Using Municipal Vehicles as Sensor Platforms to Monitor the Health and Performance of the Traffic Control System

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1 Introduction

Estimates of existing traffic volumes are used as inputs to multiple transportation-related planning and design studies, for example, network level mobility trend analysis, travel demand model calibration, level-of-service studies, and signal timing. Presently, the data that are used for such estimates are almost entirely collected by fixed-location traffic studies. In these fixed-location studies, an individual or an automatic sensor (a pneumatic road tube or a magnetic loop detector, for example) is stationed at a specific point location on a roadway segment to determine the number of vehicles that pass the point during an extended time interval. It is infeasible to deploy fixed-location sensors or human observers on every segment of spatially extensive urban networks. As a result, data are collected on very few roadway segments in an urban area. For the segments where data are collected, updates are generally conducted on an infrequent basis, possibly resulting in erroneous estimates of traffic volumes, which in turn can lead to increased traveler delay, fuel consumption, and pollutant emissions from poor design and operations decisions. For example, in Appendix 1, a numerical analysis is presented to indicate the increased vehicle delays at a typical signalized intersection that would result from erroneous traffic volume inputs.

With the increasing availability of portable and low-cost automatic sensors that can be mounted on vehicles, this project was designed to investigate the potential of obtaining traffic data from sensors on municipal vehicles operating in the traffic streams as "mobile sensing platforms." The public nature of municipal vehicle fleets would facilitate the collection and availability of the data for urban transportation planning and design. In addition, the size of some fleets would increase the spatial and temporal coverage of these mobile sensing platforms.

The increasing use of video cameras on transit buses in regular operation that was occurring near the beginning of the project motivated a focus on the use of video data collected from fixed-schedule transit buses to estimate roadway traffic volumes. Since the video sensors are implemented for other purposes of interest to the transit agencies – namely, safety, security, and liability – there would be low, if any, additional cost for sensor installation and deployment. In addition, transit bus fleets cover most important roadways in an urban area, which responds directly to the short-coming of presently used, fixed-location traffic studies. However, unlike in traditional fixed-location data collection, data collected from transit buses in operation – or for any mobile sensor operating in the traffic stream – would be of very short duration for an individual pass of the sensor past a roadway of interest. However, fixed-schedule transit buses regularly and repeatedly traverse the same segments many times per day and day after day. It is hypothesized that this repeated coverage would allow a large number of independent observations of traffic that could be aggregated to diminish the shortcoming of the short duration of the observation interval associated with a single pass.

In this study, sets of video imagery are obtained from transit buses in regular service on The Ohio State University campus and processed into time-of-day traffic volume estimates on major campus roadways. The traffic volume estimates are obtained from vehicles identified in the video imagery using an approach previously developed by the investigators to translate vehicles identified from sensors mounted on mobile platforms into traditional traffic volume estimates. Hourly volumes estimated from the processed video imagery are compared to hourly volumes obtained from concurrently collected road tube data. The results are seen to be encouraging and agree with the underlying hypothesis that volumes obtained from bus-based imagery are similar to short-duration traffic counts, which will be noisy for any one observation but which can lead to good estimates of time-of-day traffic volumes when aggregated over the multiple observations that can be obtained from a transit bus. When longer time-of-day periods are considered or when the volume estimates are used to produce estimates of vehicle distance travelled across a set of roadway segments, performance of the estimates obtained from the video imagery improves further.

In addition to showing the promise of using already available video imagery obtained at low cost from transit buses in regular service, this study included important educational and outreach components. Specifically, the empirical validation study used to assess the performance of the proposed approach was designed in the context of a term project for a transportation data acquisition and analysis class. The term project was conceived, designed, and implemented – and refined and repeated in the subsequent offering of the class – as a result of the research validation study. Empirical data obtained were used both for the research study and as the basis of the term projects. From an outreach perspective the estimates of vehicle distance travel determined for the research study were disseminated to transportation planners and administrators at The Ohio State University as the only such estimates that presently exist for the campus.

The rest of this report is organized as follows. The approach used to estimate traditional traffic volumes from vehicles identified from a sensor mounted on a mobile platform is explained in Section 2. In Section 3.1, the video data used in the empirical study are described, along with the software and steps used to preprocess the data for traffic volume estimation. The context and design of the empirical validation study and the multiple data sources and quantities of data are presented in Section 3.2. The encouraging results of the empirical study are described in Section 4. In Section 5, the unique education and outreach components of this project are explained. Finally, the highlights of the study and areas for future research are presented in Section 6.

2 Estimating Segment Volumes from Video Imagery

The approach used to estimate traffic volumes from vehicles observed in the video imagery of a bus pass over a segment was originally developed by the project investigators when considering the use of LiDAR data collected from sensors that would need to be installed on a sufficient number of municipal vehicles for the purpose of traffic monitoring (McCord, et al., 2017). The approach, which is illustrated in the time-space diagram of Figure 2.1, is a modification of the moving observer method (Wardop and Charlsworth, 1954) that allows for estimation of traffic volume in one direction on a roadway segment from a single pass of the bus traveling in the opposite direction on the segment. The schematic on the left of the figure depicts the segment of interest between locations x_o and x_e, with the vehicles to be detected traveling in the left lane from top to bottom ("Direction 1"), and the bus traveling in the right lane from bottom to top ("Direction 2"). The time-space diagram is presented on the right, with distance from x_o increasing from bottom to top. Therefore, the trajectory of the bus has positive slope, while the trajectories of the vehicles to be detected have negative slopes. An intersection of the bus and a trajectory of a vehicle moving in the opposite direction indicates that the bus and the vehicle are at the same location (in different lanes) at the same time. This is when the vehicle traveling in Direction 1 would be detected by the bus-based sensor traveling in Direction 2.

The bus trajectory indicates that the bus entered the segment ($x = x_o$) at time t_o and exited the segment ($x = x_e$) at time t_p. Of interest is the time $t_1 = t_p - t_o$ that the bus took to traverse the segment. In the illustration, the bus-based sensor detects four vehicles during this time, as indicated by the bus trajectory intersecting four vehicle trajectories.

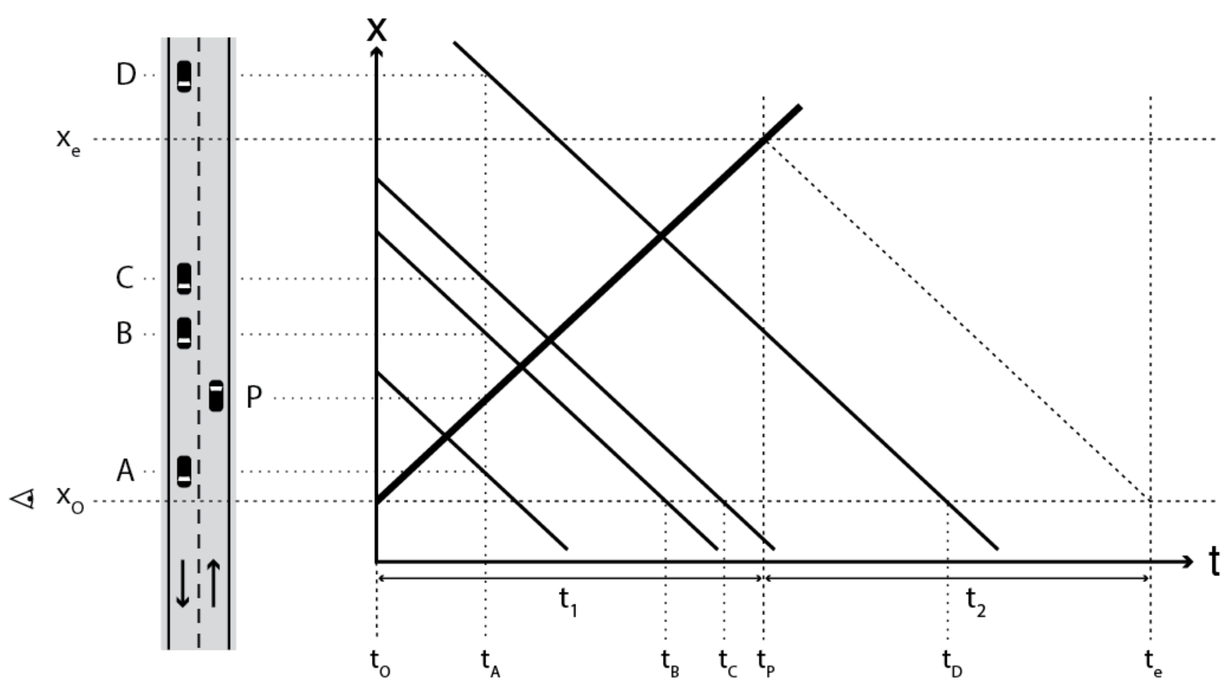

Figure 2.1: Illustration of the modified moving observer method used to estimate traffic volume from a bus traveling in the opposite direction of the traffic flow

To estimate a traffic volume, a hypothetical "virtual observer" is considered to be stationed at the downstream end of the segment. In Figure 2.1, this virtual observer is indicated by the "eyeball" located at x_o to the left of the roadway schematic. Assuming no vehicles exit the segment before reaching the downstream end of the segment where the virtual observer is assumed to be located – an assumption that is consistent with traditional, fixed-location traffic studies – all detected vehicles would eventually pass the virtual observer some time after detection by the bus-based sensor. To determine the time that the last event observed by the bus-based sensor (which could be observing a vehicle or, more likely, observing that a vehicle was not present at the time the sensor passed) would take to reach the virtual observer, a "virtual vehicle" is considered to enter the segment at this instant. The (hypothetical) trajectory of this virtual vehicle is depicted with dashes as the rightmost trajectory. Of interest is the time $t_2 = t_e - t_p$ required for this virtual vehicle to traverse the length of the segment and reach the virtual observer. This virtual vehicle travel time t_2 could be determined in several ways. Two approaches are used in the empirical validation study below.

