freeway traffic evolution. *Transportation Research Part A*, Vol. 35, 2001, pp. 881-894.

[30] Coifman, B. and Wang, Y., The Velocity of Waves Propagating Through Congested Freeway Traffic, *Proc. of The 16th International Symposium on Transportation and Traffic Theory*, July 19-21, 2005, College Park, MD, pp. 165-179.

[31] Edie, L., Discussion of traffic stream measurements and definitions, *Proc. Second International Symposium on the Theory of Traffic Flow*, OECD, Paris, France, 1963, pp. 139-154.

[32] Smith, S.A., *Freeway Data Collection for Studying Vehicle Interactions*, Technical Report, Report No. FHWA/RD-85/108, 1985.

[33] Wang, Y., Foster, D. and Coifman, B., Measuring wave velocities on highways during congestion using cross spectral analysis. *2004 IEEE Intelligient Transportation Systems Conference*, Washingtong, D.C., 2004, pp. 544-547.

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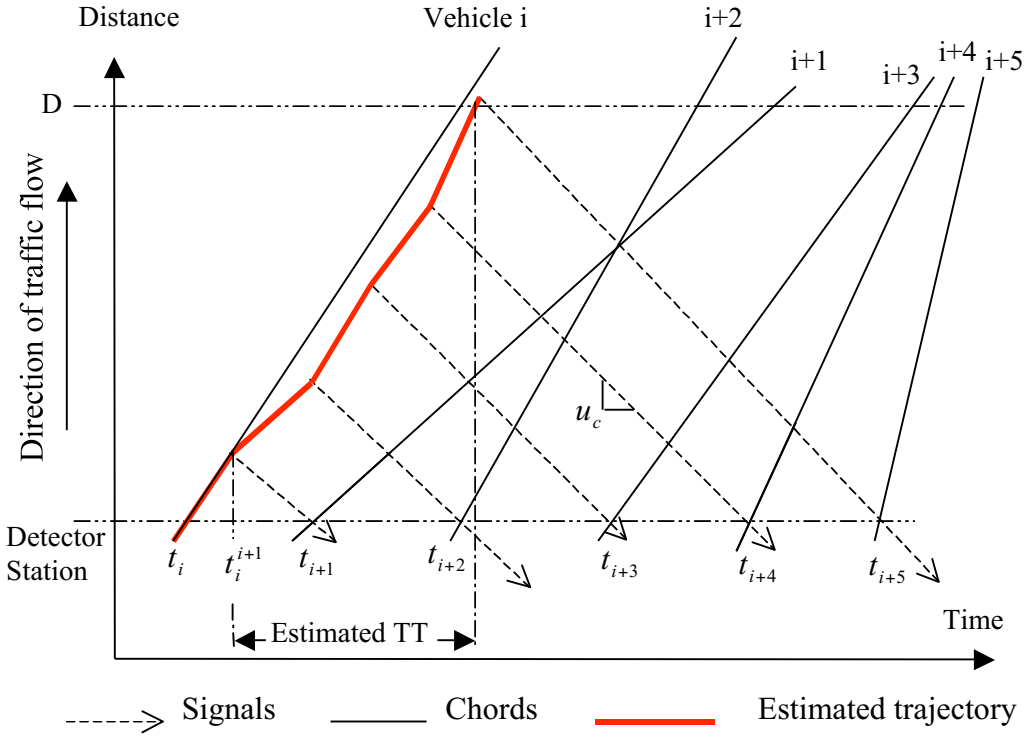

Figure 1 Estimated travel time and trajectory for vehicle i (adapted from (21)).

