Determining Segment and Network Traffic Volumes from Video Imagery Obtained from Transit Buses in Regular Service: Developments and Evaluation of Approaches for Ongoing Use Across Urban Networks

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1 Introduction and Overview

Traffic volume estimates for given time-of-day periods are important inputs for a variety of transportation planning, operations, and monitoring purposes. Traffic volume, by definition, is the number of vehicles passing a point on a roadway over a specified time period (FHWA, 2022). Traffic volumes are traditionally determined from vehicle counts collected at a fixed location on the roadway, either automatically with permanent (e.g., inductive loop detectors) or temporary (e.g., pneumatic tube detectors) sensors, or manually by human observers. It is infeasible to deploy fixed-location sensors or human observers on every roadway segment in a network over the period of interest. Therefore, many segment volumes must be estimated, often by sampling the segments for a short time period and imposing on these “coverage counts” a temporal pattern derived from a few “control” segments where the traffic counts are obtained during the entire period (Kumapley and Fricker, 1997; Roess et al., 2004; Jiang et al., 2006; FHWA, 2022). Inaccuracies resulting when superimposing temporal patterns obtained from control counts on coverage count samples and the large resources required to obtain traffic counts across the entire network on a continuing basis have led to different attempts to obtain accurate, ongoing traffic volume estimates in a cost-effective manner.

Video-imagery obtained from cameras mounted on transit buses can conceivably be used to obtain traffic volumes across urban networks on an ongoing basis. Cameras are already mounted on many transit buses for safety, security, and liability reasons. Outward looking cameras image roadway traffic while the buses are in regular service. The public nature of transit agencies could make the data available at little marginal cost. Since transit buses cover most major streets in an urban network day after day, this approach would allow extensive geographic coverage on an ongoing basis. A method presented in McCord et al., (2020) has been developed to produce the equivalent of a traditional, fixed location traffic count from imagery obtained from an individual bus traversal over a roadway segment. Any one bus pass would provide the equivalent of a very short-duration traffic count. However, the repeated traversals of transit buses over the same segments would lead to many counts, and the aggregation of these counts is expected to allow for accurate estimates of traffic volumes on the segments for specified time-of-day intervals.

In the study covered in this report, modifications to the methodology previously developed to estimate traffic volumes for a given time-of-day interval from video imagery obtained from transit buses in regular service are developed. Empirical evaluation of the modifications illustrate that they improve estimation accuracy. In addition, regression models are estimated that indicate general characteristics that lead to better or worse estimation accuracy. An empirical study is also conducted that demonstrates very good accuracy in estimating network-level vehicle miles traveled (VMT) from traffic volumes obtained from bus-based video imagery. The study also demonstrates that the bus-based VMT estimates accurately depict important changes in aggregate and temporal traffic patterns over time and that a presently popular data source does not allow such temporal monitoring and produces very poor VMT estimates.

The VMT study and validation studies in the previous sections are based on estimating traffic volumes for a time-of-day interval on a specific day. For off-line planning applications, it is generally of more interest to estimate a time-of-day traffic volume for an “average day.” An empirical study is therefore also conducted that demonstrates very good accuracy in estimating average time-of-day volumes, compared to estimating the volume on a specific day. In addition, an analytical framework is developed to investigate the quality of the average estimate as a function of the number of days on which time-of-day volumes are sampled. Application of the framework with the empirical data collected indicate that accurate average time-of-day volumes can result from only a few days of bus-based data collection.

The empirical studies are centered on concurrently collected video-based imagery and ground truth traffic volume data on roadway segments across the campus of The Ohio State University (OSU). The OSU campus is one of the largest university campuses in the world and contains multiple land uses. Therefore, the campus serves as a "living lab" that is representative of many elements of urban areas. Video imagery is collected from OSU operated buses while they are in regular transit service. The ground truth data are obtained from targeted road tube and manual traffic count data collections.