The interval during which the virtual observer would observe the n vehicles detected by the bus would therefore be $t_1 + t_2$ (which, as evident in Figure 2.1, is the same as $t_e - t_0$), leading to a volume of n vehicles in time interval $t_1 + t_2$. Assuming that t_1 and t_2 are measured in minutes, the estimated hourly volume V^h would therefore be:

$$V^h = \frac{n}{t_1+t_2} \times 60 \tag{2.1}$$

where n is the number of vehicles (traveling in "Direction 1") detected by the bus-based sensor while the bus is traversing the segment (in "Direction 2"), t_1 is the time in minutes taken by the bus to traverse the segment in its direction of travel ("Direction 2"), and t_2 is the time in minutes it would take a "virtual vehicle" to traverse the segment in the direction of the vehicles being detected ("Direction 1").

3 Empirical Data Collection and Processing

A major emphasis in this project was placed on investigating the performance of the approach presented in the previous section to estimate roadway segment traffic volumes from video imagery obtained by transit buses in regular operation. Therefore, empirical studies were conducted to produce volume estimates from video imagery and compare the results to volume estimates obtained from traditional data collection studies. The data and the context of the empirical studies are described in this section. The results of the studies are presented in Section 4.

3.1 General Video Data Collection and Preprocessing

Video Data: The project team has a close association with The Ohio State University (OSU) Transportation and Traffic Management (TTM) and collaborates with its leadership, management, and staff on a number of initiatives. TTM is responsible for all transportation planning and operations on the OSU campus excluding parking operations. Among other functions, TTM manages the OSU Campus Area Bus Service (CABS). Before the 2020 covid-19 pandemic altered operations and ridership, in its fixed service operations the CABS fleet contained approximately forty 40-foot buses that served approximately 5 million passengers per year across 6 routes of approximately 50 route-kilometers in total length. TTM recently installed cameras on its CABS buses for safety, security, and liability purposes. (Project investigators worked with TTM on camera selection and installation, in part to allow the type of video imagery used in this project.)

TTM does not archive the CABS bus video imagery, but only uploads pertinent video files saved on a bus's hard-drive when a need arises for TTM or when a request is received by TTM for incident investigations. Given the finite storage capacity of a bus's hard-drive, the latest recorded video imagery regularly overwrites the oldest imagery saved on the hard-drive. Depending on the total number of cameras on each bus, their resolutions, the storage capacity of a bus's hard-drive, and the duration during which a bus is jn service, all of which vary across the bus fleet, a given video file remains on a bus's hard-drive between three to four weeks before it is overwritten. Because of the history of collaboration between project investigators and TTM/CABS, investigators were able to request and receive video files for specified days, times-of-day, and bus routes on several occasions. Requests were made to the TTM Transportation Systems Coordinator, the staff member responsible for operations, use, and upkeep of the video cameras on the CABS fleet. After receiving these requests, this individual would upload the specified video files from the buses' hard-drives before the video files were overwritten from ongoing video recording. He would then share the files with the project team.

At the beginning of the project, video files were received from two different cameras on a bus – a forward-looking camera mounted outside the bus on the driver's side at the rear of the bus and a forward-looking higher resolution camera mounted inside the bus behind the windshield. The positions of the two cameras on the bus and example frames are shown in Figure 2.2. After experimenting with both cameras, the project team decided that the improved resolution of the inside, windshield camera would be of only marginal benefit and would not warrant the increased handling difficulties that resulted from the large file sizes. Therefore, video from the side-mounted camera was subsequently requested from TTM and is used in the empirical studies presented below.

Figure 2.2: Driver's side exterior and windshield interior cameras mounting locations and sample frames

3.2 Targeted Empirical Study: Design and Data

3.2.1 Overview

A targeted empirical study was designed to compare roadway traffic volumes estimated from video imagery to traffic volumes estimated from traditional data collection studies. This targeted study was designed in the context of a class term project in Autumn 2018 and repeated in the subsequent offering of the class. The setting of the class project is described in Section 5, where the education and outreach components of this project are explained. Here, the design of the study for the research investigation of performance is presented. Results of the investigation are presented in Section 4.

The empirical study consisted of estimating traffic volumes from bus-based video imagery between 7 a.m. to 7 p.m. on October 25, 2018 on a network of major roadway segments on The Ohio State University campus and comparing these estimates to traffic volumes estimated from traditionally collected, fixed-location traffic counts for the same roadway segments during the same time period. The network of roadway segments is depicted in Figure 3.1. This network consists of 21 bi-directional roadway segments, and therefore 42 directional roadway segments, which total 6.26 directional miles.

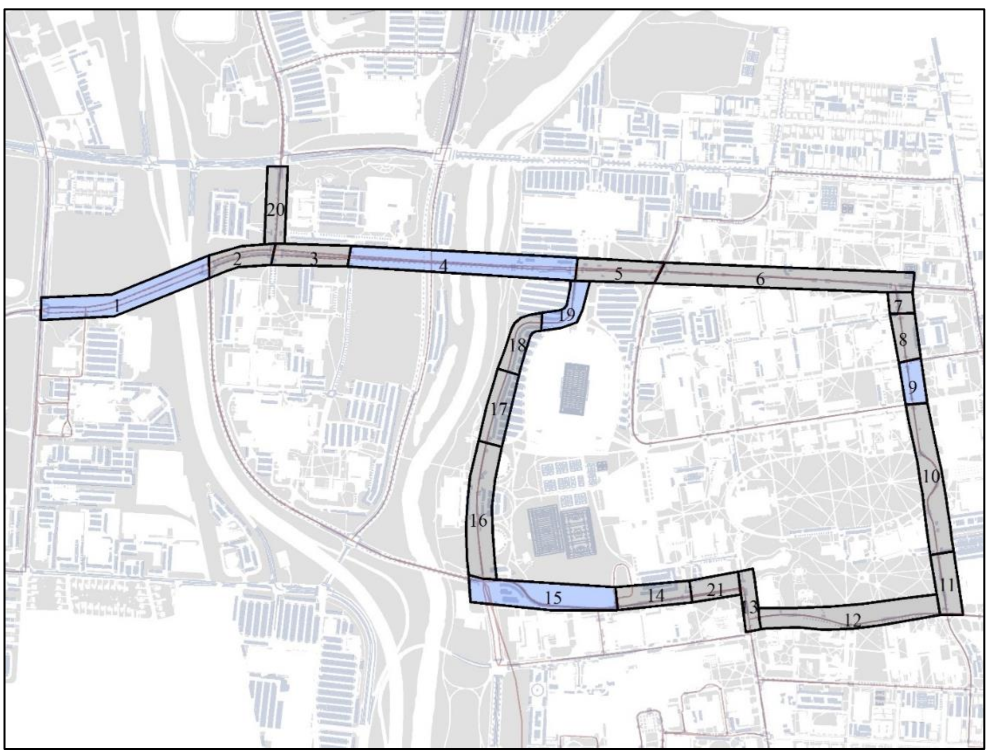

Figure 3.1: OSU roadway network used in 2018 empirical study; numbers refer to segment numbers; blue shading indicates segments where road tubes were placed

The class project was repeated, with slight variations in Autumn 2019. The network of segments of interest in that project was expanded to the 7.86-directional mile network illustrated in Figure 3.2, and the hours of analysis were reduced to 8 a.m. to 6 p.m. to allow coverage of the limited number of manual data collectors over this his expanded network (see below).

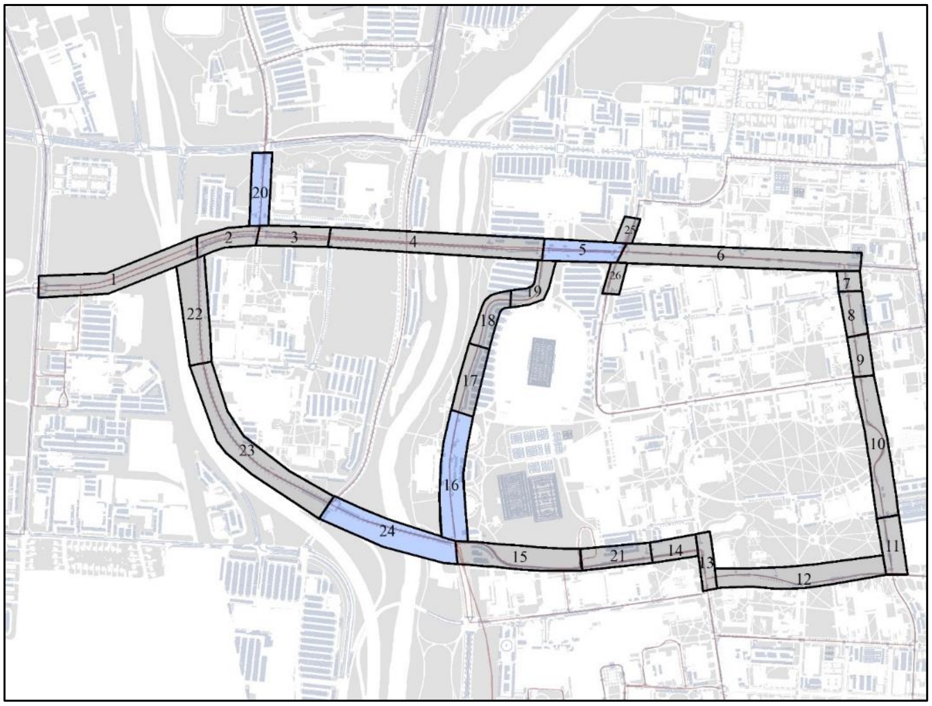

Figure 3.2: OSU roadway network used in 2019 class project; numbers refer to segment numbers; blue shading indicates segments where road tubes were placed

3.2.2 Data Collection

Video Data: For the 2018 study, approximately 60 hours of total video were obtained on October 25, 2018 from 6 different buses on 3 different bus routes that collectively covered all the segments of interest in the study between 7 a.m. and 7 p.m. on the day of the study. For the 2019 study, 72 hours of video were obtained on October 24, 2019 from 6 different buses on 5 different bus routes that collectively covered all the segments of interest in the study between 8 a.m. an 6 p.m. on the day of the study.

Manual Traffic Counts: Pairs of students in the class were assigned to conduct manual traffic counts for specified segment-hours to cover a subset of the large number of segment-hours, as would be done in a typical small network traffic study. (Different pairs of students were formed for different times based on availability.) In addition, funded undergraduate and graduate students working in the Campus Transportation Lab assisted with data collection. Specifically, 54 and 49 segment-hours of manual traffic counts were obtained, respectively, from among the total 252 (21 segments x 12 hours) and 260 (26 segments x 10 hours) segment-hours of interest in the 2018 and 2019 studies.

