EXPERIMENTAL VERIFICATION OF TIME-DEPENDENT ACCUMULATION PREDICTIONS IN CONGESTED TRAFFIC

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ABSTRACT

This paper shows, with experimental traffic data from a 4-mile long congested road, that traffic delays and vehicle accumulations between any two generic observers located inside the road section can be predicted quite accurately from the traffic counts measured at the extremes of the section. Predictions can be made with a streamlined version of the kinematic wave theory that does not rely on ambiguous traffic stream characteristics such as “density”. The predictions were found to not require re-calibration on the day of the experiment, and to work well despite what appeared to be location-specific driver behavior.

KEY WORDS:
Traffic flow theory; congestion prediction; traffic spillovers; bottleneck effects; experimental verification

INTRODUCTION

Although experiments have shown that density and flow disturbances move through traffic at random but predictable speeds, i.e., as waves (see e.g. [1-5]), plots of flow-density data have also shown quite complex patterns, particularly in the congested region (see e.g. [6,7]). Therefore, it is fair to ask whether these complexities prevent a theory of waves (such as the kinematic wave (KW) theory) from predicting large-scale phenomena. This paper presents experimental results that indicate that large-scale effects such as vehicle accumulations (the main determinants of queue spillbacks) and trip times can be predicted with the KW model in the congested region without recalibration. This paper shows how to calibrate the parameters of a prediction procedure, and then demonstrates the calibration and prediction process with the data set described in [8]. Familiarity with the data set in this reference is not necessary, but may help those readers who wish to extend or test the ideas presented here.

This data set contains detailed observations of both queued and unqueued vehicle arrivals upstream of an actuated traffic signal. These data were collected on two days along a single lane of a two-lane highway with virtually no points of access or egress and negligible passing; see Fig. 1a. Reference [8] describes the field experiment that was designed to limit errors in arrival counts to 2% at all times, and the resulting data set. The data were summarized in the usual way by cumulative curves of vehicle number (N-curves).

Qualitative properties of the data noted in [8] suggest behavior consistent with existing theories, as well as other behavior that cannot be explained easily by current models. This paper focuses on the latter and shows how approximate vehicle accumulations and trip times between observers can be predicted even in the presence of such behavior.

The paper is organized as follows. The introduction concludes with a closer look at the unexpected queued behavior observed in the data. In section 1, a simple methodology that will be used to calibrate the KW theory and predict the N-curves is reviewed. This methodology is applied to experimental data in section 2 and the results are interpreted in section 3. A brief summary of the main findings is then presented in section 4.

Unexpected queued traffic behavior. Looking at periods of long queues, such as the one depicted in Fig. 1b, we see that the cusps of the N-curve for observer 8, N(8,t), which corresponds to a location about 250 feet upstream of the traffic signal, were usually "rounded" and the troughs were usually "sharp". [N(j,t) refers to the synchronized cumulative count recorded by observer *j* at time t.] This suggests, for the most part, that the acceleration waves emitted from the location of the traffic signal at the start of each green phase were transmitted to observer 8 sharply, as "shocks", and that the decelerations caused by the beginning of the red phases were not.

However, the acceleration shocks did not always remain sharp. An acceleration shock will remain sharp as long as drivers accelerate reasonably fast somewhat independently of the precise motion of the car in front. Close examination of the data reveals that both the cusps and troughs could become rounded upstream of observer 8, and that the pattern was not consistent. The erratic pattern for observers 7, 6, … suggests that wave propagation and the detailed shape of the N-curves were influenced by the idiosyncrasies of particular drivers affected by each wave.

The particular form of smoothing that was observed is noteworthy because it is inconsistent with the KW theory of traffic flow proposed by [9,10]. For example, if the flow-density curve in the queued regime was linear (implying a constant wave speed), the N-curves for observers 7, 6, 5, and 4 would be identical or very similar to N(8,t) except for a vertical and horizontal translation, as explained in [11]. There would be no rounding of the cusps and troughs. More generally, if the flow-density relationship were curved rather than straight, then only the cusps or only the troughs would become smooth, depending on whether the flow-density relation were convex or concave. Furthermore, the smoothing pattern would continue as one moves upstream from one observer to the next, and eventually all oscillations would disappear. Obviously, the long period oscillations shown in Fig. 1b for curves N(4,t) and N(5,t) should not have arisen if the KW theory were valid at this fine level of detail.

1 REVIEW OF KW THEORY WITH PIECEWISE LINEAR N-CURVES

It is well known that if the flow-density relation for a homogeneous highway is known and one is given well-posed N-curves at its upstream and downstream ends, then one can predict the N-curves at any intermediate points with the KW theory. Reference [11] proposed a simple procedure for linear flow-density relations, and a more laborious one for concave ones. A more complicated procedure also exists for the more general case in which the flow-density curve is unimodal [12]. The latter procedure, which can be streamlined significantly when the N-curves are piecewise linear, will be used for our study, allowing us to determine the best fitting flow-density relation from the widest possible family of curves. This section reviews the methodology when it is applied to a queued highway section that is enclosed by two observation points: “U”-upstream and “D”- downstream. In this special case of queued traffic the methodology predicts any upstream N-curve from the downstream N-curve, N(D,t). It will be assumed that the raw input data curve N(D,t) has been approximated by a piecewise linear curve A(D,t) and the procedure will be applied to the latter.

The use of piecewise linear approximations is justified because the KW procedure is a “contraction mapping” in the space of N-curves. That is, if the KW procedure is applied to two input N-curves then the maximum separation that results between the two predicted N-curves is at most equal to the maximum separation between the two input curves [12]. Therefore, if one approximates N(D,t) to within an acceptable tolerance level by a piecewise linear curve A(D,t), and then applies the KW procedure to the piecewise linear curve, one can be assured that the resulting approximation of the upstream curve A(U,t), will be within the same tolerance level of the exact prediction of the upstream curve, N(U,t). This is useful in practice because it can help us choose an appropriate approximation level for A(D,t). A similar result holds for errors in the flow-density relation; i.e. the maximum vertical separation between two N(U,t) curves built from two different flow-density relations cannot exceed the product of the maximum density discrepancy in the two relations and the length of the UD section.

The procedural simplifications arise from three postulates that are equivalent to the KW theory but pertain to operations on piecewise linear N-curves (see [12]). The first postulate (stationary reproducibility) states that vehicle accumulations should be replicable within a queue for any (long) time interval in which the average flow for the interval is the same. More precisely, if a downstream curve N(D,t) does not deviate much from a straight line with slope q for an extended period of time, and traffic is queued, then curve N(U,t) should become approximately parallel to N(D,t) and remain above it by a reproducible number of vehicles, $m_{UD}(q)$. This separation is the average accumulation of vehicles between observers U and D. We will say that this postulate holds approximately if N(U,t) and N(D,t) fluctuate within reasonable bounds about parallel trendlines that are $m_{UD}(q)$ vehicles apart, and if this separation only depends on the slope q. The separation should not depend on anything else; e.g., the history of the system. Note that the postulate can be satisfied approximately even if there are stop-and-go oscillations, and that it could be useful (if proven true) even if the remaining postulates of the KW theory are not accurate.

This postulate is also interesting because it applies to inhomogeneous road sections and does not require that one define a "density" for every point on the road. Instead, vehicle accumulation (an observable number with no ambiguity) becomes the fundamental variable to be predicted. In what follows, the relationship $m_{UD}(q)$ will replace the "fundamental diagram" of KW theory. An example of such a curve is shown in Fig. 2a.

If one believes that on a particular road the accumulation $m_{UD}(q)$ between any two points U and D only depends on these points through the distance that separates them and one also believes that the dependence is proportional (i.e., the road is homogeneous), then the $m_{UD}(q)$ can be normalized by the distance between points, L_{UD}, and replaced with $\kappa(q) = m_{UD}(q)/L_{UD}$ for the resulting function of q. This normalized vertical separation, $\kappa(q)$, has units of "density", but will be called here the normalized average accumulation to avoid confusion with the various possible definitions of density. The reader can verify that the $\kappa(q)$ is simply Edie's [13] generalized definition of density for the time-space rectangle describing the intervening space between the observation points for the (long) time interval during which the system is stationary. This quantity is unambiguously defined even if the two observation points are so close that a single vehicle doesn't fit in between.

The second postulate states that the transition between two queued stationary states propagates as a wave from D to U. This is depicted in Fig. 2b, where the transitions at U and D are idealized by breakpoints in the N-curves. [In the KW theory, some transitions tend to spread, causing the corners of the N-curves to become smoother as the wave moves upstream. This complication can be captured by means of a third (stability) postulate, as explained in [12]. Because corner effects do not change the predictions significantly when the stationary states persist for a long time, as will be the case in this paper, the third postulate is not introduced here.]

If the slopes (q_1, q_2) and the separations $\left(m_{UD}(q_1), m_{UD}(q_2)\right)$ between the two sets of parallel lines are given, we see from the geometry of Fig. 2b that the "N-vector" that points from one breakpoint to the other is also given. Simple geometric considerations reveal that the dimensions of the horizontal and vertical components of this vector, w_{12} and n_{12}, are related to the slopes and separations by:

$$w_{12} = -\left(m_{UD}(q_1) - m_{UD}(q_2)\right) / \left(q_1 - q_2\right)$$

and

$$n_{12} = m_{UD}(q_1) + q_1 w_{12}$$

The time-component of the N-vector represents the wave trip time, and the count-component the number of vehicles that encounter the wave between locations U and D.

These two quantities have simple graphical interpretations on an accumulation-flow plane, such as Fig. 2a, that contains the two stationary states, "1" and "2". Consideration of this figure shows that w_{12} is the negative slope of the line connecting the two state-points and n_{12} is the intercept of said line with the accumulation axis.