In addition to researching the potential of using video imagery from transit buses in regular service to estimate and monitor time-of-day traffic volumes and derive related network measures, this study included important educational and outreach components. The concept of replacing or complementing traffic volumes obtained from costly and resource-intensive traditional traffic counts with volume estimates obtained from available bus-based imagery formed the basis of the term project in an annually offered transportation data collection OSU course. Term project tasks were modified with each offering, but each semester students collected and processed both traditional traffic count data and video-based traffic imagery, and analyzed and compared the resulting volumes and network related measures. In addition, the term projects provided the students with the opportunity to work in teams and communicate assumptions, approaches, results, interpretations, and conclusions, aspects that are important to emphasize and have been increasingly emphasized in engineering education in general.

From an outreach perspective, the actual VMT estimates obtained in the research effort, the trends in these network travel estimates over the years, and the time-of-day patterns determined were presented annually to OSU transportation planners and administrators. 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, and while the OSU community is surveyed through questionnaires that ask for socioeconomic and travel information, these VMT values are the only in situ traffic flow estimates available for the roadways on and around the OSU campus.

The rest of this report is organized as follows.

The data sources and roadway network used in the empirical studies are presented in Section 2.

In Section 3, the previously developed estimation methodology and software-based implementation of the methodology are described, and modifications to the methodology and additional automated implementation components developed in this project are described. Empirical studies demonstrate the improved performance of the methodological modifications.

Estimation errors associated with video-based estimates of hourly and 10-hour volumes are presented in Section 4. As expected, 10-hour estimation is seen to be much more accurate than hourly estimation. Moreover, hourly estimation is seen to be statistically more accurate on what would likely be considered more important roadway segments, those with higher volume and with longer lengths.

Estimated video volumes are used in Section 5 to determine values of network-wide vehicle miles traveled (VMT) over a 10-hour period. Very good accuracy is seen when the video-based VMT estimates are compared to VMT estimates obtained from volumes determined from road tube data representing the ground truth. VMT estimates are also calculated from volumes available from a popular Location Based Service (LBS) data aggregator and provider. When these LBS-based VMT estimates are compared to the road tube-based ground truth estimates, much worse, and unacceptable, accuracy is observed. Video-based and LBS-based VMT estimates are also used to monitor VMT over four years. Yearly changes seen in the video-based VMT values are reasonable, whereas those seen in the LBS-based VMT values are not. In addition, time-of-day VMT patterns obtained from video-based volumes are seen to be much more accurate and meaningful than patterns obtained from LBS-based volumes, which do not exhibit any interpretable patterns.

In Section 6, an empirical study is presented that is designed to investigate the ability of video-based hourly volumes obtained over multiple days to estimate representative average time-of-day hourly traffic volumes. Average hourly video volumes are seen to be very close to average volumes determined from manual traffic counts in each of multiple time-of-day periods. An analytical approach is then developed to model the accuracy of a sample average time-of-day volume with respect to the underlying true average time-of-day volume as a function of the number of days sampled, both when the sample average is based on video-based volumes and when the sample average is based on true traffic volumes. The empirical data collected are used to estimate values of input variables to the analytical framework developed. The results indicate that very good accuracy can be obtained with a relatively small number of daily estimates of the video-based hourly volume.

The use of the concepts developed in this research as the focus of OSU course term projects is presented in Section 7. In addition, the provision of annual empirical estimates of vehicle miles traveled on the OSU roadway network to campus transportation planners and administrators is described.

A summary of findings and conclusions drawn are presented in Section 8.

2 Data

Large, concurrent data collections were central to empirical investigations and validating the improvements offered by methodological developments of this project and to enabling the associated educational and outreach aspects The validation and empirical investigation studies in subsequent sections are based on the traffic data sets obtained over time on a network of roadways on the campus of The Ohio State University. The "supernetwork" of all the roadways considered is depicted in Figure 2-1. The numbers in the figure correspond to the segment numbers used in this report. When needed for clarity, the northbound or eastbound traffic direction of segment *S* is referred to by segment-direction *S.1*, whereas the southbound or westbound traffic direction of segment *S* is referred to by segment-direction *S.2*. In subsequent sections, traffic volumes in each direction of a segment are considered separately unless otherwise noted.