Working in teams of two, human data collectors recorded traffic volumes using the common short-break and alternating count approaches to manual data collection. Specifically, a pair of students would record a 4-minute traffic volume in one direction on a segment, break for one minute to rest and ensure proper data entry, then record a 4-minute traffic volume in the other direction on the same segment, break again for one minute, then record a 4-minute traffic volume in the original direction, and so on. This approach was begun five minutes before the hour of interest and continued until five minutes after the hour of interest to allow for interpolation of all 5-minute intervals not directly observed because of the alternating counts.

Road Tube Traffic Counts: Long-standing relationships between the project investigators and the Mid-Ohio Regional Planning Commission (MORPC), which serves as the Metropolitan Planning Organization for the Central Ohio area, led to MORPC agreeing to lay road tubes on five segments on the October 25, 2018 and October 24, 2019 study dates. MORPC agreed to collect these counts if counting the segments was of interest to MORPC's ongoing planning efforts. Discussions led to agreement as to locations that were of mutual interest to MORPC, to the research tasks, and to the class project. Five locations were selected in each year, with all five segments being located on the project network in 2018 (see Figure 3.1) and four segments being located on the project network in 2019 (see Figure 3.2) The fifth road tube segment in 2019 is a major arterial on the border of campus that carries large volumes of through traffic. This segment was not of interest for the targeted class project but will be of interest in future investigations because of its different traffic characteristics. The MORPC road tubes recorded 15-minute traffic volumes in each direction of the segments for the entire day of the project.

3.2.3 Data Processing and Volume Estimation

Video Data: A Graphical User Interface (GUI) previously developed by the project team was used to semi-manually process video data into information that could be used to estimate vehicle volumes on specified segments. Figure 3.3 shows two example images of the GUI. It presents the video with a reference line superimposed across the road, along with a suite of buttons for the user to enter data and control the video. A user records a vehicle passage by pressing a key any time a vehicle crosses the reference line, and the corresponding frame number is stored as a vehicle observation for later processing. The video controls include navigation controls (e.g., play/pause, slider to select position in the video), file controls (e.g., open, save), and data recording controls (e.g., vehicle passage, undo last record).

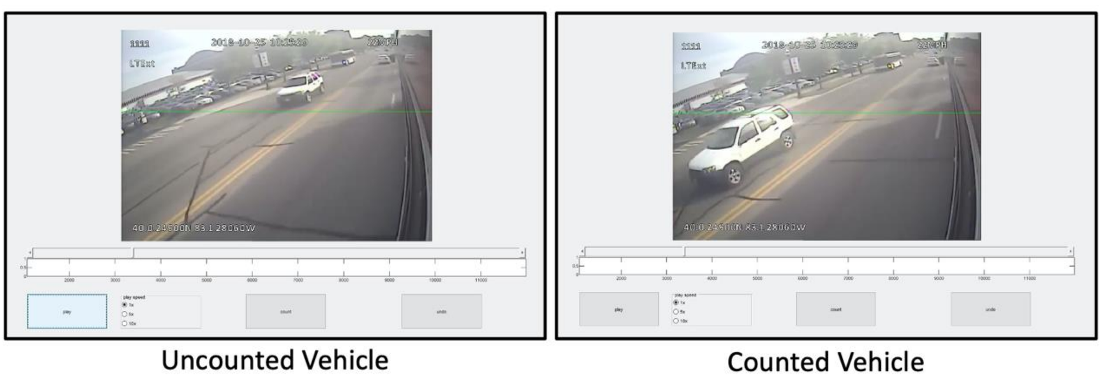

Figure 3.3: Example images of the GUI used to record vehicle observations

The GUI was used to implement three steps involved with extracting data from the video imagery and forming inputs to the estimation approach described in Section 2. The first step involves "clipping" the video files to eliminate long stretches of imagery recorded by the bus's camera when the bus was travelling on segments not of interest for analysis. The second step consists of determining the video frame numbers at which the various roadway segments began and ended. This is done by watching the video, usually in sped up mode, and identifying when the bus began or ended a segment. A few undergraduate student researchers who are familiar with the bus routes conducted this step after training by an experienced graduate student researcher. In the third step, a student watches the video, sometimes in sped up mode (depending on the traffic conditions) and clicks when a vehicle is seen crossing the reference line in the direction opposite that of the movement of the bus. This step was conducted by student research assistants and students enrolled in the course, as part of their term project, after they were trained by experienced student researchers and the course instructors, who are project investigators. (It is noted that the second and third steps can be done in either order.) Using this process, approximately 40 hours of video were prepared for the validation study reported below.

The output of these three steps produced, for each roadway segment-direction and bus pass, the number of vehicles *n* detected on the segment-direction and the frame numbers at the beginning and end of the segment-direction. Using the frame rate (10 frames per second for the side camera used in the empirical study), the difference in end frame number and beginning frame number on the bus pass of the segment-direction can be converted to the time t_1 that the bus took in traversing the segment-direction on the pass. As described in Section 2, different approaches can be used to estimate the time t_2 of the virtual vehicle on a bus pass. Two approaches are used in the empirical studies reported below. One approach – designated "$t_2 = t_1$" – determines t_2 for a pass as t_1, the time taken by the bus to traverse the segment (in the opposite travel direction of the virtual vehicle) on the pass. The second approach – designated "$t_2 = SL\text{-}time$" – approximates t_2 for a pass as the distance of the segment divided by the speed limit. (More refined approaches for determining t_2 are left for future research.) With these values of n, t_1, and t_2, Equation (2.1) can then be used to calculate two hourly volume estimates (one for each of the two approaches used to determine the value of t_2) for each bus pass of the segment-direction.

<u>Manual Traffic Counts</u>: As discussed above, 54 and 49 segment-hours, and therefore 108 and 98 direction-segment-hours of manual counts were collected using the short break, alternating count method for the 2018 and 2019 studies, respectively. The manual traffic counts were used to estimate hourly directional volumes by linearly expanding the 4-minute counts obtained with the short break method to 5-minute volumes and linearly interpolating between observed periods to provide an estimate of unobserved periods that results when using the alternating count method (see, e.g., Roess et al., 2004).

In addition, to determine hourly two-direction estimates for segments that did not have any direct manual observations for the hour, the typical approach of using control counts (see, e.g., Zhang, et al, 2006; Roess et al, 2004) was used. This approach assumes that the ratio of a volume occurring during one time period, say T_1, to the volume occurring during another time period, say T_2 (which could contain T_1), is the same for all segments in a defined class of segments. Therefore, obtaining volumes (usually from direct counts) during periods T_1 and T_2 on a "control count" segment and a volume (again usually from a direct count) on a "coverage count" segment during period T_2 allows determination of the volume on the coverage counts segment during time period T_1. This approach allows limited resources (student data collectors in this case) to be distributed over a subset of the segment-hours of interest, as was done in the class project. Multiple segments or combinations of count segments can typically be used to determine the control count volumes during periods T_1 and T_2 for use with a specified coverage count segment. Similarly, multiple periods T_2 might also be used. Several options were indeed available in this study, and the different student groups estimated traffic volumes with different assumptions in the "traditional" approach, but all options resulted in obtaining 2-direction traffic volumes obtained from non-video data on all 252 segment hours in the 2018 study. The variability in the results, emanating from the assumptions used are discussed further in Section 4.2.

Road Tube Data: MORPC provided the road tube data to the research team as 15-minute vehicle counts by direction. The 15-minute counts were simply summed across the relevant periods to obtain the traffic volume of interest.

4 Validation Study Results

The hourly estimates for a segment-direction obtained from the video data are determined for a time-of-day period by averaging all the hourly volume estimates obtained using Equation (2.1) for all bus passes within the time-of-day period of interest. To validate the reasonableness of the video-based approach, these averaged hourly volumes are compared to hourly volumes determined from the concurrent road tube volumes for the same segment-direction for a specified time-of-day period. In addition, an estimated of vehicle distance traveled determined from video-based volumes is compared to the vehicle distance traveled value determined from road tube-based volumes for the set of segments where road tubes were placed and also compared to estimates that would be obtained from traditional approaches for the expanded network. It is noted that although the video-based estimates are compared to the road tube-based volumes, measurement errors associated with the road tube data imply that the road tube-based volumes are not necessarily "ground truth." Therefore, in what follows the comparisons are referred to as "differences," rather than "errors."

4.1 Segment-based Validation

4.1.1 Segment-based Validation in Multi-hour Periods

In a first validation exercise, video and road tube data from the 10/25/2018 data collection effort are used to determine average flows on that date for three time-of-day periods:

- 7:30-10:00, which is called the Morning (M) period
- 12:00-2:00 pm, which is called the Noon (N) period
- 2:00 – 4:00, which is called the Afternoon (A) period

All the video based hourly volume estimates (one from each bus pass) during the period are averaged to produce a single hourly volume estimate $V_{p,sd}^{h-vid(avg)}$ estimate for each period *p = M, N, A*, and segment direction *sd.* Average hourly video-based estimates are determined separately for each of the two approaches – the $t_2 = t_1$ approach and the $t_2 = SL\text{-}time$ approach – used to determine the virtual vehicle time t_2 (see Section 3.2.3).

This video-based estimate is compared to the road tube average hourly estimate $V_{p,sd}^{h-tub(avg)}$ for the same period *p* and segment direction *sd*. The road tube average hourly volume is determined by dividing the total volume during the period by the number of hours in the period (2.5, 2.0, and 2.0 for the M, N, and A periods, respectively).

The relative difference for each period *p* and segment-direction *sd,* defined as:

$$RD_{p,sd} = \frac{V_{p,sd}^{h-vid(avg)} - V_{p,sd}^{h-tub(avg)}}{V_{p,sd}^{h-tub(avg)}} \tag{4.1}$$

is computed for each period and segment direction combination. A positive (negative) value of $RD_{p,sd}$ indicates that the video-based estimate is greater (less) than the tube-based estimate for the time-of-day period and segment direction combination. In addition, the absolute value $ABS(RD_{p,sd})$ of this measure of difference is also determined to allow computation of aggregate statistics on the magnitude of the differences.