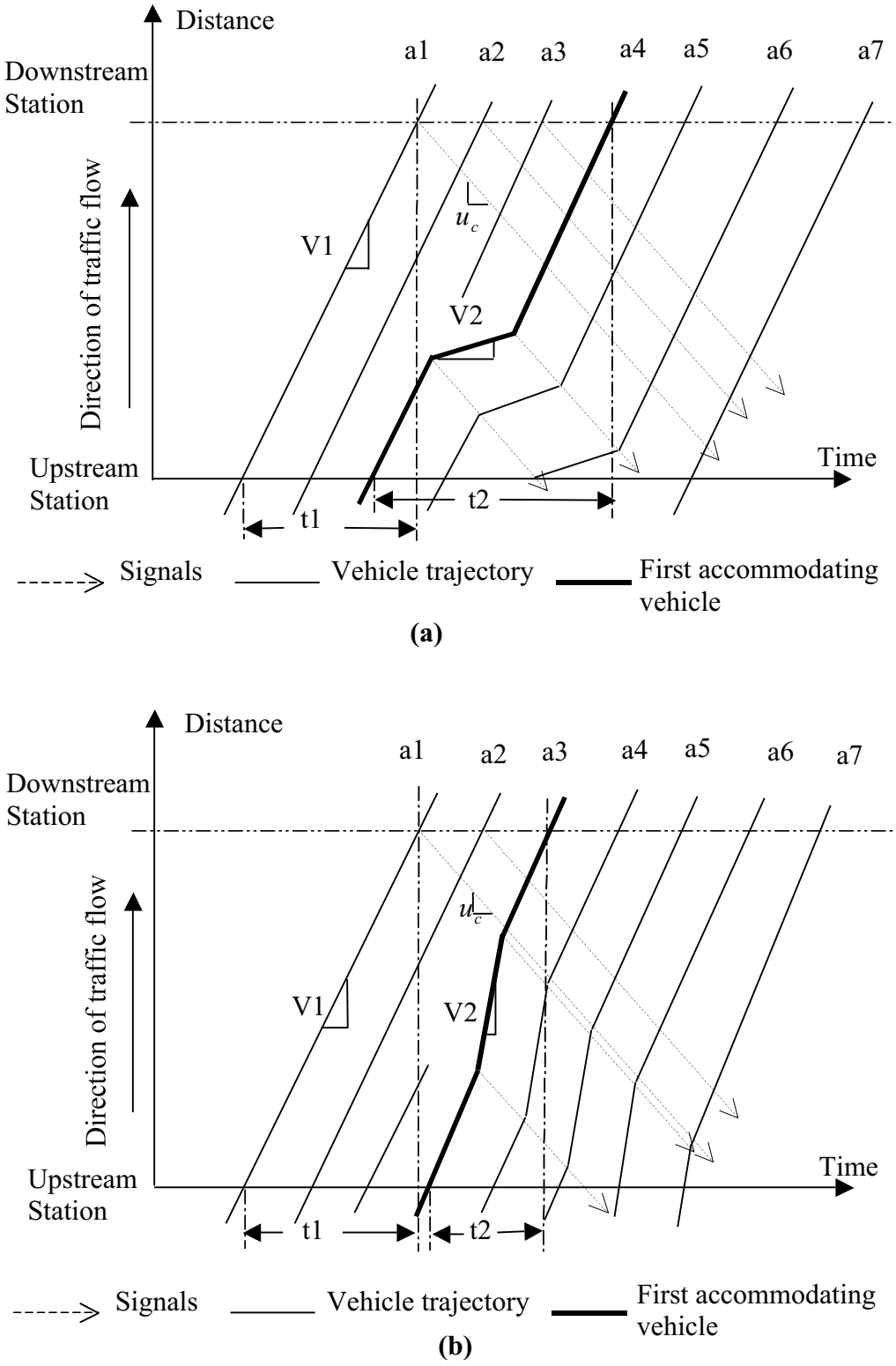

Figure 2 **Time space diagram showing (a) how an entering vehicle causes delay; (b) how an exiting vehicle reduces delay.**