In the special case where the $m_{UD}(q)$ relationship is linear, we see from Fig. 2a that the coordinates of the N-vector are independent of the two states. Consequently, all the N-vectors of a piecewise linear curve N(D,t) with multiple breakpoints must be identical and the curve N(U,t) is therefore an exact translation of the curve N(D,t) in its totality, as noted originally in [11].

Procedures based on the above-mentioned ideas will be used in the next section to determine the $m_{UD}(q)$ curves that best fit the data observed on one day at the site in [8], and then to predict the N-curves at the same site on a *different* day.

2 APPLICATION TO EXPERIMENTAL DATA

In order to apply the methodology of Section 1, two input curves are required: a piecewise linear approximation of the downstream-most observer data, A(D,t), and an $m_{UD}(q)$ relationship. Sections 2.1 and 2.2 below explain how these curves were developed. Section 2.3 describes the prediction procedure.

To control the statistical degrees of freedom in our tests, data from the *first* day of observation were used exclusively to estimate $m_{UD}(q)$ and this relationship was then used with the A(D,t) curve from the *second* day to make predictions. The process was then repeated using the *second* day's data for calibration, and the *first* day's data for prediction. By controlling the degrees of freedom in this rigorous way, the tests should indicate clearly whether time-dependent vehicle accumulations can be predicted from day to day.

2.1 Approximation of N_D

The N-curves constructed from data collected at observer 8 exhibited the cyclic pulses of the traffic signal. A piecewise linear approximation of N(8,t) that averaged out these pulses, A(8,t), was then constructed using as few breakpoints in the curve as possible while ensuring that the maximum separation between the true and approximated curves remained within a reasonable tolerance. The design tolerance chosen for our study was twenty vehicles. This set-up allowed us to create intervals of stationary flow that were long relative to the wave trip time so as to ensure that the two basic postulates of section 1 suffice to describe the KW solution.

Breakpoints were determined by visual inspection of the trend changes in N(8,t). In order to stay within the design tolerance, seven and eight breakpoints were used on the first and second days, respectively. The resulting tolerances were sixteen vehicles on the first day and nineteen on the second day. A more refined piecewise linear approximation could be constructed using a mathematical program to select the coordinates of the breakpoints that would minimize the deviations of the A(8,t) from the true N(8,t), but this was not necessary in our case.

2.2 Accumulation-flow relationship

Both the stationary flows at the downstream-most observer (i.e., the slopes of the segments in A(8,t)) and the average accumulations of vehicles between observers were measured to estimate a relationship between normalized accumulation and flow. Average accumulations were simply the average vertical separations between each segment of A(8,t) and the corresponding portions of the curves recorded by the other observers. Average accumulations between observers 8 and *j*, (for *j* = 7, 6, …), were measured only during periods of stationary flow in which the queue reached observer *j*. The queued/unqueued status of *j* was determined in the usual way from the prevailing trip times between observers *j'* and *j* (for *j'*<*j*); see [3]. For example, in Fig. 3a one can see that the queue reached observer 6 when indicated because from then on the trip times between observers 1 (or 2, 3, 4, 5) and 6 exceeded the minimum free flow trip times. Note that prior to the onset of queuing, N(6,t) is parallel to the upstream curves, and that afterwards the horizontal gaps in N(1,t), such as G_1, present in the curves 2-5 are not propagated forward to 6.

To estimate average accumulations, each linear section of A(8,t) was translated upward toward a target curve until the deviations from the target were minimized. As an illustration of this procedure, Fig. 3b presents the approximation of N(7,t) by A(7,t) obtained from one of the segments of A(8,t) on day 1. Since changes in flow were not instantaneously felt by upstream traffic, the segment was first shifted to the right slightly by an approximate wave trip time (segment AB) and then upward. [The wave trip time was estimated using a wave speed of 12.5 mph; the estimated accumulation turns out to be rather insensitive to this particular number.] The vertical shift (segment BC) was chosen to minimize the vertical deviations between N(7,t) and the shifted segment. Note that this shift is *not* the average vehicle accumulation; as shown in Fig. 3b, the average vehicle accumulation (i.e. the vertical separation between the two linear segments) is always smaller.

For each period of fixed flow, the average vehicle accumulations between the downstream-most observer and the remaining observers were obtained with this procedure. Since there were seven stationary periods in day 1, this yielded a maximum of seven accumulation-flow data points for each observer pair (i.e., observers 7 and 8, observers 6 and 8, etc.). Although each of these points represented the state of the system for an extended period of time, we felt that there was not enough information in these data to estimate reliably a separate $m_{UD}(q)$ curve for every observer pair. This was particularly true for pairs (1,8), (2,8), and (3,8) because the queue only backed up past observer 3 briefly, and this limited severely the number of observations for these observer pairs. In view of this, the site was initially treated as a homogeneous highway so that accumulation could be normalized and then pooled for all observer pairs combined. We shall see later that the homogeneity hypothesis did not hold everywhere. The normalized accumulation-flow data points for day 1 are plotted in Fig. 4a (straight line approximation) and 4b (piecewise linear approximation).

Data points including many vehicles (e.g. those arising from long stationary intervals) are likely to yield more accurate average accumulations than those with fewer vehicles. Likewise, data points where individual vehicles are observed for a long time (e.g. those corresponding to pairs of observers located far apart) are also likely to be more reliable. To capture these effects when fitting a curve, the observations were weighted by vehicle-hours, reflected in the sizes of the circles in Fig. 4.

2.3 Prediction of N_U

The N-curves for queued locations upstream of N(8,t) on day 2 were estimated using the methodology described in section 1. Given the flow in each section of A(8,t) for *day 2*, the normalized accumulation of vehicles between observers was obtained from the $\kappa(q)$ relationship developed from the *day 1* data (Figs. 4a-b). These normalized accumulations were multiplied by the distances between observers to obtain the upward shifts that were applied to the various segments of A(8,t) to construct the upstream A-curves as shown in Fig. 3b. Because the A-curves obtained with the two $\kappa(q)$ curves only differed by a few vehicles when the curve separation was greatest, the predicted curves are only presented for the linear case of Fig. 4a.

These results are displayed in Figs. 5a-b. Note, with the exception of N(3,t), the closeness of the true and predicted curves, suggesting that the methodology worked well for most observers. The process was then repeated using *day 2* data to calibrate two $\kappa(q)$ relationships (Figs. 6a-b) and then using these relationships to reconstruct the *day 1* N-curves. The predictions for day 1 obtained with the linear $\kappa(q)$ relation of Fig. 6a are shown in Figs. 7a-b. As in the previous case, the predictions based on the piecewise-linear $\kappa(q)$ were similar and are not presented. Note that the results are qualitatively similar to those previously obtained for day 2.

3 ANALYSIS

In this section, three important issues are examined in detail. The evidence indicates that (i) the $\kappa(q)$ relationship was reproducible from day to day and that it did not curve significantly; (ii) the accuracy of the predicted counts did not deteriorate greatly with distance, despite the presence of a highway inhomogeneity; and (iii) queues formed and dissipated as expected in KW theory. The section also includes a brief comparison with a simpler prediction method.

3.1 Reproducibility of the Normalized Accumulation-Flow Relationship

Although individual $\kappa(q)$ points recorded for the first day of observation spanned a relatively narrow range of flows, the linear relationship between normalized accumulation and flow that resulted (Figure 4a) was similar to that produced with data from the second day (Fig. 6a) for the full range of flows. In fact, a comparison of Figs. 4a and 6a reveals that the two lines coincide for the highest accumulations (low flows) observed and only diverge by 7 vehs/mile for the lowest accumulation (high flows). The slopes of the two lines are also similar, yielding wave speed estimates of 10.7 MPH (Fig. 4a) and 11.7 MPH (Fig. 6a).

Although the two piecewise linear approximations of the $\kappa(q)$ relationship (Figs. 4b and 6b) were close to each other, it is apparent from the figures that they did not curve in the same way on both days. Therefore, our data did not suggest that $\kappa(q)$ was significantly curved in the range of flows observed.

3.2 Accuracy of the Predicted N-Curves

As shown in Figs. 5 and 7, the predicted N-curves for locations within the first mile upstream of the reference location (i.e. curves 4, 5, 6 and 7, upstream of 8) lay on or very near the true N-curves. At these locations, discrepancies between predicted and observed N-curves were not, in general, greater than the deviations between A(8,t) and the true N(8,t). Table 1 summarizes the maximum error in the prediction of the N-curves for observers 4 through 7 on both days. Since some average flows observed on the second day were outside the range of average flows observed on the first day, some of the normalized accumulations predicted for the second day were based on extrapolated data. Nonetheless, the predictions for the second day were quite accurate, suggesting that the estimation methodology is robust. In addition, we also see from Figs. 5 and 7 that, for the most part, the predicted and observed curves remained within ten vehicles of each other, even for the most distant of the 4 observers, and that accuracy did not deteriorate significantly with distance. Furthermore, when larger fluctuations did appear, these fluctuations did not prevent the predicted line from reapproaching the observed line in later intervals.

As marked in Figs. 5 and 7, there was some over-prediction for the third observer N(3,t) during most intervals when the queue reached that observer on both days. It appears that, for a given queue discharge rate, drivers spaced themselves more widely (and traveled faster) upstream of observer “4” than downstream. This observation could be explained in several possible ways: (i) distance measurement errors, (ii) a possible “end-of-the queue” effect, if drivers were to behave differently when approaching a queue, (iii) a location-specific effect such as an inhomogeneity in the road, or (iv) failure of the theory. We dismissed (i) because the careful distance measurements in [8] were reconfirmed on another site visit. We also dismissed (ii) because N(4,t) was not over-predicted in the same manner when the queue reached only to the fourth observer. On the other hand, we considered (iii) seriously because the over-prediction of N(3,t) occurred on both days. We do not speculate about the cause of the inhomogeneity because this may not be needed to predict accumulations; e.g. if we can find a recipe that is reasonably accurate despite inhomogeneous traffic behavior. This possibility is examined below.