As discussed in Section 3.2.2, data were collected from road tubes for each of the two directions of traffic on five different roadway segments. Considering the three time-of-day periods, 30 (= 3 periods x 5 segments x 2 direction) $RD_{p,sd}$ and 30 $ABS(RD_{p,sd})$ values are thus determined. Table 4.1 presents summary statistics of these $RD_{p,sd}$ and $ABS(RD_{p,sd})$ values when using the $t_2 = t_1$ approach and when using the $t_2 = SL\text{-}time$ approach for t_2. It is seen that the $t_2 = t_1$ approach leads to video-based estimates being less than the tube-based estimated on average (negative sign on the average of the *RD* values), and the $t_2 = SL\text{-}time$ approximation leads to video-based estimates being greater than the tube-based estimates on average (positive sign on the average of the *RD* values). It is noted, however, that the large standard deviations and small sample size (30 observations) would not imply that these values are statistically different from 0. The averages of the absolute value of the relative differences indicate that the average magnitude of difference is lower when using the $t_2 = SL\text{-}time$ approach than when using the $t_2 = t_1$ approach. Once again, the relatively large standard deviations and small sample size would not imply a statistically significant difference in these values. Nevertheless, the results indicate a slight improvement in performance when using the *SL-time* approximation.

Table 4.1: Summary statistics on relative differences *RD* and absolute value of relative differences *ABS(RD)* between video-based and tube-based hourly volumes for 30 time-of-day period and segment-direction combinations for the two approaches used to determine t_2

	Approximation for t_2	
Summary Statistics	**$t_2 = t_1$**	**t_2 = SL-time**
Average of $RD_{p,sd}$ values	-0.13	0.08
Average of *ABS*$(RD_{p,sd})$ values	0.26	0.21
Standard deviation $(RD_{p,sd})$ values	0.29	0.26
Standard deviation of *ABS*$(RD_{p,sd})$ values	0.17	0.18

To further investigate the reasonableness of the time-of-day period video volume estimates, a linear regression of the individual $ABS(RD_{p,sd})$ values against expected explanatory variables is conducted with the following specification:

$$ABS(RD_{p,sd}) = \beta_0 + \beta_1 \log(CV_{p,sd}) + \beta_2 \#Pass_{p,sd} \qquad (4.2)$$

where $\log(CV_{p,s})$ is the (natural) logarithm of the coefficient of variation of the individual video-based volume estimates (one for each bus pass) for time-of-day period and segment-direction combination p,sd, and $\#Pass_{p,sd}$ is the number of bus passes (individual estimates) for combination *p,sd*. The coefficient of variation $CV_{p,sd}$ for a combination *p,sd* is obtained by dividing the standard deviation of the individual video-based estimates in period *p* on segment direction *sd* by the mean of these video-based estimates. This variable is intended to represent the variability in the traffic on the segment direction during the time-of-day period. More variable traffic would tend to lead to more variability in the numbers of vehicles observed (higher *CV*) across individual bus passes. For a fixed number of bus passes (number of volume estimates used in the average) and all other things equal, one would expect larger *ABS(RD)* value (less accurate average video-based estimate, where accuracy is represented by the magnitude of the difference from the tube-based volume) for more variable traffic. Therefore, the *a priori* expectation is that the sign on β_1 would be positive. Similarly, all other things equal, one would expect the *ABS(RD)* value to decrease (implying increased accuracy) as the number of bus passes (number of observations, or sample size, used to determine the average) increases. Therefore, the *a priori* expectation is that the sign on β_2 would be negative.

The regression results using video volumes estimated with the $t_2 = t_1$ approach are presented in Table 4.2a, and the results obtained when using video volumes estimated with the $t_2 = SL\text{-}time$ approach are presented in Table 4.2b. The positive sign on the *log(CV)* coefficient and the negative sign on the *#Pass* coefficient in both tables agree with the *a priori* expectations discussed above, supporting the reasonableness of the video-based estimates. The low p-values, indicating strong statistical significance, associated with the coefficients in Table 4.2b, the higher p-values (indicating lower significance) in Table 4.2a, and the higher R^2 value in able Table 4.2b support the use of $t_2 = SL\text{-}time$ approach over the $t_2 = t_1$ approach based on the regression results.

Table 4.2: Regression results obtained from specification in equation (4.2)

(a) Video estimates obtained using $t_2 = t_1$ approach

Variable	**Coefficient Estimate**	**Std. Error**	**t-value**	**p-value**
Intercept	0.479438	0.089143	5.378	1.10E-05
Log(CV)	0.142884	82019	1.742	0.0929
#Pass	-0.00803	0.006598	-1.217	0.2341
Number of Observations: 30 R^2 : 0.1954				

(b) Video estimates obtained using t_2 = *SL-time* approach

Variable	Coefficient Estimate	Std. Error	t-value	p-value
Intercept	0.553083	0.070615	7.832	2.02E-08
Log(CV)	0.259731	0.072577	3.579	0.00133
#Pass	-0.011308	0.005519	-2.049	0.0503
Number of Observations: 30 R^2: 0.5039				

In Table 4.2 the variability among the individual video-based estimates, modeled by the *Log(CV)* variable is seen to influence the accuracy of the results (as measured by *ABS(RD)*) in the expected direction (positive sign on the associated estimated coefficient). It is further hypothesized that the variability in the estimates would be less for larger traffic volumes (which would generally lead to more stable volumes in the short periods during with the bus sensor observes vehicles) and for larger duration of the observation periods. To investigate these hypotheses, a linear regression of the individual $log(CV_{p,sd})$ values is conducted with the following specification:

$$\log\,(CV_{p,sd}) = \beta_0 + \beta_1 V_{p,sd}^{h-vid(avg)} + \beta_2\, AvgTime_{p,sd} \tag{4.3}$$

where $\log(CV_{p,sd})$ is, again, the (natural) logarithm of the coefficient of variation of the individual video-based volume estimates for time-of-day period and segment-direction combination *p,sd*; as above, $V_{p,sd}^{h-vid(avg)}$ is the average of the video-based hourly volumes for combination *p,sd,* and$AvgTime_{p,sd}$ is the average of the $t_1 + t_2$ (the duration of the time considered in the estimation for a single pass) values taken across all the bus passes (individual volume estimates) in minutes for combination *p,sd*. It is noted that tube-based estimates are not used to determine any of the variables in this specification. Therefore, a data record can be determined for every *p,sd* combination in which video-based volume estimates are obtained. There are, therefore, 3 time-of-day periods x 21 segments x 2 directions = 126 observations (sample size) used in this estimation.

The estimation results are presented in Table 4.3, with the results obtained using video volumes estimated with the $t_2 = t_1$ approach presented in Table 4.3a, and the results obtained when using video volumes estimated with the t_2 = *SL-time* approach presented in Table 4.3b. The negative signs on the $V_{p,sd}^{h-vid(avg)}$ and $AvgTime$ coefficients and the low p-values indicate statistically significant correspondence to the expected results discussed above, again supporting the reasonableness of the video-based estimates. The results are again better with the t_2 = *SL-time* approach than with the $t_2 = t_1$ approach – higher R^2 values (indicating better fit) and lower p-values on the coefficients of the $V_{p,sd}^{h-vid(avg)}$ and $AvgTime$ variables (indicating greater statistical significance on these expected explanatory variables). When combined with the results in Tables 4.1 and 4.2, these results indicate that using the $t_2 = SL\text{-}time$ approach is better than $t_2 = t_1$ approach.

Table 4.3: Regression results obtained from specification in Equation (4.3)

(a) Video estimates obtained using $t_2 = t_1$ approach

Variable	Coefficient Estimate	Std. Error	t-value	p-value
Intercept	-0.0755044	0.081226	-0.93	0.354
$V_{p,sd}^{h-vid(avg)}$ (hourly volumes)	-0.0013563	0.0002225	-6.096	1.30E-08
AvgTime (minutes)	-0.1538255	0.0214598	-7.168	6.17E-11
Number of Observations: 126 R^2:0.3684				

(b) Video estimates obtained using $t_2 = SL\text{-}time$ approach

Variable	Coefficient Estimate	Std. Error	t-value	p-value
Intercept	0.0180806	0.0755396	0.239	0.811
$V_{p,sd}^{h-vid(avg)}$ (hourly volumes)	-0.0011489	0.0001522	-7.548	8.57E-12
AvgTime (minutes)	-0.2500388	0.0309605	-8.076	5.21E-13
Number of Observations: 126 R^2: 0.4643				

4.1.2 Segment-based Validation in Hourly and 12-Hour Periods

The video-based estimates are further compared to the tube-based volume estimates at the hourly level and at the 12-hour level. Specifically, hourly video-based volumes and tube-based volumes are determined from the October 25, 2018 data for each of the 12 hours between 7 a.m. and 7 p.m. and for each of the 10 segment-directions where road tube data are available. The video-based volumes are determined using the $t_2 = SL\text{-}time$ approximation, given that this approximation appears to be better than the $t_2 = t_1$ approximation, as discussed in Section 4.1.1.

The hourly video-based and tube-based volumes are presented in Table 4.4. (The segments are denoted according to the numbering seen in Figure 3.1, with each segment *s* having two segment directions leading to notation *s.1* and *s.2* for the segment directions.) Also presented in the table are the numbers of bus passes from which an individual video-based hourly volume is estimated using Equation (2.1), the 12-hour 7 a.m.-7 p.m. segment-direction volumes, and the segment lengths. The 12-hour volumes are computed as the sum of the estimated hourly volumes.