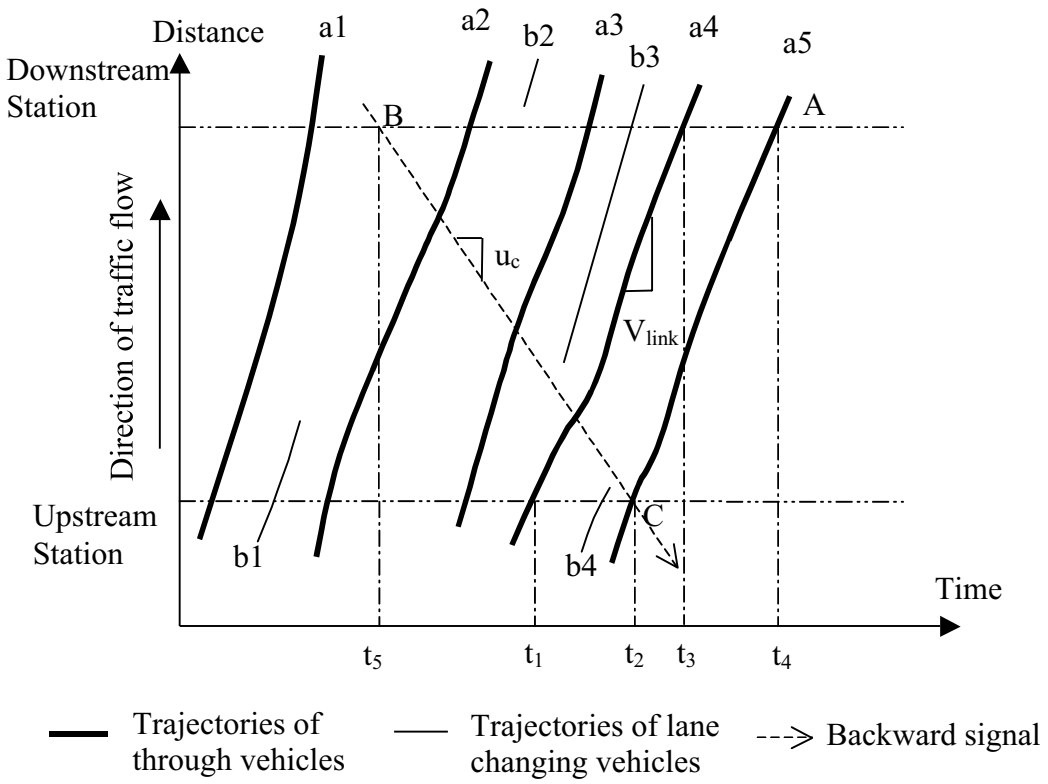

Figure 3 Diagram showing the methodology to study the impact of LCMs on delays.

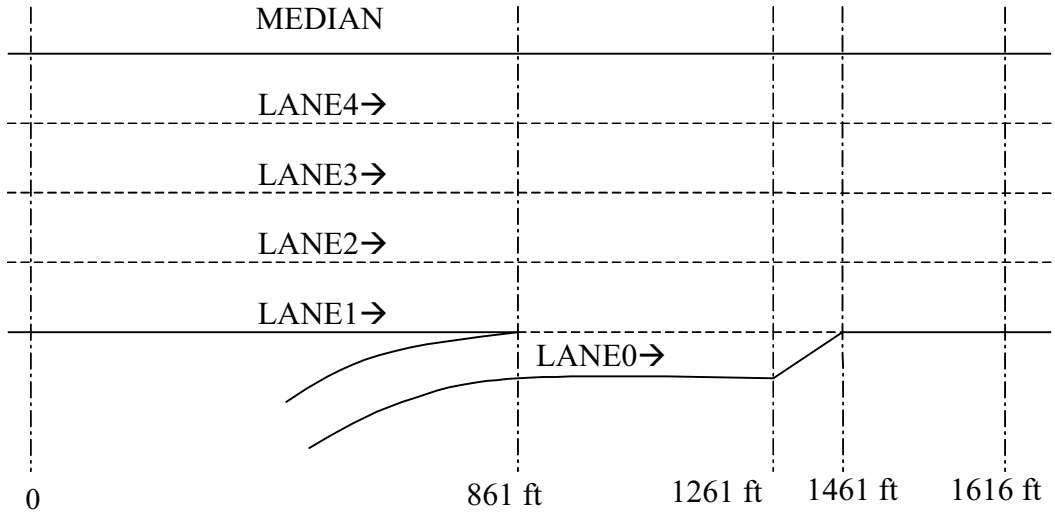

Figure 4 Schematic of I-405 section in Los Angeles, not to scale (adapted from (32)).