A separate $m_{38}(q)$ relationship was derived for observer 3 using only data from the *first* day. N(3,t) curves were then predicted for the *second* day with the new $m_{38}(q)$ relationship rather than the normalized $\kappa(q)$ relationship. Fig. 8 presents the results of the prediction from 7:20 am to 8:10 am, the only interval when traffic was queued at observer 3. The improved prediction suggests that the effects of inhomogeneity are reproducible and that traffic backups can indeed be estimated with the KW theory despite location-specific traffic behavior.

Visual inspection of the results showed good prediction of the transition between states. The most striking way to see this is by imagining that each segment of a predicted N-curve is introduced in sequence as one steps through time, and to note what would happen to the figure if the introduction of a new segment was delayed or omitted. The effect is shown particularly well in Fig. 5b. Note how just as soon as the true and predicted N-curves diverged by an amount greater than the design tolerance, another segment was introduced into the solution. If the transition from one stationary state to another had not occurred close to that moment, the discrepancy between predicted and observed N-curves would have grown too large. This indicates that the theory works similarly well during the transitions between states as it does during periods of stationary flow. Note in particular that the change in trend between states (positive or negative) seems to propagate cleanly and sharply from observer to observer, in agreement with the second postulate.

The overall results strongly suggest that it is possible to predict N-curves quite accurately over distances comparable with one mile and for time periods encompassing several hours without the need for calibrating a model on the day of the predictions.

3.3 Queue Formation and Dissipation

Figs. 5, 7 and 8 also shed some light on the queue formation and dissipation process. If the flow-density relation is linear for uncongested traffic (i.e., constant “free flow” speed), then an N-curve at a location *j* that has undergone several episodes of queued and unqueued traffic can be constructed in the following way. The N-curve will be the lower envelope of the predicted (queued) curve from A(8,t), obtained as described above, and the (unqueued) curve obtained by shifting N(1,t) to the right by the free-flow trip time from 1 to *j* [11]. In other words, if this version of the KW theory holds then the shifted N(1,t) curves should be above and to the left of the shifted queued curves obtained from A(8,t) when traffic is queued, and they should be below and to the right at other times. The reader can easily verify from Figs. 5, 7 and 8 that this is the case (approximately) with our data.

3.4 Single Shift Method

Predictions did not change much with the piecewise linear $\kappa(q)$ curves; therefore a linear relationship between normalized accumulation and flow seems reasonable for the conditions of the site in [8]. We have already seen that when this relationship is linear, the downstream A-curve can be translated as a whole, in a single shift, upward and to the right in order to construct any of the upstream A-curves. Because the shift is independent of the piecewise linear approximation used for the N-curve, the procedure can be applied to an N-curve with as many breakpoints as desired; i.e. it can be applied to the raw data curve. This simplifies matters further. We will refer to this methodology as the “single shift” method. An advantage of this method is that it can be applied without smoothing the data and therefore can be used for real-time predictions.

This method worked well and a sample of the results are shown in Fig. 9, including corrections for the inhomogeneity in the road between observers 3 and 4. Over short distances, the predicted N-curves matched the true N-curves well. However, over longer distances, the maximum deviations in predictions appeared to be just slightly larger than the maximum deviations using the linear approximation procedure. This occurred because the KW wave does not correlate well the detailed wiggles in the curves near the bottleneck with those upstream of it, as noted qualitatively in [8]. This suggests that the finer details of the N-curves do not propagate as a simple KW wave at our site, although their gross behavior does. Fortunately, it is this gross behavior that is the most important determinant of traffic backups and the necessary control responses.

4 CONCLUSION

The results presented here suggest that, even when queued traffic appears to behave in a manner that is inconsistent with the kinematic wave theory on a fine level of detail, a reproducible relationship between normalized accumulation and flow exists. The results also suggest that it is possible to predict vehicle accumulations and queues approximately on a coarse level of detail.

Cumulative counts inside queues were predicted with errors bounded by an acceptable error in the input data. Error tolerances of sixteen and nineteen vehicles in the input data led to smaller prediction errors with only one exception, despite the long duration of the study. We also observed that predictions did not deteriorate appreciably during the transition between states; i.e. that these transitions seem to propagate sharply through the traffic stream.

It is also important to remember that the test site is a single lane road with no passing. The experiment should be repeated with data from multi-lane highways to see which of the phenomena also occur there. However, given the fact that the methodology performed well for this site, where individual drivers can have a more significant impact, it is not unreasonable to expect that time-dependent backups can also be predicted similarly well (or perhaps even better) on facilities where passing is possible.

We still do not know what is it that drivers do to generate some of the patterns observed in our data. For example, in Fig. 1b we observed that the acceleration wave was transmitted sharply from the traffic signal to the downstream-most observer and that the deceleration toward the end of the queue was not. It is possible that this could be explained if most drivers were to decelerate in two stages: (i) first taking their foot off the acceleration pedal (coasting) as soon as they recognized that they would have to stop (e.g., because they can see the signal and/or many vehicles ahead), and (ii) waiting to apply the brakes until the last minute. The signal to coast would then be transmitted very rapidly and the signal to brake more slowly. The passage of the coasting signal past observer 8 would be marked by the beginning of the curvature of each cusp, and the passage of the braking signal by the end of the curvature. If this were true, one would expect these curved cusps to grow from one observer to the next (e.g. from 8 to 7) and this appeared to happen in most cases.

We also observed that the acceleration shocks did not always remain sharp. We note that the traffic signal could be seen by drivers from location 7 (1/4 mile away), but not from location 6 (1/2 mile away). This suggests that drivers may have been motivated to not miss the ‘green’ phase when they were close to the signal and that they might have driven differently farther upstream. This could lead to an erratic pattern of wave propagation.

In addition, we do not understand the source of the long period oscillations observed at locations 4, 3 and 2 on both days, and whether this is a peculiarity at our site. Thus, it is important to look into these issues further, both with this data set and at other sites, and we hope that the results in this paper will encourage others to verify or disprove our findings in the future.

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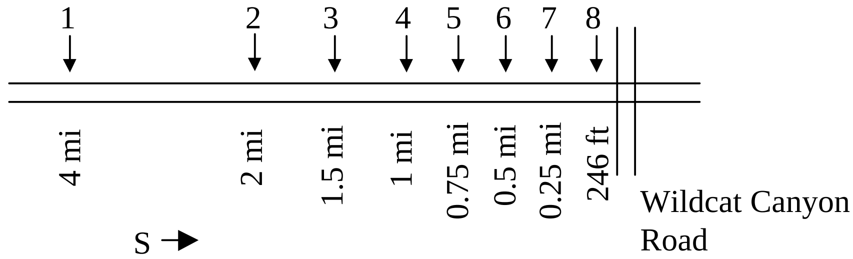
LIST OF FIGURES AND TABLES