Table 4.4: Video- and road tube-based volumes, number of bus passes used to determine hourly video-based volume, and lengths of segments

Segment and Direction	Sd. Length (miles)	Variables	Start Time of 1-hour period												12-hour Period
			7	8	9	10	11	12	13	14	15	16	17	18	
1.1	0.2563	Video Volumes	706	630	398	330	310	358	192	262	182	640	320	185	4512
		Tube Volumes	695	679	455	334	297	360	303	268	342	463	406	297	4899
		# passes	4	4	3	3	4	3	4	3	3	4	4	3	42
1.2	0.2563	Video Volumes	275	423	276	154	412	332	309	377	539	757	851	442	5147
		Tube Volumes	278	277	232	269	346	422	338	505	479	662	766	453	5027
		# passes	3	4	4	4	3	3	3	4	4	3	3	3	41
4.1	0.3262	Video Volumes	671	849	656	504	373	410	353	292	467	558	420	322	5876
		Tube Volumes	775	814	654	502	356	436	353	353	423	442	455	360	5923
		# passes	6	9	9	8	8	10	9	8	9	10	10	9	105
4.2	0.3262	Video Volumes	164	236	257	266	345	371	384	432	550	478	669	551	4703
		Tube Volumes	192	202	237	304	319	451	349	506	581	643	725	560	5069
		# passes	8	10	9	10	9	9	9	9	7	9	10	10	109
10.1	0.2316	Video Volumes	149	164	174	178	141	226	168	227	285	225	424	174	2535
		Tube Volumes	110	120	135	147	147	186	182	180	193	235	270	216	2121
		# passes	4	6	4	6	4	6	6	5	4	5	5	5	60
10.2	0.2316	Video Volumes	135	90	164	116	104	274	191	165	196	200	199	162	1997
		Tube Volumes	115	119	150	151	166	153	146	139	183	165	283	182	1952
		# passes	4	4	4	2	3	3	4	4	4	4	1	4	41
15.1	0.1939	Video Volumes	725	667	247	349	320	343	352	311	209	320	301	374	4518
		Tube Volumes	547	461	327	275	284	349	283	287	284	308	299	408	4112
		# passes	4	5	4	5	6	5	6	6	4	6	6	6	63
15.2	0.1939	Video Volumes	429	233	266	305	188	378	402	366	673	807	965	593	5605
		Tube Volumes	332	201	252	217	296	296	297	341	458	590	576	392	4248
		# passes	3	3	4	4	4	3	4	4	3	4	3	4	43
19.1	0.1121	Video Volumes	90	210	153	179	226	400	154	376	267	183	435	188	2862
		Tube Volumes	80	100	131	166	161	181	174	230	257	235	308	181	2204
		# passes	4	3	4	4	4	3	3	4	4	3	4	4	44
19.2	0.1121	Video Volumes	363	183	196	203	109	133	157	90	143	137	215	207	2136
		Tube Volumes	350	320	237	188	175	196	186	204	160	175	170	147	2508
		# passes	3	5	3	5	5	5	6	3	3	3	4	4	49

RD values are computed for each segment-direction-hour using the equivalent of Equation (4.1), and *ABS(RD)* values are again computed by taking the absolute value of the corresponding *RD* value. For each segment-direction, the mean and standard deviation of the distribution of the 12 *RD* values (one for each hour interval) are presented in Table 4.5, and similarly for the *ABS(RD)* values. In addition, the single *RD* and *ABS(RD)* values corresponding to the 12-hour volumes for each segment-direction are presented. The rows at the bottom of the table portray the means and standard deviations of the distribution of 120 (10 segment-directions x 12 hours) hourly values and 10 (one for each segment-direction) 12-hour values.

Table 4.5: Summary statistics of relative differences, *RD*, and absolute Value of relative differences, *ABS(RD)*, for hourly and 12-hour segment-direction volumes

Segment-Direction	Hourly Volumes					12-hour volumes		
	N	RD		ABSRD		N	RD	ABSRD
		Mean	SD	Mean	SD			
1.1	12	-0.1019	0.2310	0.1755	0.1762	1	-0.0790	0.0790
1.2	12	0.0225	0.2511	0.1918	0.1531	1	0.0238	0.0238
4.1	12	-0.0069	0.1171	0.0844	0.0775	1	-0.0080	0.0080
4.2	12	-0.0468	0.1316	0.1192	0.0647	1	-0.0721	0.0721
10.1	12	0.1992	0.2384	0.2580	0.1660	1	0.1954	0.1954
10.2	12	0.0489	0.3266	0.2582	0.1913	1	0.0232	0.0232
15.1	12	0.0776	0.2186	0.1789	0.1394	1	0.0987	0.0987
15.2	12	0.2730	0.2698	0.3341	0.1799	1	0.3195	0.3195
19.1	12	0.3235	0.4545	0.3793	0.4047	1	0.2986	0.2986
19.2	12	-0.1290	0.2865	0.2612	0.1607	1	0.0334	0.0334
Mean	120	0.0660		0.2241		10	0.0652	0.1267
SD		0.2968		0.2046			0.1603	0.1122

The mean *ABS(RD)* of all the hourly volumes is 0.2241, which indicates a difference of over 20% "on average" between the hourly video- and tube-based volumes. This average is fairly large, but it is important to note that the video-based volumes are determined from bus passes on only one day. As explained previously, the motivation for using transit buses as sensing platforms is the ability to obtain recurring observations over many days and weeks to estimate typical volumes, and not just one day as was done in this study. In addition, Table 4.5 shows variability in the mean *ABS(RD)* values across segment-directions. Determining segment-direction characteristics that would lead to better or worse video-based estimates is a topic for future research. However, one characteristic that is expected to be associated with the quality of the estimates is the duration of the "observation period" over which the volumes were estimated. To investigate the hypothesis that better video estimation performance would be obtained with longer observation periods (either from the bus spending more time on the segment or from combining more bus passes in the estimation) the segment-direction-hour *ABS(RD)* values are regressed against the sum, across all bus passes in the hour, of the t_1 and t_2 values on the bus passes. The following equation was estimated:

$$ABS(RD_{h,sd}) = 0.329541 - 0.012349\ Total(t_1 + t_2)_{h,sd} \tag{4.4}$$

where $ABS(RD_{h,sd})$ is the absolute value of the relative difference for hour *h* and segment direction *sd*, and $Total\ (t_1 + t_2)_{h,sd}$ is the sum across all bus passes for hour *h* and segment direction *sd* of the t_1 and t_2 times, in minutes, associated with the bus passes. The R^2 (0.1132) is low, indicating that other factors are influencing the magnitude of the differences and that the total observation time may not affect the accuracy ~~of~~ the estimates linearly. However, the coefficient of the total observation time variable has low p-values (0.000172), and its negative sign supports the expectation that increase observation time will lead to lower errors.

In Table 4.5, one also sees that the magnitude of the mean of the 120 hourly *RD* values is much less than the magnitude of the mean of the 120 *ABS(RD)* values (0.0660 vs. 0.2241). This indicates that there is a distribution of negative (indicating a lower video-based volume estimate than tube-based volume estimate) and positive (indicating a higher video-based volume estimate than tube-based volume estimate) *RD* values. This pattern (i.e., the magnitude of mean hourly *RD* values being less than the mean *ABS(RD)* values) is seen to hold for all 10 segment-directions. This pattern implies that for more aggregate measures, overestimates and underestimates would be expected to "cancel out" and produce lower differences. This expectation is confirmed by the *ABS(RD)* values for the 12-hour volumes presented in Table 4.5. Specifically, the mean of the ten *ABS(RD)* values corresponding to the 12-hour volumes is only 0.1267, which is much less than the 0.2241 mean of the ten hourly *ABS(RD)* values, indicating better performance for volumes estimated over longer periods. Indeed, the 12-hour *ABS(RD)* value is less than the mean *ABS(RD)* value for each segment-direction.

4.2 Network-based Validation

Segment volumes serve as inputs to aggregate, network-level measures of vehicle travel. Arguably, the most common network measure of vehicle travel over a set of roadway segments is vehicle distance traveled (VDT), defined as the sum, taken over all vehicles traveling on the segments, of the miles traveled by the vehicles on the set of segments during the period considered. In most studies, VDT is more easily determined by calculating the mathematical equivalent (under fairly loose assumptions), as:

$$\text{VDT} = \sum_{sd} Volume_{sd} \times Length_{sd} \tag{4.5}$$

where $Volume_{sd}$ is the traffic volume on segment-direction *sd* during the period of interest, and $Length_{sdi}$ is the length of segment *sd*. When distance is measured in miles, vehicle miles traveled (VMT) is obtained.

In Table 4.5, one sees that the 12-hour volume *ABS(RD)* value is less than the mean of the hourly *ABS(RD)* values for each segment-direction, indicating that the over- and under-estimates (when compared to the target road tube counts, which as mentioned above are also subject to measurement errors) associated with video-based volumes on a segment would be expected to cancel out when averaged over segments. From Equation 4.5, VDT is seen to be a weighted (by segment length) average of the volumes. Therefore, it is expected that VDT values from video-based volume estimates would, in general, be more accurate than the estimates of the segment-level volumes used.

In Table 4.6 12-hour (7 a.m. to 7 p.m.) VMT values for the Figure 3.1 network on October 25, 2018 are determined from what are called "traditional" volume estimates and from the video-based volume estimates. The corresponding relative differences are also presented, where the relative differences are determined as with Equation (4.1), but using VMT instead of period volumes, subtracting VMT obtained from the traditionally determined volume estimates from the VMT obtained from the video-based volume estimates, and using the VMT obtained from the traditionally determined volume estimates in denominator. Two different networks (sets of segments) are considered. In one network, only the five segments on which road tubes were placed are considered. The traditionally estimated volumes are determined directly by summing the road tube counts over the 12 hours. In the other network, all twenty segments shown in Figure 3.1 are considered. For the segments on which road tubes were not placed, coverage counts were obtained during selected segment-hours and "expanded" to determine

12-hour volumes for all segments using traditional "small network" estimation methods, as discussed in Section 3.2.3. As discussed there, different assumptions can be made when implementing this expansion, and the five student groups organized for the term project (see Section 5) were free (with instructor feedback and documentation of approaches used) to implement approaches they thought appropriate for the term project. Some groups determined VMT from two different small network expansion approaches. As a result, seven different VMT estimates were determined from the five student groups. The seven values ranged from 20,568 to 25,709 [vehicle miles]. The 22,589 traditionally estimated VMT value presented in Table 4.6 is the average of seven different traditionally estimated VMT values provided by the student groups.

Table 4.6: Twelve-hour (7 a.m. to 7 p.m.), October 15, 2018 vehicle miles traveled estimates determined from traditional volume estimates and from video-based volume estimates for road tube and entire Figure 3.1 network, with relative differences

Network Considered	VMT from video-based volume estimates	VMT from traditional volume estimates *	Relative Difference
Segments with road tubes*	9,581	9,221	0.0390
Entire network shown in Figure3.1**	23,554	22,589	0.0476

*For network consisting of road tubes, 12-hour traditional volume estimates are determined directly from road tube volumes.
**For entire network, 12-hour traditional volume estimates are determined by student groups as part of a class term project using approaches described in Section 3.2.3.