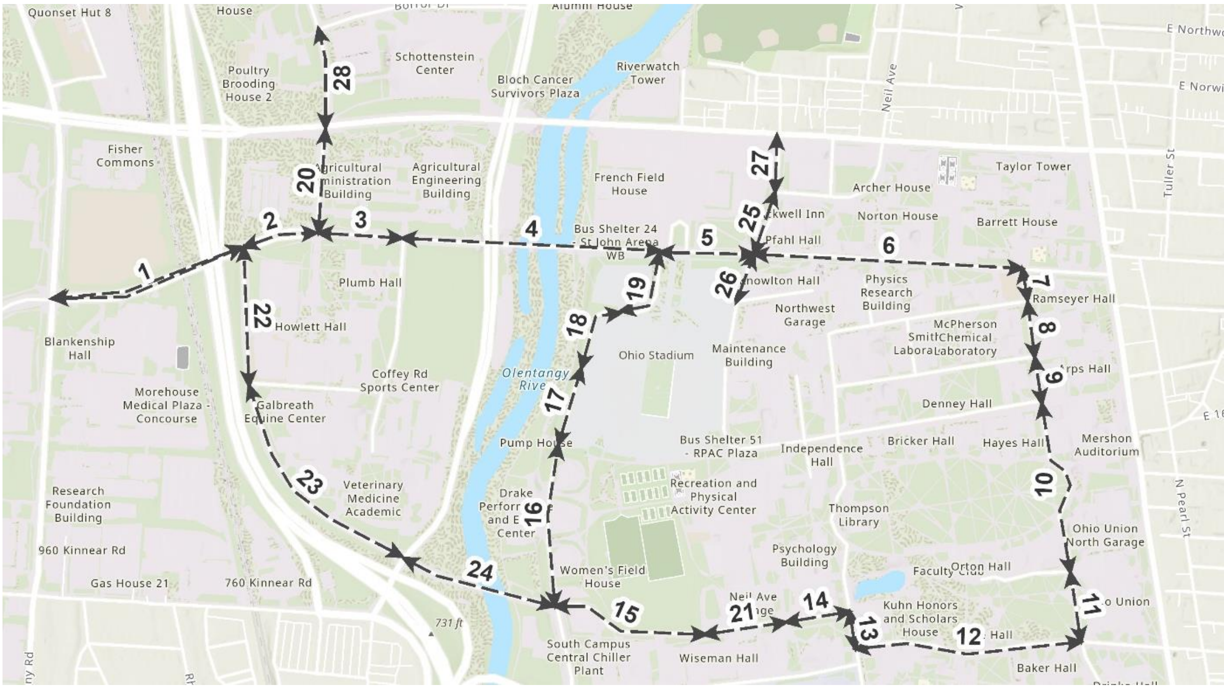


Figure 2-1: Illustration of "supernetwork" consisting of the union of all segments considered across the five years (source for background map: esri, ArcGIS World Topographic Map, https://www.arcgis.com/home/item.html?id=7dc6cea0b1764a1f9af2e679f642f0f5)

A list of the segments and their lengths is presented in Table 2-1. Four different types of volume data were obtained for subsets of the segments at different times. These types of data are described next, and indications of when the various types of data were collected on the various segments are provided in Table A-1 of Appendix A.

Table 2-1: Segment description and lengths of segments in "supernetwork" considered in empirical studies

Segment Number	Segment Name	Segment length (mi)
1	Woody/Kenny to Woody/JohnHerrick	0.256
2	Woody/JohnHerrick to Woody/Fyffe	0.100
3	Woody/Fyffe to Woody/Coffey	0.111
4	Woody/Coffey to Woody/Cannon	0.326
5	Woody/Cannon to Woody/Tuttle	0.120
6	Woody/Tuttle to Woody/College	0.343
7	College/19th to College/Woody	0.039
8	College/18th to College/19th	0.070
9	College/AnnieJohn to College/18th	0.063
10	College/Hagerty to College/AnnieJohn	0.232
11	College/12th to College/Hagerty	0.092
12	12th/Neil to 12th/College	0.291

Table 2.1 (continued): Segment description and lengths of segments in “supernetwork” considered in empirical studies