(a)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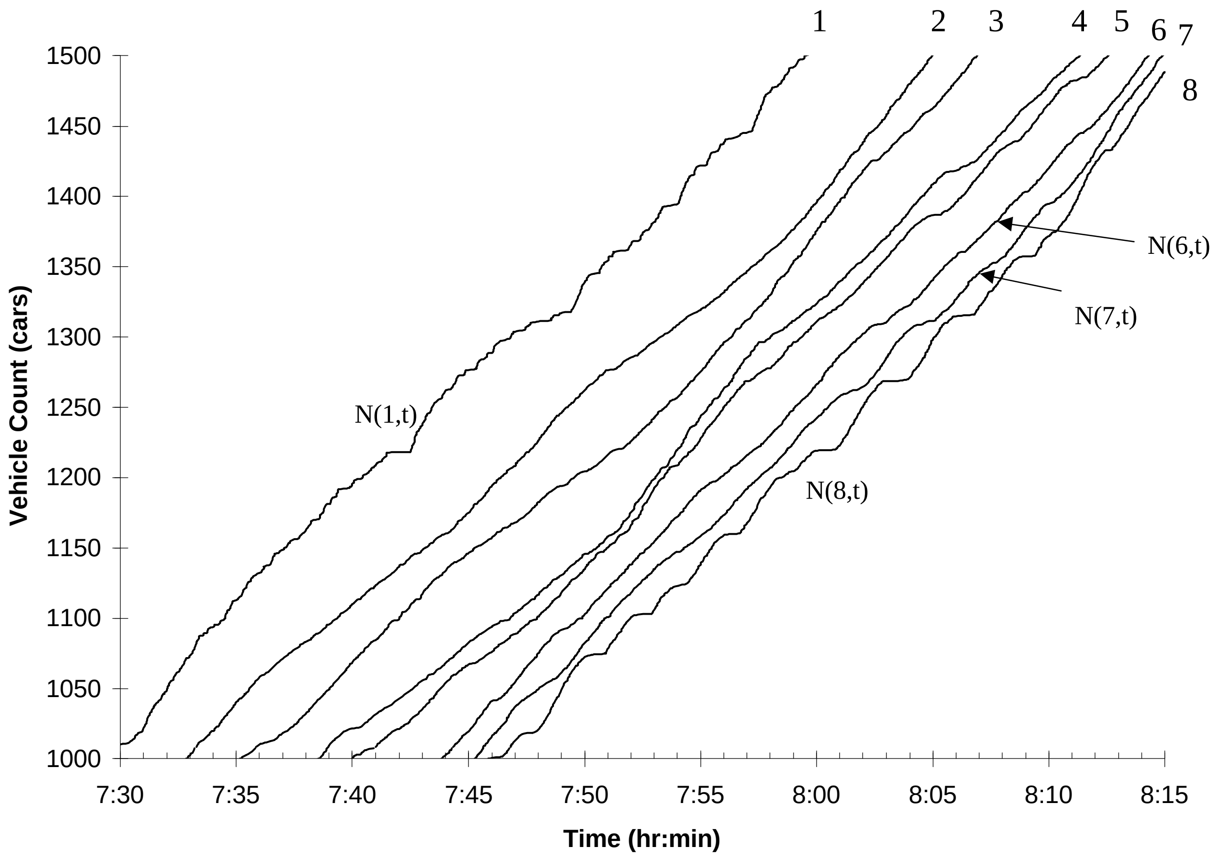
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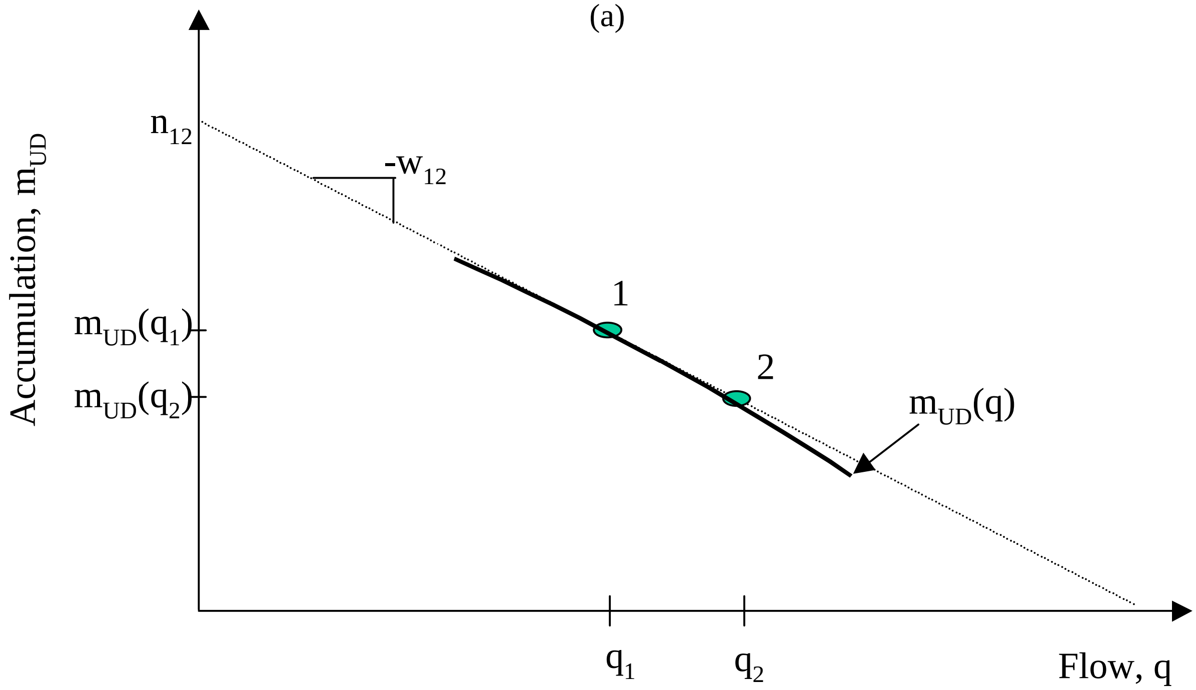
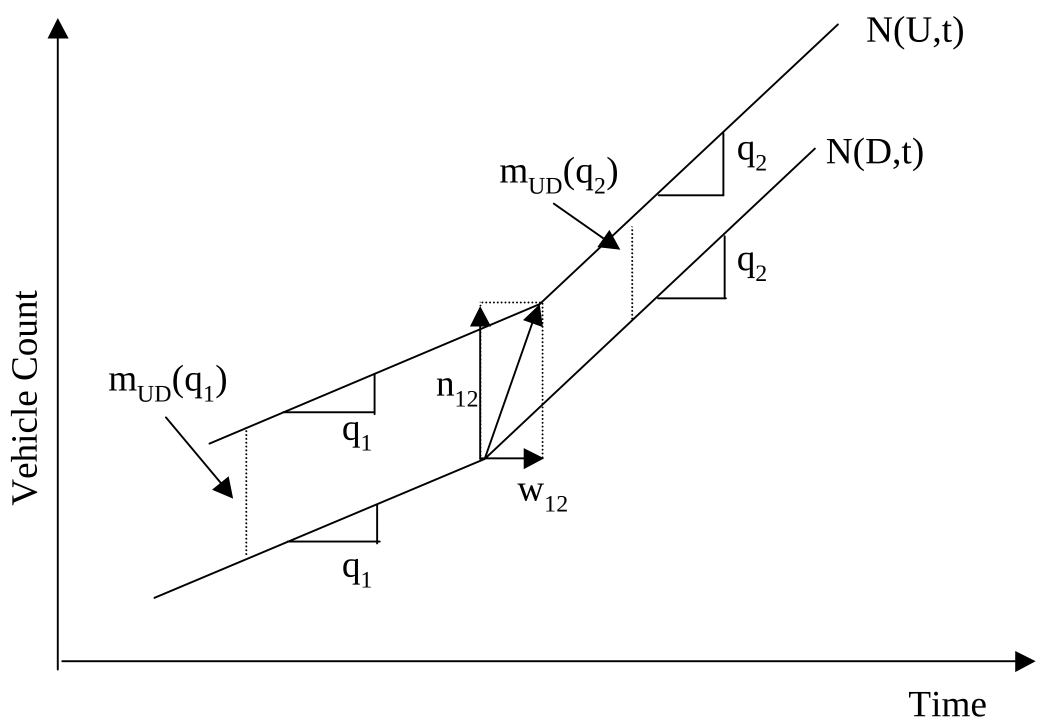
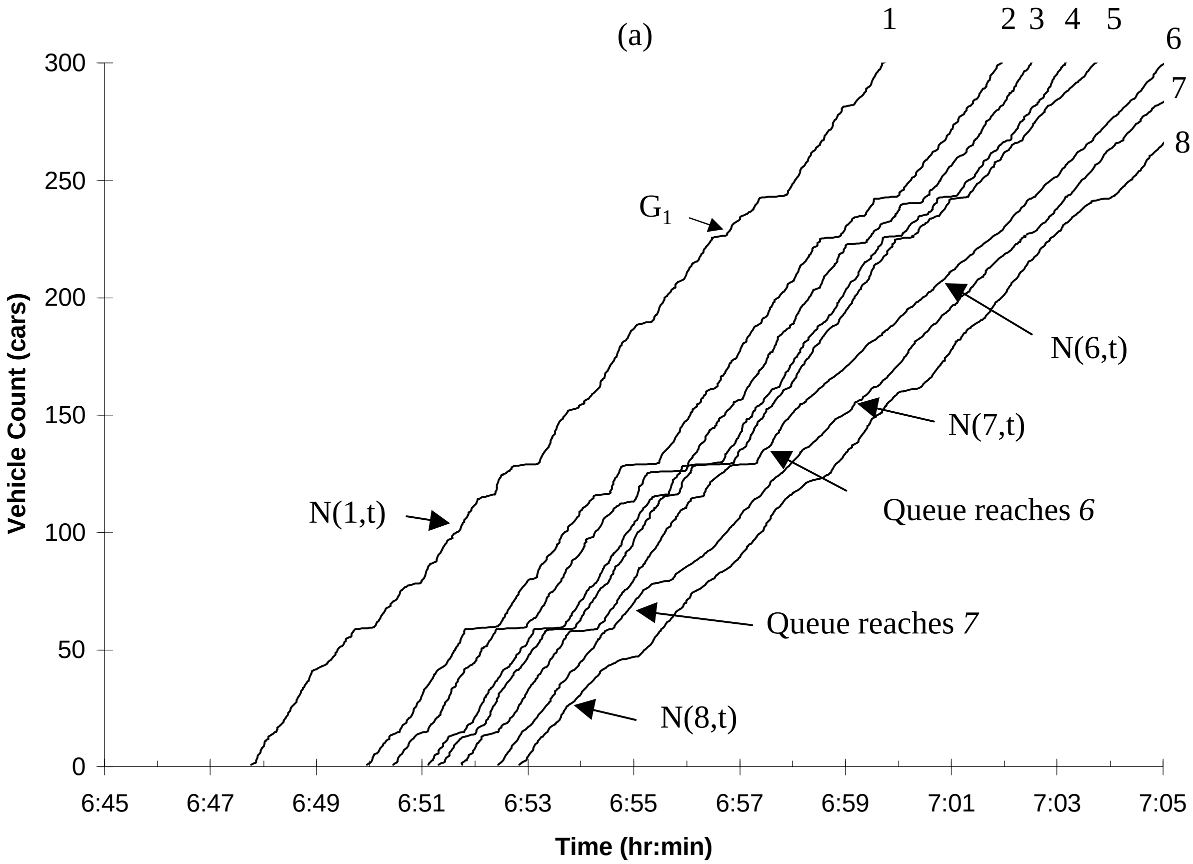
7
8
N(1,t)
N(6,t)
N(7,t)
N(8,t)
Vehicle Count (cars)
1500
1450
1400
1350
1300
1250
1200
1150
1100
1050
1000
7:30
7:35
7:40
7:45
7:50
7:55
8:00
8:05
8:10
8:15
Time (hr:min)