As expected, the relative differences of 0.0390 when considering the "road tube network" and of 0.0476 when considering the entire network are less than the average ABS(RD) value – and even of lower magnitude than the average RD value – shown in Table 4.5. Since there does not appear to be a systematic over- or under-estimation in the video-based volume estimates, the weighted average used when determining VMT averages out errors to produce better estimates.

As discussed above the traditionally determined VMT estimates produced by the class groups for the entire network ranged from 20,568 [veh-mi] to 25,709 [veh-mi]. This range of 5,141 [veh-mi] is over 20% of the 22,589 [veh-mi] value presented as the traditionally estimated VMT value. Estimates produced by professional traffic engineers would likely have less variability than those produced by student groups. Nevertheless, different assumptions can be made even by the professional engineers when expanding sample coverage counts to longer period estimates, and the less than 5% differences seen when using video-based estimates for either the road-tube network or the entire network are very encouraging in light of the variability that would be involved with traditional traffic studies, especially when considering that the video-based estimates can be determined from video data obtained for other purposes, whereas traditional estimates require added costs for data collection.

5 Education and Outreach Components

As mentioned above, the traditional data for the validation studies were collected in the context of a course project. *CIVILEN 5720: Traffic Engineering Data Collection Studies* is an elective Civil Engineering course that focusses on understanding, collecting, and processing traditional and emerging types of transportation data. The course is co-taught by two of the project investigators and is taken by both Civil Engineering undergraduate and Civil Engineering and City and Regional Planning graduate students specializing in transportation. In 2018, 27 undergraduate and 3 graduate students took the course. In 2019, 16 undergraduate students and 6 graduate students took the course.

A major component of this course relates to traffic volume data collection and analysis and the approach of using control and coverage counts to estimate traffic volumes on roadway segments across small, regional, and statewide roadway networks. In the past, students would use traditional data collection techniques to estimate traffic volumes on three or four OSU campus roadway segments for an hour or two. The research project summarized in this report inspired the co-instructors of the course to add a term project involving estimating hourly flows for an extended period of time (12 hours in 2018 and 10 hours in 2019) over a connected network of campus segments (see Figures 3.1 and 3.2) using both traditional methods and the video-based estimation methods being developed in this course.

As mentioned above students worked in groups of two to manually collect volume counts for a subset of the segment-hours of interest. When the project investigators explained the class project and the potential outreach component (see below) to the transportation directors at the Mid-Ohio Regional Planning Commission (MORPC), which serves as the Metropolitan Planning Organization for the region, MORPC agreed to put down road tubes on a small subset of the segments on the day of the study. The students combined the road tube and manually collected data using techniques learned in the class to estimate hourly volumes across the set of segment-hours. In addition, OSU Transportation and Traffic Management uploaded video imagery from its buses on the day of the data collection and supplied the imagery to the project investigators. The research project team prepared the video imagery so that the students in the class could individually use the Graphical User Interface described in Section3.2.3 to digitize vehicles in the imagery into information that could be processed by software developed in this project to estimate traffic volumes for each bus pass of a segment direction. (As part of this course, the students had previously learned the estimation techniques described in Section 3.2.3.) The estimated traffic volumes were then averaged into hourly volumes.

Students were assigned to teams, and each team developed hourly traffic volumes from the traditional data sources and compared the video-based results to those determined from traditionally collected data. The student teams also used both sets of traffic volumes to estimate vehicle miles traveled across the network during the period and compared the results in terms of estimated fuel consumption during the study period. Each team prepared a written report documenting approaches, assumptions, and results using technical communication techniques emphasized in the course.

In addition to addressing the overall topic – collecting and processing data obtained in traditional and emerging ways and analyzing the results – the term project fulfilled more general objectives of increasing interest to engineering programs, namely, working in teams, effectively communicating technical material, and analyzing “laboratory” data. Conducting this project in the campus setting, where students are familiar with general traffic flow patterns, had the advantage of making this project much more understandable to the students. No formal evaluation of the project was conducted. However, most students seemed more engaged in the project than in other aspects of the course. In addition, one student commented afterward (without solicitation) that the project was a topic of discussion in a job interview with his eventual employer and that his ability to articulate the project and show enthusiasm for it were aspects that he believed helped him receive an employment offer.

In addition to the research project forming the basis of a term project in two offerings of a course, the vehicle miles travelled estimate determined across the campus network for the "typical weekday while the semester is in session," was provided to The Ohio State University's Transportation and Traffic Management (TTM). As mentioned above, TTM is responsible for all transportation planning and operations, excluding parking operations, at the university. Although the university has undertaken long-term transportation planning and ascribes to environmental sustainability principles, it has no ongoing program to directly monitor motorized VMT. As seen in Table 4.6, the VMT values obtained from the video-based data are very close to those obtained when using traditional traffic study approaches. Because of the ability to monitor changes with ongoing video imagery, the video-based VMT values are what were presented to TTM. It is also noted that, in part because of the institutional relations strengthened through this project and the unique datasets that can be obtained from the approaches developed in this project, two of the project investigators have been invited to discussions on data sources for university carbon footprint monitoring.

6 Summary and Discussion

This project was conceived to investigate the potential of mounting inexpensive sensors on fleets of municipal vehicles that would operate in traffic streams to provide observations of surrounding traffic conditions in urban areas. Fleets of municipal vehicles would be expected to cover large portions of urban networks where traffic information is presently unavailable from traditional, fixed-location sensors. Moreover, the public nature of the fleet would increase the likelihood that the data could be obtained at low cost.

Video cameras are now being installed on transit bus fleets around the world for safety, security, and liability reasons. This phenomenon makes fixed route transit buses an appealing set of vehicles to act as mobile platforms for traffic data acquisition. Transit bus fleets are generally public sector, and the data can therefore be expected to be made available for municipal traffic monitoring. Since the video imagery is being collected for other purposes, there would be little, if any, additional cost for sensor installation or platform deployment. The buses cover most, if not all, major surface roadways of an urban network, and they do so on a repeated basis. This repeated coverage would allow for large sample sizes when estimating typical time-of-day traffic patterns. Because of these observations, the focus in this project was placed on using video imagery obtained from fixed route transit buses in regular service.

Established relations with the Transportation and Traffic Management at The Ohio State University allowed the project investigators to obtain video imagery from buses deployed in regular passenger service on the OSU campus. The video imagery obtained was used with software previously developed by project investigators to semi-automatically digitize vehicle locations in the imagery into data that could be used as input to software developed to estimate traffic volumes. This latter software is based on an approach previously developed by the project investigators for use with other sources of data collected from a mobile sensing platform.

The ability to convert bus-based video imagery into traffic volume estimates motivated the design and implementation of a large-scale empirical validation study. Video imagery from multiple buses on multiple routes traversing a roadway network consisting of 21 bi-directional roadway segments over a 12-hour period was obtained and processed into hourly and 12-hour traffic volumes. Concurrent volume estimates were obtained on 5 of the 21 roadway segments from road tubes placed by the Mid-Ohio Regional Planning Commission for use in the study.

Results show the promise of using bus-based video imagery for traffic volume estimation. The magnitudes of the relative differences between the hourly estimates obtained from the video and from the road tube data average approximately 20%, which might be considered a relatively large difference. However, regression results show a statistically significant decrease in the relative difference with measures associated with increased length of the observation period (number of bus passes sampling the hourly volume or total equivalent observation time of the bus passes). Since transit buses are able to obtain large numbers of observations from their repeated service over the same roadway segments day after day, the statistical relations indicate the potential for increased performance when taking advantage of the many more estimates that can be obtained from transit buses in regular service. Moreover, the differences between the estimates obtained from the video imagery and from the road tube data tend to cancel out when estimating traffic volumes over longer time periods. Specifically, the average magnitudes of relative differences (between video- and road tube-based values) for estimates of 12-hour traffic volumes decrease to approximately 10%. Furthermore, the relative difference in calculated network vehicle miles traveled (VMT) over the 12-hour period obtained from the video-based and road tube-based volume estimates is less than 5%, a difference proposed to be much less than the range of VMT estimates resulting when making necessary assumptions with traditional traffic data collection approaches.

The results obtained in the large-scale empirical study are encouraging, but they also motivate additional research. As with all first-time empirical studies, it would be helpful to conduct an analogous study to see if similar results are obtained. Additional data collected during this project will allow conducting an analogous validation study in a follow-on project. In addition, the statistically significant results demonstrating that accuracy would increase with increased duration of the observation period motivate an empirical demonstration of this effect. It is possible that the additional data collected in this study and data that will continue to be collected in a follow-on study will allow such an empirical demonstration.

Improvements to estimating traffic volumes from the observations in the video imagery should also be explored. In this study, better estimates were systematically obtained when the time assumed for the "virtual vehicle" to traverse the segment – an important input value when determining the video-based estimate – was determined using one of two approaches considered (namely, determining the time from the speed limit and length of the segment). Other options for determining this virtual time should be developed and tested. Similarly, other options to determine a time-of-day volume estimate from the multiple individual estimates should be developed and tested. In this study, the multiple individual estimates were combined through a simple average. A weighted average of the multiple estimates (where the weights are determined by the equivalent observation period) or an approach that accounts for temporal trends within the time-of-day period are possible approaches.

In addition, the study conducted in this project was one where traffic volume estimates were obtained with no prior information of the volumes. If video imagery from transit buses in regular operations were to be used for traffic volume estimation, the data would be collected on an ongoing basis. Traffic estimates would therefore be available, either from previous bus passes or from traditional traffic studies. Determining a way to use the video-based traffic estimates in an ongoing, “updating” manner would be valuable for practical implementation.

In addition, if the approach considered in this research is eventually to be used in an ongoing manner, it would be important to develop more efficient ways to process the imagery into the data used as input to the volume estimation module. Presently, a semi-automated Graphical User Interface tool is used to provide these input data. Although the time to transform the video imagery into a final volume estimate using the present software is less than would be required to conduct a traditional traffic study, the motivation for using existing bus-based video imagery is the ability to provide estimates on many more segments and on a much more frequent basis than is associated with present traffic studies. To take advantage of the bus-based imagery, ways to automatically identify vehicles in the imagery obtained from a mobile platform and to automatically segment the video clips into appropriate roadway segments should be developed.