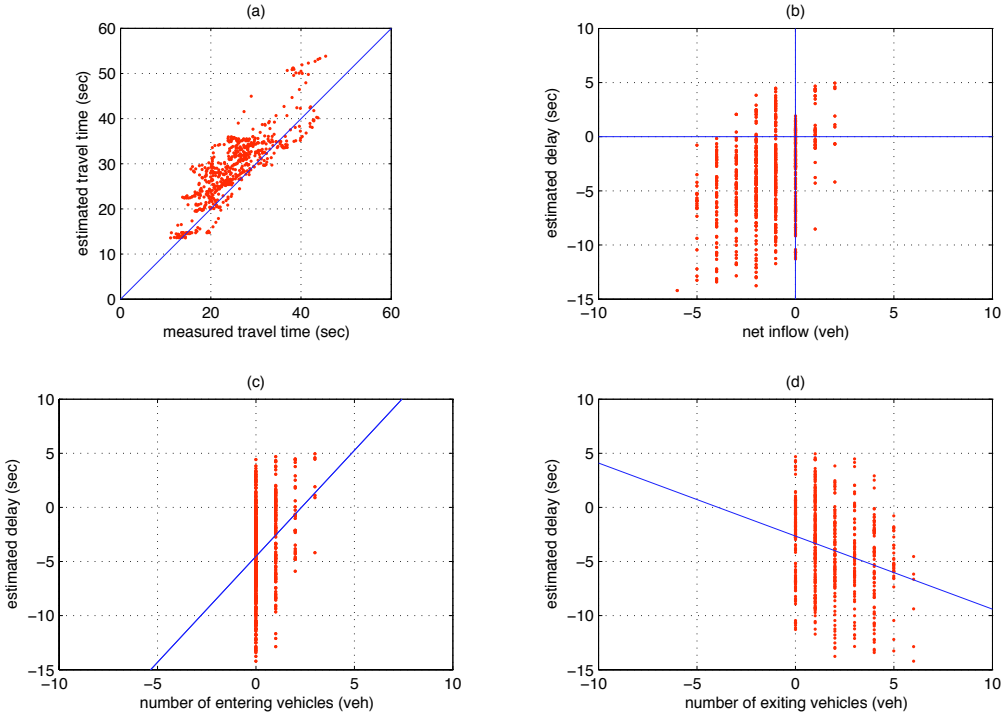

Figure 5 **Concurrent scatter plots from half hour of I-405 data (a) measured travel time versus estimated travel time; (b) estimated delay versus inflow; (c) estimated delay versus N_{EN}; (d) estimated delay versus N_{EX}.**

Table 1 Linear Regression Results of three Model Specifications

	Variable	Estimated Coefficient	Standard Error	t-statistic
Model 1	Intercept	-3.21	0.22	-14.35
	N_{EN}	2.19	0.23	9.60
	N_{EX}	-0.78	0.09	-8.49
	No. of observations = 646, $\overline{R}^2$ = 18.3%			
Model 2	Intercept	4.83	0.69	6.96
	N_{EN}	1.55	0.21	7.26
	N_{EX}	-0.84	0.08	-10.11
	K_{dn}	-0.09	0.01	-12.11
	No. of observations = 646, $\overline{R}^2$ = 33.4%			
Model 3	Intercept	2.74	0.60	4.56
	N_{EN}	1.44	0.22	6.45
	N_{EX}	-0.61	0.09	-7.05
	$1/V_{dn}^{a}$	-94.74	8.99	-10.54
	No. of observations = 646, $\overline{R}^2$ = 30.3%			