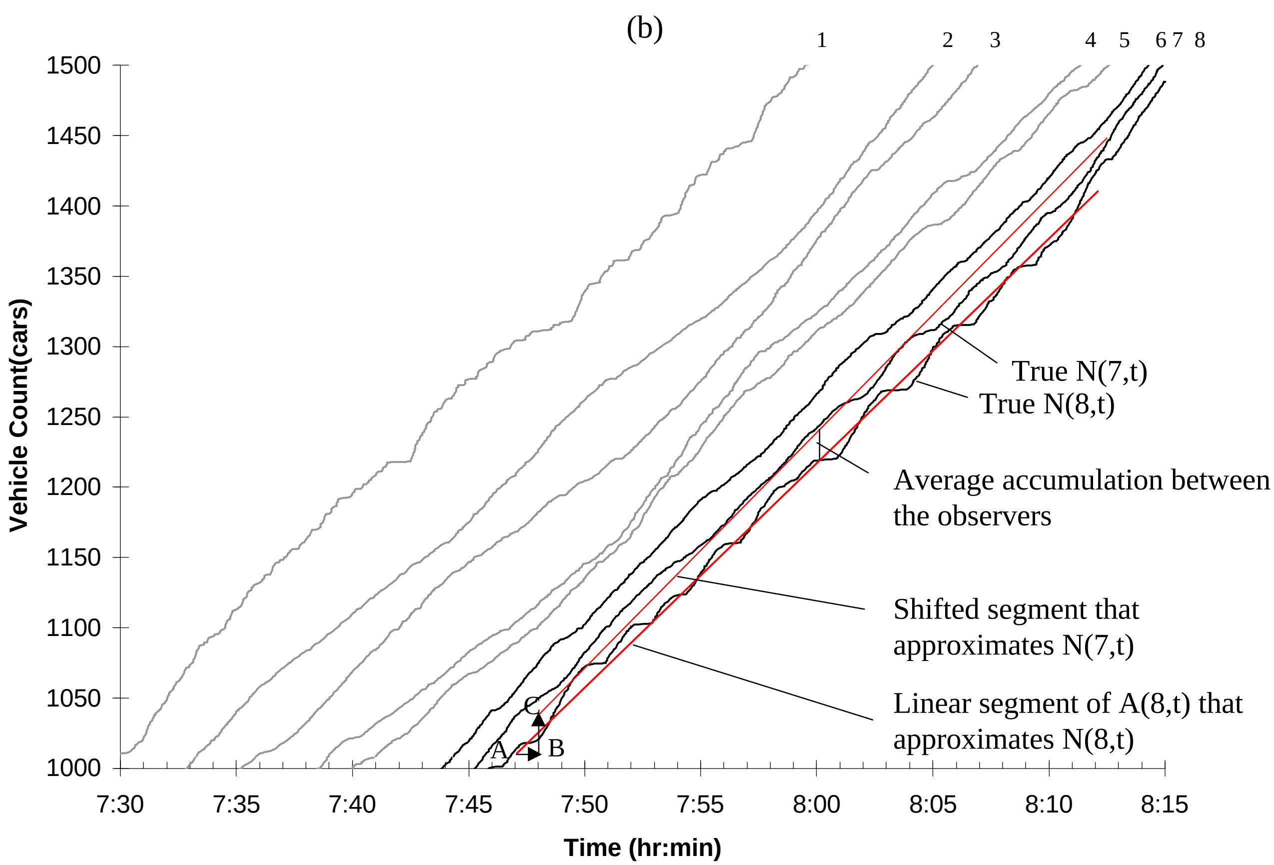
(a)


Accumulation, m_{UD}
n_{12}
$-w_{12}$
1
2
$m_{UD}(q_1)$
$m_{UD}(q_2)$
$m_{UD}(q)$
q_1
q_2
Flow, q

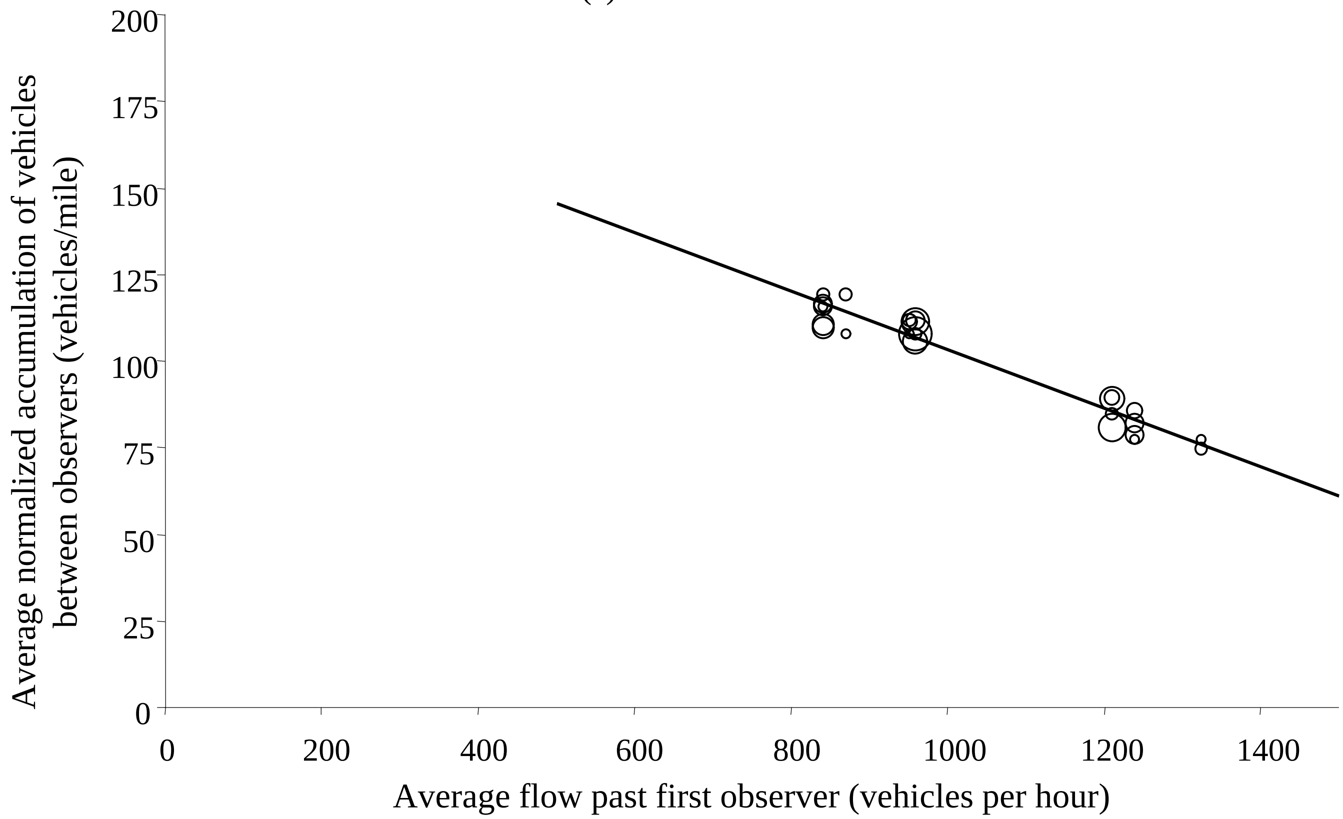
(b)


N(U,t)
N(D,t)
$m_{UD}(q_2)$
q_2
q_2
$m_{UD}(q_1)$
n_{12}
q_1
q_1
w_{12}
Vehicle Count
Time