This project also had important education and outreach components. The large-scale empirical validation study was designed to complement a class project in a transportation engineering course taken by approximately 30 students per year. Because of the research study, two of the project investigators, who are co-instructors of the class, designed a study for the 2018 class offering where students collected traditional “coverage” traffic counts over a 12-hour period across the campus roadway network of The Ohio State University. The students then worked in groups to combine their manually collected coverage counts with concurrently collected “control counts” obtained from road tubes using traditional, fixed-location traffic study approaches to estimate hourly volumes and network-level vehicle miles of travel (VMT) during the study period. In parallel, the students processed video data collected from OSU buses over the network during the same period to determine hourly volumes and VMT from the video-based volume estimates and made comparisons with traditionally estimated values. Approaches, assumptions, and results were documented in group reports using technical communication practices as presented in the class. A similar study was conducted in the subsequent year. Informal instructor observations and student comments indicate that the term project contributed to the educational and professional development aspects of this course.

From an outreach perspective, the estimate of network VMT determined in this study was provided to university transportation planners and administrators. University decision makers are increasingly interested in environmental sustainability on campus. The otherwise unavailable VMT estimates can be used as baseline measures for campus travel monitoring. VMT estimates using data collected in this study will be determined in a follow-on study and provided as an annual update to the campus transportation and sustainability administrators. Partly because of the unique datasets and ongoing discussions of intermediate results, two of the project investigators have recently been asked to join campus discussions on carbon footprint monitoring.

In summary, the empirical validation study conducted in this project supports the potential of using imagery already being collected on transit buses in regular operation to estimate traffic volumes across urban roadway networks at low cost. Although additional research is warranted to improve estimates obtained and to obtain the estimates more efficiently, the validation results indicate very good performance for extended time-of-day periods and for network-level traffic measures. Indeed, these results have already been provided as otherwise unavailable benchmark information in an outreach function at The Ohio State University (OSU). Such use of the output of the concepts being developed and evaluated should improve the likelihood of ongoing use at OSU and of expanded use in other settings.

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9 Appendix 1. Numerical Evaluation Study Indicating Potential Savings in Vehicle Delays Obtained by Eliminating Errors in Traffic Volume Estimates at Signalized Intersections

9.1 Evaluation Methodology

In this appendix, the impact of poor estimates of traffic volumes on signal timing is illustrated using a simplified D/D/1 queuing system approach (Mannering and Washburn, 2011) at a hypothetical, two-phase, four-approach signalized intersection. Each phase is assumed to control two movements. For example, one phase would control northbound and southbound movements, while the other phase would control eastbound and westbound movements. A critical approach is considered for each phase. Specifically, the critical approach is considered to be that where the ratio of the arrival flow (volume) Q^a to the saturation flow (volume) Q^s is greatest among all movements for the phase. (In this case the approach with greater Q^a/Q^s is considered, since there are only two approaches during each of the phases.) Determination of cycle times and green splits at the intersection are determined based on the characteristics of the critical approaches. To indicate performance of the cycle times and green splits, vehicle delays are similarly determined only for the critical approaches. In this simplified model, only through movements on the critical approaches are considered, and these movements are assumed not to be affected by any turning movements.

The physical characteristics of the hypothetical intersection are patterned on an intersection of two major arterials, Lane Avenue and Kenny Road, that cut through The Ohio State University campus. Based on this intersection, two lanes of through traffic are considered for each segment approaching the intersection. From the curb-to-curb intersection widths, the location of the stop lines, and the speed limits at this intersection, the intergreen times (the time to clear vehicles through the intersection after the end of a green signal on a phase) are determined to be approximately 8 seconds for each approach. The sum of the "amber time used as green" (the times after the signal turns yellow until vehicles stop being processed past the stop line) is determined to be approximately 4.5 seconds for each approach. Finally, the start-up delay time (the time to begin moving a queue of traffic after traffic signal turns green for the phase) is assumed to be 1.5 seconds on each approach. These values lead to total (*i.e.*, summed across the two phases) lost time (time during the cycle not used to process vehicles through the intersection, which equals the sum, across critical streams, of the startup delay plus the intergreen time minus the amber time used as green) of 10 seconds. This value is used to determine the total effective green time that can be split between the two phases, given a specified cycle time according to the governing equation:

$$C = \sum_{all\ phases,i}(G_i' + L_i) \tag{9.1}$$

where C is the cycle time for the intersection, G_i' is the effective green time (time used to process vehicles through the intersections) associated with the critical approach on phase *i,* and $L_i$is the lost time associated with the critical approach on phase *i*. Given the values assumed for this two-phase intersection, where the two phases are denoted A and B, Equation (9.1) becomes:

$$C = G_A' + G_B' + 10 \tag{9.2}$$

where the cycle time C and effective green times G_A' and G_B' are measured in seconds, and the value of 10 is that associated with the sum of the loss times across the two critical approaches..

The numerical evaluation conducted is based on a 15-minute period with cycle time *C*, (effective) green times G'_A and G'_B , arrival flow rates on the critical streams Q^a_A and Q^a_B , and saturation flow rates Q^s_A and Q^s_B on the critical approaches assumed to remain constant throughout the period. The saturation rates are assumed to be 1.0 [vehicle/second/lane] for both critical approaches

The performance measure considered is the Total Vehicle Delay *TVD* taken over all the vehicles on the two critical approaches during the 15-minute period. *TVD* is defined as the sum, taken over all vehicles on the critical approaches during the period, of the delay to the vehicle. Numerically, *TVD* for a critical approach can be found by integrating, over time, the queue length on the critical approach at time *t*. (The queue length on an approach at time *t* is equal to the difference between the cumulative number of vehicles that arrived to the stop line at *t* and the cumulative number of vehicles that passed the stop line at *t*.) Because the cycle time, green splits, arrival rates, and saturation rates are all assumed to be constant throughout the 15-minute period, the queued vehicles on an approach will either clear every cycle (when $Q^a_i C < Q^s_i G'_i$) or some of the vehicles will not clear each cycle and queues will continue to grow each cycle. By integrating the queue lengths, the *TVD* for a critical approach during the 15-minute (900-second) period can be found as:

$$TVD_i = \frac{450 \times N^L_i \times Q^A_i \times (C - G'_i)^2}{C \times (1 - {Q^a_i}/{Q^s_i})}, if\ Q^a_i\ C < \ Q^s_i\ G'_i \tag{9.3a}$$

$$TVD_i = N^L_i \left[\frac{450\left(Q^a_i C^2 - Q^s_i {G'_i}^2\right)}{C} + (900 - C)(Q^a_i C - Q^s_i G'_i) \right], if\ Q^a_i\ C \geq \ Q^s_i\ G'_i \tag{9.3b}$$

for critical approaches *i = A, B,* where N^L_i is the number of (through) lanes on critical approach *i,* and the other notation is defined above with C and G'_i in units of [seconds], Q^a_i and Q^s_i in units of [vehicles per second per lane], and *TVD* is in units of [vehicle-seconds] (for the 15-minute or 900-second period). As mentioned above, $N^L_A = \ N^L_B = 2$ (2 through lanes for each of the critical approaches), and $Q^s_A = \ Q^s_B = 1.0$ (saturation rate of 1.0 [vehicle/second/lane] for each of the critical approaches).

Given the additional values of Q^a_A, Q^a_B, C, G'_A, and $G^{;}_B$, Equation (9.3a) or (9.3b) is used to determine TVD_A *and* TVD_B, and the two values (TVD_A *and* TVD_B) are summed to determine *TVD* across the two critical streams during the 15-minute period. In the evaluation study, values of Q^a_A are Q^a_Bassumed as discussed below, and values of C, G'_A, and $G^{;}_B$ are those that are found to minimize *TVD* (= $TVD_A + TVD_B$). Cycle times between 15 and 180 seconds are considered, and only positive effective green times are considered. (Note that from Equation (9.2), given a cycle time and one of the effective green times, the other effective green time is uniquely determined.) In this way, the approach used is one that determines the solution to:

Min: $TVD_A + TVD_B$ (9.4a)

subject to:

$$G'_B = C - \ G'_A - 10 \tag{9.4b}$$

$$15 \ \leq C \ \leq 180 \tag{9.4c}$$

$$G'_A\ ,\ G'_B \geq 0 \tag{9.4d}$$

$$C, G'_A, G'_B \ \text{ integer} \tag{9.4e}$$

Formulation (9.4) is solved numerically by considering all 1-second values of C between 15 and 180 seconds and, for each value of C, all 1-second values of G'_A greater than 0 and less than the smallest value that leads to a non-positive value of G'_B, as determined by (9.4b).

9.2 Application of Methodology to Evaluation Study

The evaluation study is developed to indicate the value of improving the estimates of traffic volumes, which are represented by the arrival flows Q_i^a. To bound the value of this improvement, the reduction in total vehicle delay that would be achieved by knowing true flow values $Q_i^{a,true}$, rather than erroneously estimated flow values of $Q_i^{a,est}$, is determined. The approach is described in the following "Vehicle Delay Savings Approach."

Vehicle Delay Savings Approach

Step 0. *Input values:* Given number of through lanes on critical stream approach A and B (2 lanes each in this study), sum of lost times across phases (10 seconds in this study), and saturation flow rates (1 vehicle/second/lane on both approaches in this study). Assume true values ($Q_A^{a,true}$, $Q_B^{a,true}$) and estimated values ($Q_A^{a,est}$, $Q_B^{a,est}$) of arrival flow rates Q_A^a and Q_B^a.

Step 1. *Suboptimal signal timing*: Solve Formulation (9.4a-e) for cycle time and effective green times $\left(C^{est}, G_A^{\prime,est},\ G_B^{\prime,est}\right)$ using estimated arrival flows ($Q_A^{a,est}$, $Q_B^{a,est}$) to determine the signal timing values that would be selected with the erroneous estimates of arrival flows.