Segment Number	Segment Name	Segment length (mi)
13	Neil/12th to Neil/JohnHerrick	0.048
14	JohnHerrick/NeilDr to JohnHerrick/Neil	0.084
15	JohnHerrick/Cannon to JohnHerrick/HUBdepart	0.194
16	Cannon/JohnHerrick to Cannon/ShoePark1	0.210
17	Cannon/ShoePark1 to Cannon/ShoePark2	0.102
18	Cannon/ShoePark2 to Cannon/ShoePark3	0.101
19	Cannon/ShoePark3 to Cannon/Woody	0.112
20	Fyffe/Woody to Fyffe/Lane	0.134
21	JohnHerrick/HUBarrive to JohnHerrick/NeilDr	0.115
22	JohnHerrick/Vernon to JohnHerrick/Woody	0.160
23	JohnHerrick/Olentangy to JohnHerrick/Vernon	0.316
24	JohnHerrick/Olentangy to JohnHerrick/Cannon	0.202
25	Tuttle/Woody to Tuttle/Neil	0.084
26	Tuttle/Ives to Tuttle/Woody	0.063
27	Tuttle/Neil to Tuttle/Lane	0.071
28	Fyffe/Lane to Fyffe/Boror	0.050

2.1 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), which operates a fleet of approximately fifty 40-foot transit buses serving close to 3.5 million passengers per year (approximately 5 million per year, pre-pandemic) on fixed route, scheduled services.

Like many transit agencies, TTM has 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 length of time a bus is in service, all of which vary across the bus fleet, a given video file typically remains on a bus’s hard-drive between two to four weeks before it is overwritten.

Because of the history of collaboration between project investigators and TTM, the investigators were able to request and receive video files for specified days, times-of-day, and bus routes on several occasions. Video imagery used in the studies reported in this document were obtained from a forwardlooking camera mounted outside the bus on the driver's side at the rear of the bus (see Figure 2.1-1) Requests were made to the TTM Transportation Systems Coordinator, who is the staff member responsible for operations, use, and upkeep of the video cameras on the CABS fleet. After receiving these requests, the coordinator 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.

Figure 2.1-1: Driver's side exterior camera used to record imagery used in empirical studies with sample frame of video imagery shown in project's Graphical User Interface

In conjunction with a course project (see Section 7), video imagery from CABS buses in regular operations was obtained for 10-hour periods and subsets of the segments of the supernetwork illustrated in Figure 2-1 on five days, 10/25/2018, 10/24/2019, 11/05/2020, 11/04/2021, and 11/01/2022. Video data collected on two of these days, 10/25/2018 and 10/24/2019, were collected and reported on in a previous project (McCord et al., 2020). However, the video data are used again and in different ways in the project covered by this report. Video imagery was also obtained for segment-direction 4.1 (see Figure 2-1 and Table 2-1) on a series of days in 2022. The days and hours for which video data were obtained on the various segments are indicated in Table A-2 of Appendix A.

2.2 Manually Collected Traffic Counts

Students conducted manual traffic counts on segments of the Figure 2-1 supernetwork. The "short-break" method (Roess, et al., 2004) was used, where students would count for four minutes, take a one-minute break from counting to reduce the monotony and to make sure data were being recorded properly, then repeat the four-minute count and one-minute break sequence for the duration of their assigned traffic count period. A volume for the five-minute period encompassing the four-minute count and the following one-minute break was estimated by linearly expanding the four-minute count to the five-minute period.

Attempts were made to cover most segments of predefined subnetworks of the Figure 2-1 supernetwork with manual counts for an hour or more in conjunction with the course projects discussed in Section 7 on 10/25/2018, 10/24/2019, 11/05/2020, 11/04/2021, and 11/01/2022. As with the video day, manual data collected on 10/25/2018 and 10/24/2019 were collected and reported on in McCord e al., (2020), but like the video data, these data are again used in different ways in the project covered by this report. On these days, traffic counts were taken with an "alternating count" approach (Roess, et al., 2004), where the direction of the segment for which the traffic counts were taken was alternated every five minutes. The five-minute volumes for the intervals when counts were not taken were determined as the average of the preceding and following five-minute interval volumes, where, as discussed above, the five-minute volumes used for the interpolation were estimated by expanding the four-minute counts taken in that direction during the interval to a five-minute volume estimate.

As discussed in Section 6, a targeted study was undertaken based on the traffic on segment-direction 4.1. Traffic counts were systematically taken on this segment-direction for specified hours over the Spring 2022 and Autumn 2022 academic semesters. These counts were again taken for four minutes, followed by a one-minute break, but since only one traffic direction was of interest, counts were always taken in the same eastbound direction. Therefore, volume estimation only needs to address the one-minute break gaps.