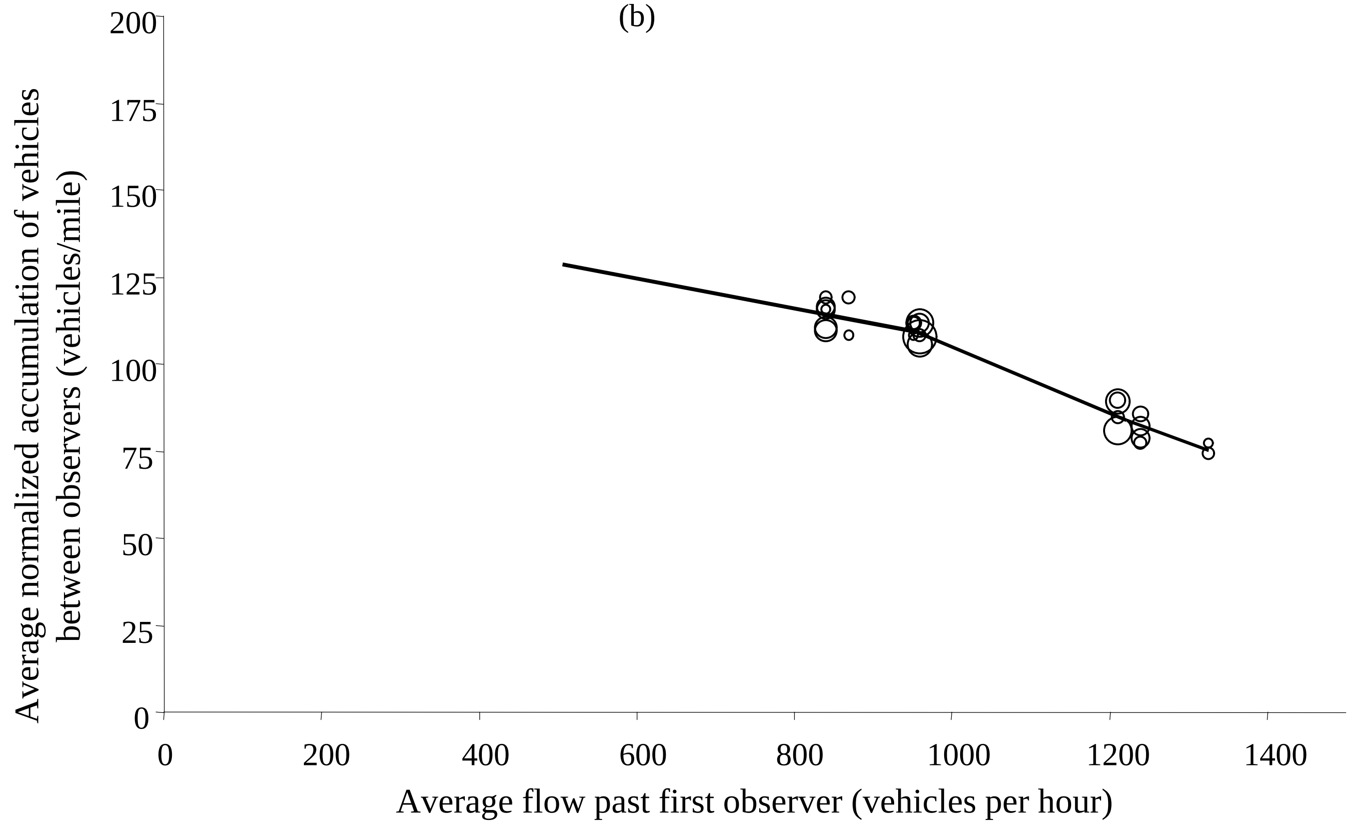

(a)
1
2 3 4 5
6
7
8
300
250
200
150
100
50
0
Vehicle Count (cars)
G1
N(1,t)
N(6,t)
N(7,t)
Queue reaches 6
Queue reaches 7
N(8,t)
6:45
6:47
6:49
6:51
6:53
6:55
6:57
6:59
7:01
7:03
7:05
Time (hr:min)

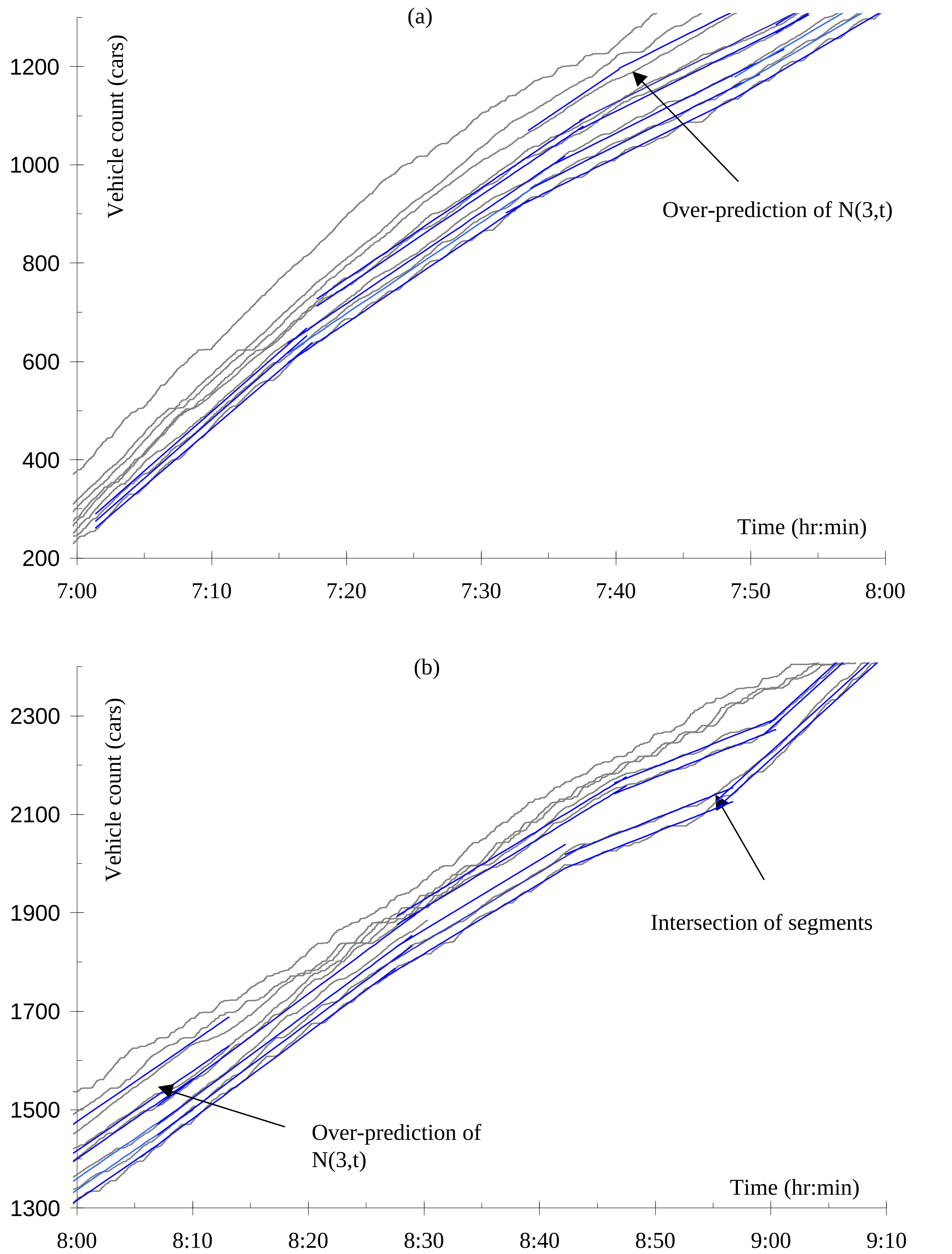

(b)
1
2
3
4
5
6 7 8
1500
1450
1400
1350
1300
1250
1200
1150
1100
1050
1000
Vehicle Count(cars)
True N(7,t)
True N(8,t)
Average accumulation between the observers
Shifted segment that approximates N(7,t)
Linear segment of A(8,t) that approximates N(8,t)
C
A
B
7:30
7:35
7:40
7:45
7:50
7:55
8:00
8:05
8:10
8:15
Time (hr:min)

(a)

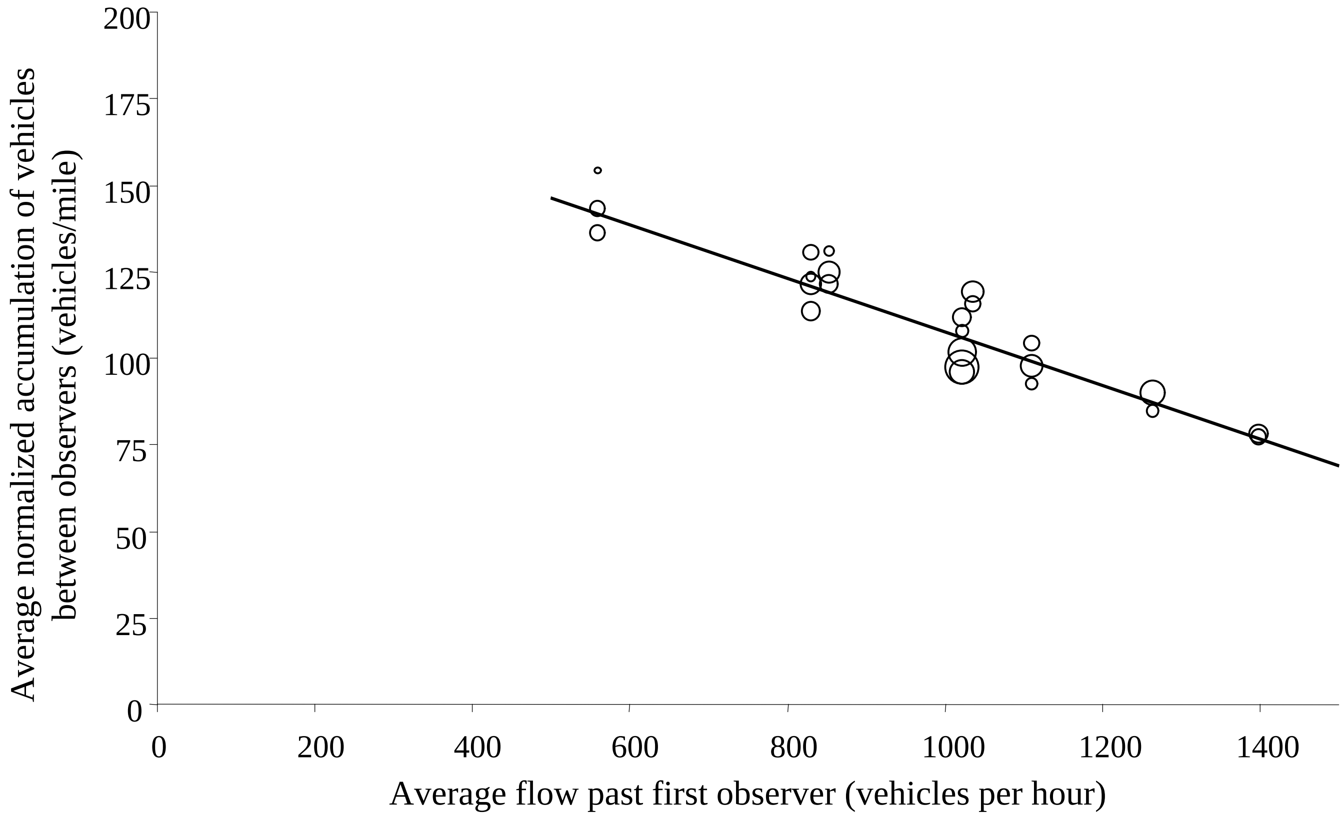

200
175
150
125
100
75
50
25
0
Average normalized accumulation of vehicles between observers (vehicles/mile)
0
200
400
600
800
1000
1200
1400
Average flow past first observer (vehicles per hour)