Step 2. *Total vehicle delay with suboptimal signal timing*: Use Equation (9.3a,b) with $\left(C^{est}, G_A^{\prime,est},\ G_B^{\prime,est}\right)$ (from Step 1) and *true* arrival flows ($Q_A^{a,true}$, $Q_B^{a,true}$) (from Step 0) to determine the 15-minute total vehicle delay for each critical stream, TVD_A^{est} and TVD_B^{est}, resulting from the use of the erroneous flow estimates in developing the signal timing. Determine the total 15-minute vehicle delay TVD^{est} resulting from the use of the erroneous estimates by summing the two values, $TVD^{est} = TVD_A^{est} + TVD_B^{est}$.

Step 3. *Optimal signal timing*: Solve Formulation (9.4a-e) for cycle time and effective green times $\left(C^{opt}, G_A^{\prime,opt},\ G_B^{\prime,opt}\right)$ using true arrival flows ($Q_A^{a,true}$, $Q_B^{a,true}$) (to determine the optimal signal timing values that would be selected when using the true estimates of arrival flows.

Step 4. *Total vehicle delay with optimal signal timing*: Use Equation (9.3a,b) with $\left(C^{opt}, G_A^{\prime,opt},\ G_B^{\prime,opt}\right)$ (from Step 3) and true arrival flows ($Q_A^{a,true}$, $Q_B^{a,true}$) (from Step 0) to determine the 15-minute total vehicle delay for each critical stream, TVD_A^{opt} and TVD_B^{opt}, resulting from the use of the true flow estimates in developing the signal timing. Determine the total 15-minute vehicle delay TVD^{opt} resulting from the use of the true estimates by summing the two values, $TVD^{opt} = TVD_A^{opt} + TVD_B^{opt}$.

Step 5. *Savings in total vehicle delay*: Determine the 15-minute savings ΔTVD as $\Delta TVD = \Delta TVD^{est} - \Delta TVD^{opt}$, where ΔTVD^{est} tand $\Delta TVD^{opt}$are determined in Steps 2 and 4, respectively.

This Vehicle Delay Savings Approach is run for multiple combinations of "true" and "estimated" flow inputs, $(Q_A^{a,true}, Q_B^{a,true})$, $(Q_A^{a,est}, Q_B^{a,est})$. Specifically, the following values of true arrival flow on critical approach B are considered:

$$Q_B^{a,true} = 0{,}15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45 \text{ [veh/lane/sec]}. \quad (9.5a)$$

For each value of $Q_B^{a,true}$, three values of true arrival flows on critical approach A are considered:

$$Q_A^{a,true} = K \times Q_B^{a,true}, \text{ K = 1, 2, 3.} \quad (9.5b)$$

In this way, K = 1 represents identical arrival flows on the two streams, and K = 2 and K = 3 represent increasingly more disparity between the true arrival flows on the two streams.

For each input pair of *true* arrival flows $(Q_A^{a,true}, Q_B^{a,true})$ determined from (9.5a) and (9.5b), nine pairs of input *estimated* arrival flows $(Q_A^{a,est}, Q_B^{a,est})$ are considered, namely:

$$(Q_A^{a,est}, Q_B^{a,est}) = (\alpha \times Q_A^{a,true}, \beta \times Q_B^{a,true}),\ \alpha = 0.5, 1.0, 1.5,\ \ \beta = 0.5, 1.0, 1.5. \quad (9.5b)$$

Values of 0.5 (1.5) for α or β indicate that the estimated flows are less than (greater than) the true flows, whereas values of 1.0 indicate no error in the estimated flows. (Note that when both α and β are equal to 1.0, one would set the signal timing values according to estimated arrival values that equal the true arrival flows, and no savings would result from estimating the arrival flows better, since they are assumed to be known without error in this case.)

All combinations (Q_B, K, α, β) determined in this way are considered such that the intersection is not saturated when assuming the true values of the arrival rates, that is, such that values of $(Q_A^{a,true}$, $Q_B^{a,true})$ can lead to some $\left(C^{opt}, G_A^{\prime,opt}, G_B^{\prime,opt}\right)$ combination that allows the queues to clear for both approaches in the recurring cycle. Note that the queues would not necessarily clear when using the estimated arrival rates or when using the true arrival rates with the cycle and (effective) green times determined with the estimated arrival rates. The resulting savings in total vehicle delay are shown in Figure 9.1 as a function of the input $Q_B^{a,true}$, K, α, and β values.

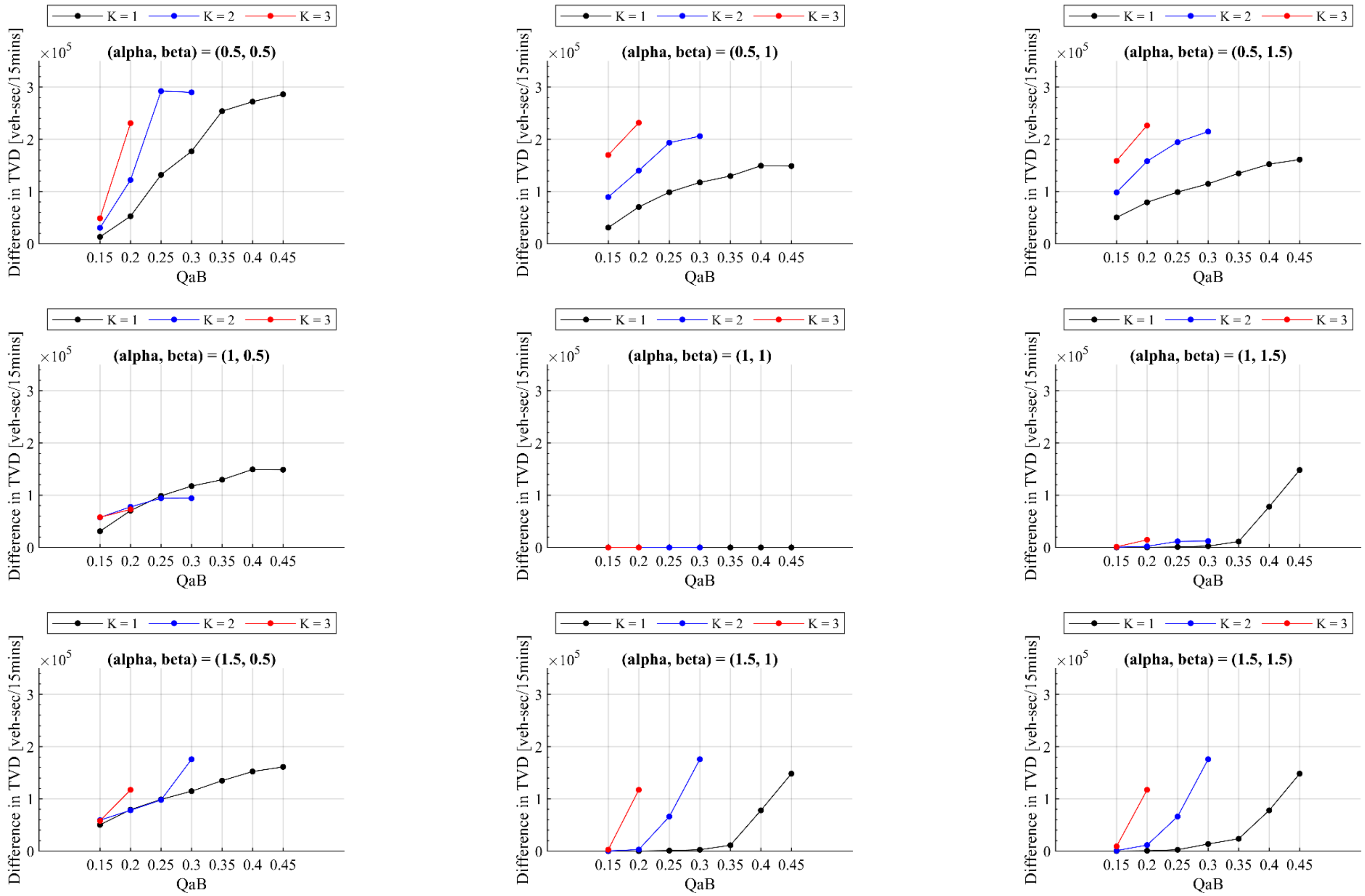

Figure 9.1 Reduction in total vehicle delay for 15-minute period across two critical streams for simulated intersection; Q_B = true arrival rate in vehicles per second per lane on minor approach (approach B); K = factor for true arrival rate on major approach (approach A), Q_A = K x Q_B; alpha = factor assumed for estimated arrival rates on major approach, Q_A^{esr} = alpha x Q_A; beta = factor assumed for estimated arrival rates on minor approach, Q_B^{est} = beta x Q_B

From the graphs, it is noted that the savings in knowing true arrival flow rates (volumes) depend on the values of the arrival flow rates, $Q_a = KQ_B$ and Q_B, and, depending on the true arrival flow rates, whether the true arrival flow rates are overestimated (alpha or beta >1) , underestimated (alpha or beta <1), or estimated correctly (alpha or beta = 1). However, as would be expected, the saving is generally greater at heavier volumes (higher Q_B and K values). It is also noted that, although the queuing and delay models are simplified representations of real vehicle performance at an intersection, the values of α and β representing differences between true and erroneously assumed values on arrival flows are only crude parameter values, and one would not be able to eliminate all error in assumed arrival flows with better traffic monitoring, the approximately $1.0(10^5)$ [vehicle-seconds] (= 27.8 [vehicle hours]) or greater of delay savings during the 15-minute analysis period seen at many of the evaluated values are substantial. These large values would be attributable to an inability to clear the queues during a cycle when using erroneous volumes to determine signal timings.

10 Appendix 2. Research Products from this Project

10.1 Conference Presentations

McCord, M.R., and Mishalani, R.G. The Ohio State University Campus Transit Lab: A Living Laboratory Platform for Research, Education, and Outreach. TransitData 2020 6th International Symposium, Toronto, Canada, August 11-13, 2020.

Mishalani, R.G., McCord, M.R., Coifman, B., and Hansel, G. Roadway Traffic Flow Estimation using Video Imagery Data Collected from Transit Bus Cameras, TransitData 2019 5th International Workshop and Symposium, Paris, France, July 7-11, 2019.

10.2 Data

Dataset containing hourly volumes determined from video data, from road tube data, and from manually collected data, and numbers of bus passes used in hourly estimations are available at https://osu.box.com/s/9rgftpe72zene85cpj4hcu7dmta4p1ck