(b)


200
175
150
125
100
75
50
25
0
Average normalized accumulation of vehicles between observers (vehicles/mile)
0
200
400
600
800
1000
1200
1400
Average flow past first observer (vehicles per hour)

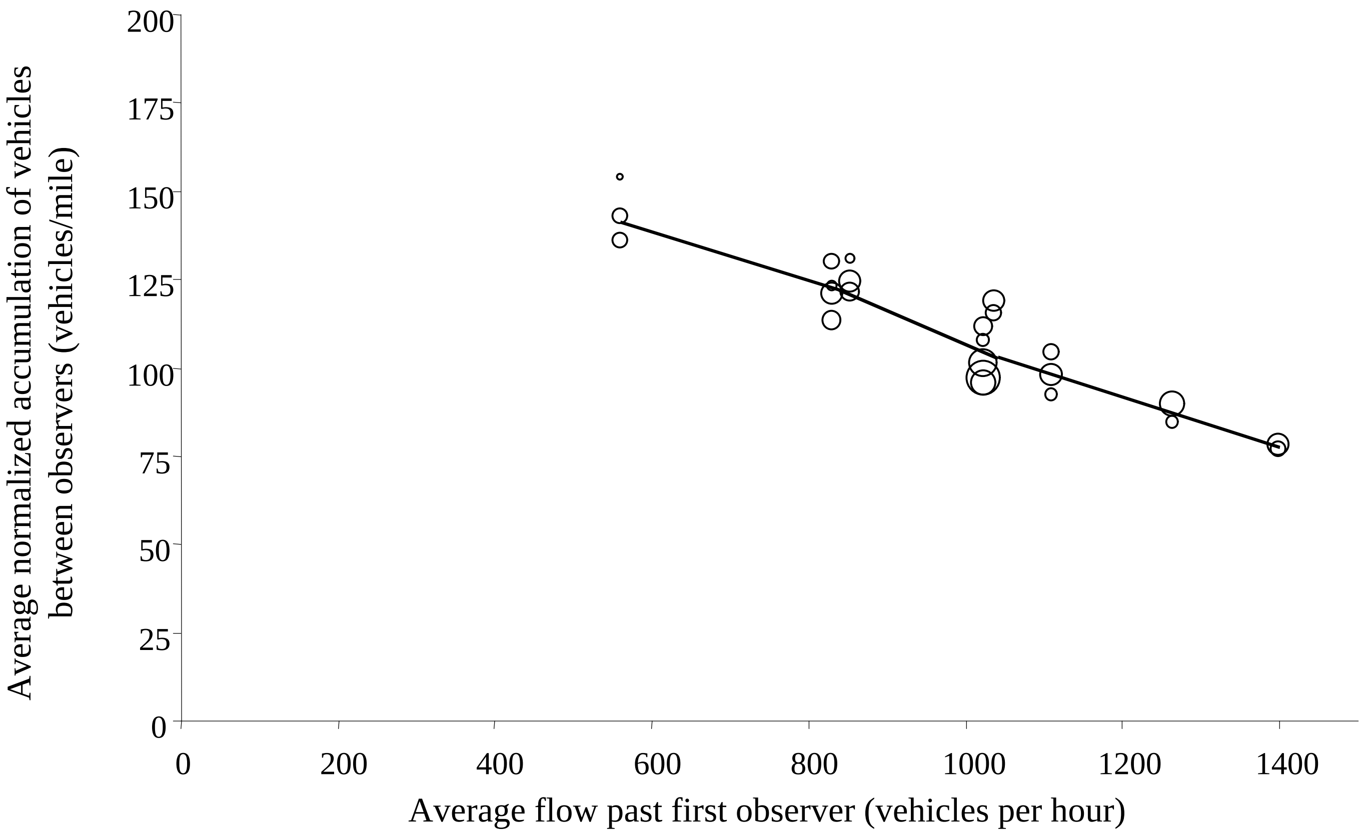

(a)
Vehicle count (cars)
1200
1000
800
600
400
200
Over-prediction of N(3,t)
Time (hr:min)
7:00
7:10
7:20
7:30
7:40
7:50
8:00
(b)
Vehicle count (cars)
2300
2100
1900
1700
1500
1300
Intersection of segments
Over-prediction of N(3,t)
Time (hr:min)
8:00
8:10
8:20
8:30
8:40
8:50
9:00
9:10

(a)

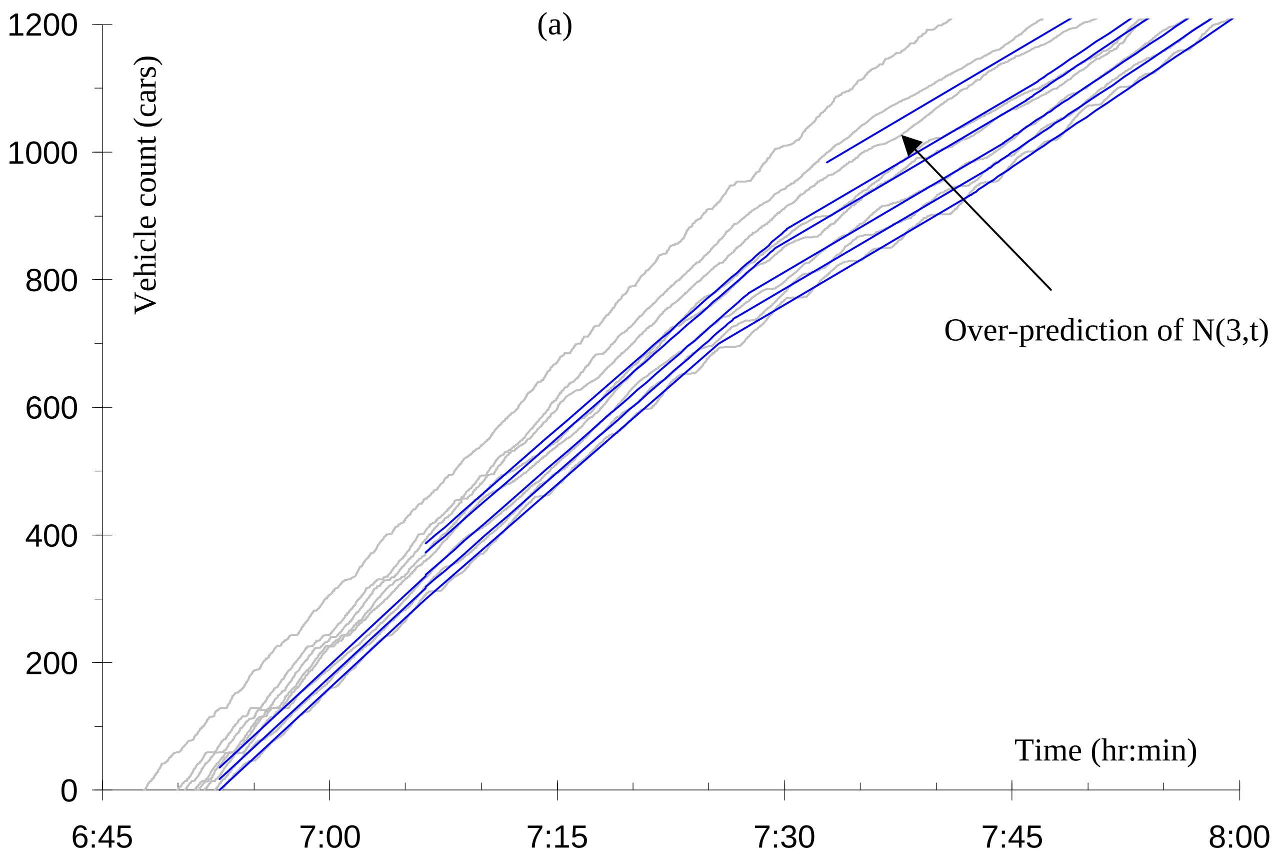


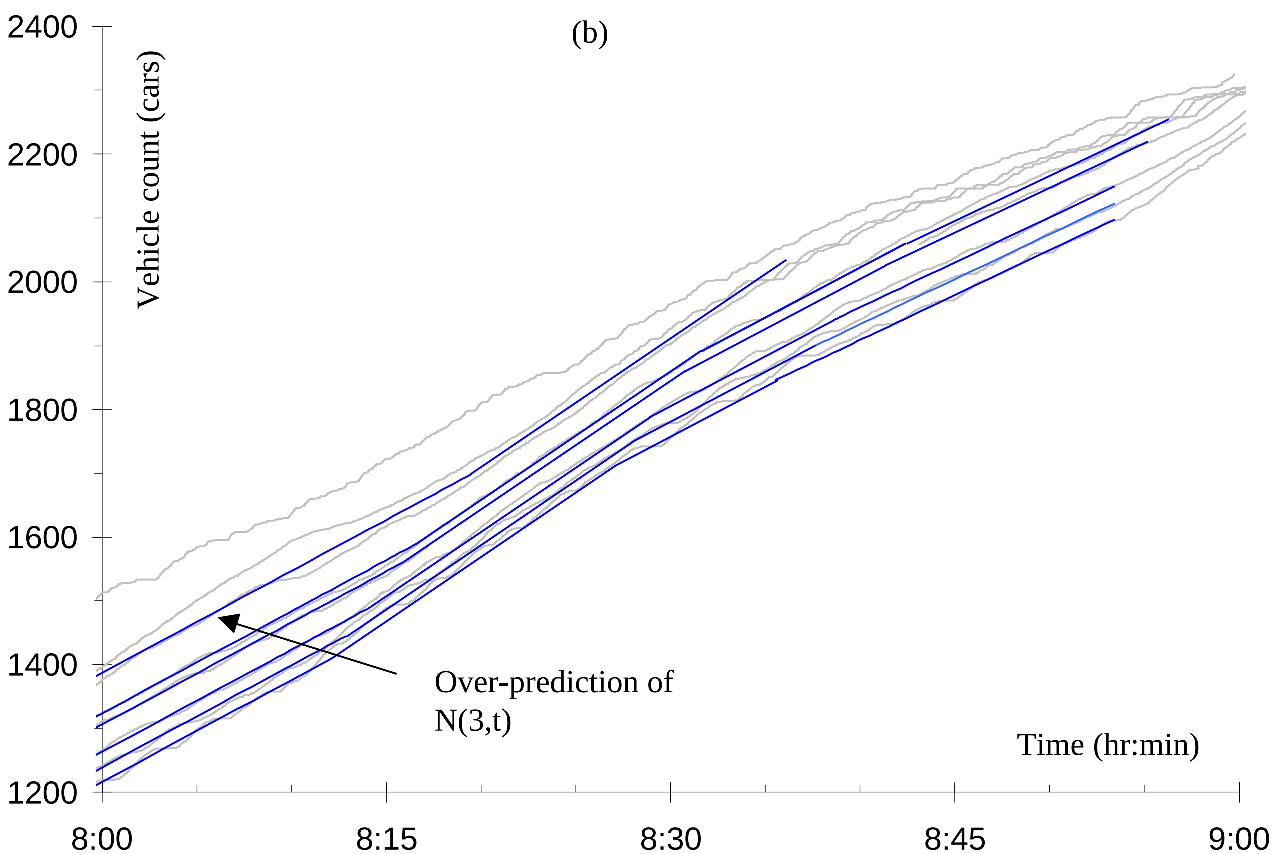
Average normalized accumulation of vehicles between observers (vehicles/mile)
0
25
50
75
100
125
150
175
200
0
200
400
600
800
1000
1200
1400
Average flow past first observer (vehicles per hour)

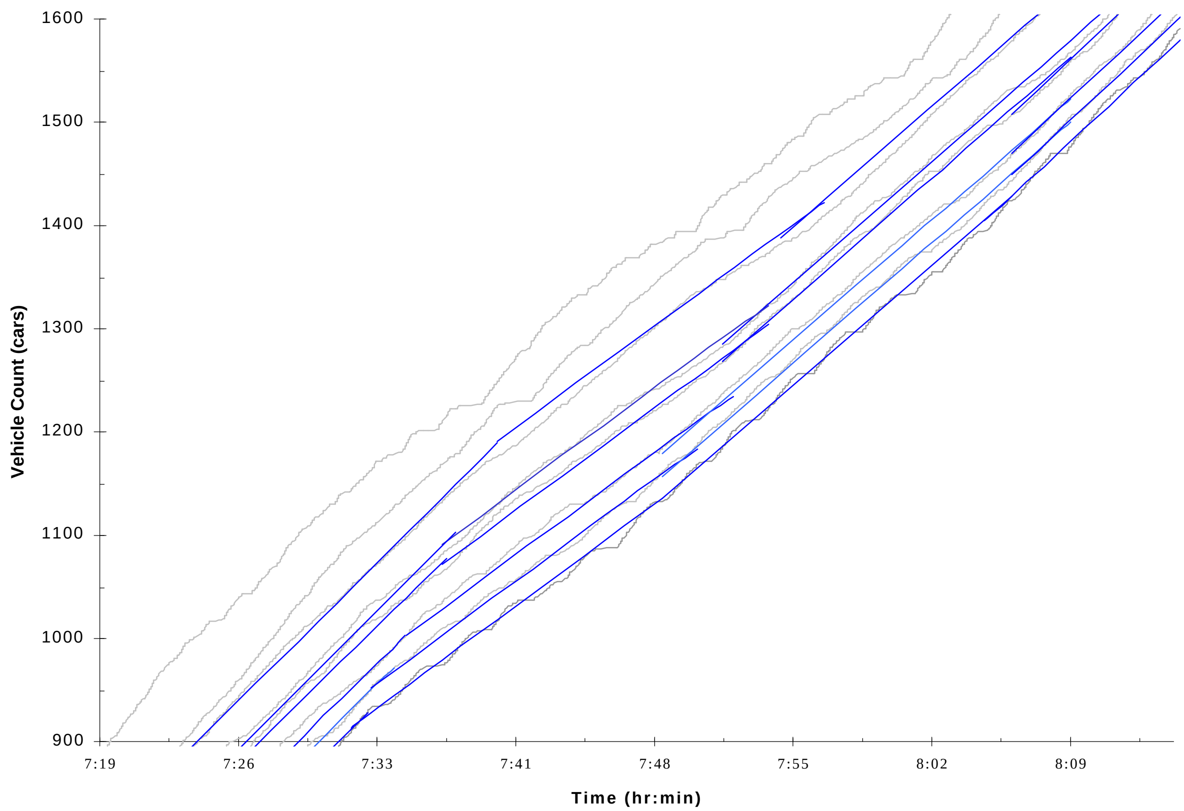
(b)

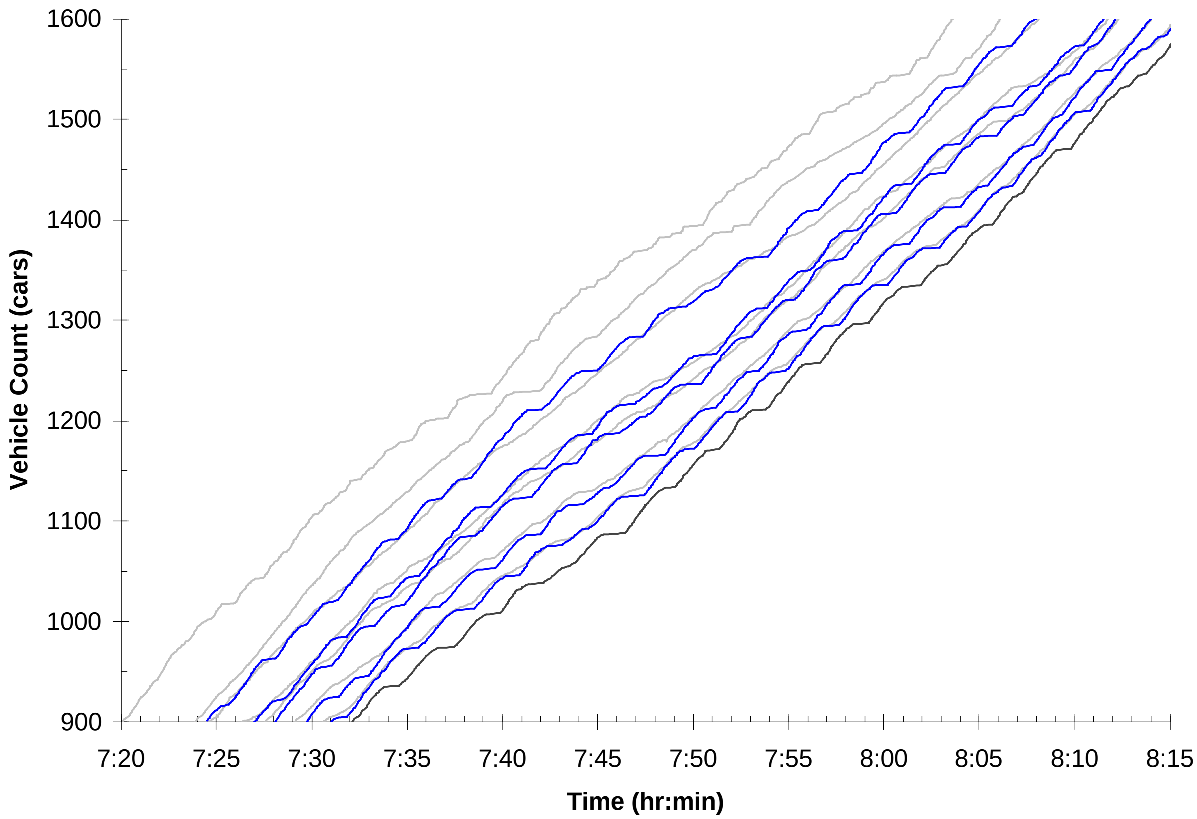


Average normalized accumulation of vehicles between observers (vehicles/mile)
0
25
50
75
100
125
150
175
200
0
200
400
600
800
1000
1200
1400
Average flow past first observer (vehicles per hour)


(a)
Vehicle count (cars)
1200
1000
800
600
400
200
0
Over-prediction of N(3,t)
Time (hr:min)
6:45
7:00
7:15
7:30
7:45
8:00


(b)
Vehicle count (cars)
2400
2200
2000
1800
1600
1400
1200
Over-prediction of N(3,t)
Time (hr:min)
8:00
8:15
8:30
8:45
9:00


1600
1500
1400
1300
1200
1100
1000
900
Vehicle Count (cars)
7:19
7:26
7:33
7:41
7:48
7:55
8:02
8:09
Time (hr:min)


1600
1500
1400
1300
1200
1100
1000
900
Vehicle Count (cars)
7:20
7:25
7:30
7:35
7:40
7:45
7:50
7:55
8:00
8:05
8:10
8:15
Time (hr:min)

N-Curve	**Maximum Deviation (number of vehicles)**	
	First Day	Second Day
Input		
N(8,t)	16 vehicles	19 vehicles
Predicted Curves		
N(7,t)	< 16 vehicles	17 vehicles
N(6,t)	19 vehicles	13 vehicles
N(5,t)	< 16 vehicles	16 vehicles
N(4,t)	< 16 vehicles	19 vehicles