The tables in Appendix A indicate the date and segment-hour-directions for which manual volumes were estimated.

2.3 Road Tube Counts

The Mid-Ohio Regional Planning Commission (MORPC), which serves as the Metropolitan Planning Organization for the Central Ohio area, placed road tubes on both directions (separate tubes in each direction to obtain directional counts) of a few segments of the supernetwork on 10/25/2018, 10/24/2019, and 11/05/2020. Five, four, and five segments, respectively, were selected, on the days in 2018, 2019, and 2020. (As with the video and manual data, the 10/25/2018 and 10/24/2019 road tube data were collected and reported on in McCord et al., 2020). Like those data, the road tube data collected previously are used again and for different studies in the project covered by this report.) The MORPC road tube data consist of 15-minute traffic volumes in each segment-direction for the entire day. Hourly volumes were determined by adding the 15-minute volumes during the intervals corresponding to the hour of interest. The segment-directions on which road tubes were collected are indicated in Appendix A.

2.4 Location Based Services Volumes

Location based services (LBS) data resulting from the use of services that rely on the use of the Global Positioning System are becoming an increasingly popular source of obtaining traffic volumes. Recently established companies are accessing LBS data from communication, information, and mobility service providers and aggregating them to provide on-demand traffic volume information to public agencies and private organizations for statewide or metropolitan planning, analysis, and design purposes (MacFarlane, 2020; Koupal et al., 2022). LBS data were obtained for a targeted study described in Section 5. The segments and days on which the LBS data were obtained are indicated in Appendix A.

3 Time Interval Volume Estimation Methodology

The overall focus of the research concept related to this project is estimating traffic volumes on roadway segment-directions for specified time-of-day (TOD) periods using video imagery obtained from transit buses in regular service and using these volume estimates to derive representative segment or network traffic measures. The approach developed consists of the following:

- Processing the bus-based imagery into vehicle observations on roadway segments
- Using the processed observations to estimate traffic volumes for a time-of-day (TOD) period of interest for the day on which the imagery was collected
- Using the TOD traffic volumes as input to determine aggregate traffic measures of interest

A review of the imagery processing previously used and automated developments for this processing are presented in Section 3.1. Similarly, a review of the volume estimation methodology previously developed and improvements to this methodology developed in the context of the project are presented in Section 3.2 along with validations studies supporting the improvements. Additional improvements to the estimation methodology that show promise, but where results are considered preliminary, are presented in Section 3.3.

3.1 Processing of Imagery

The approach presented in McCord, et al. (2020) forms the basis of the approach presently used to process the video imagery into vehicle observations that are used to estimate traffic volumes on a roadway segment-direction. The approach is applied to video imagery obtained from Ohio State University (OSU) Campus Area Bus Service (CABS) busses while in regular service. The video imagery is received from OSU's Transportation and Traffic Management (TTM). The TTM videos are first converted from the .avi file format to the .mp4 file format. After converting the video files, the following steps are used to associate vehicle observations in the imagery to roadway segments during a time period of interest (see McCord et al., 2020):

- "Clipping": This step involves "clipping" the video files to identify long stretches of imagery recorded by the bus's camera when the bus traveled on segments not of interest for the analysis.
- "Segmenting": This step involves determining the video frame numbers when the bus on which the camera in installed entered and exited a specified sequence of roadway segment-directions so that the frame numbers associated with vehicles detected in the next step can be mapped to the segment-directions where the vehicles are detected.
- "Vehicle detection": This step involves identifying the frame number in which a vehicle travelling on a roadway segment in the direction opposite to the bus direction of travel crosses a specified location approximately midway along the length of the bus.

As reported in McCord et al. (2020), these steps were previously implemented in a "semi-automated" manner with the assistance of a specialized Graphical User Interface (GUI) which had previously been developed for these tasks. To "clip" the videos, a trained graduate student would visually identify the sections of the video files of interest by beginning and end frame numbers, which are subsequently used as inputs to the GUI to only playback the sections of interest during the vehicle detection step. To segment the clipped videos, graduate and undergraduate students who were trained and familiarized with the campus roadway segments would watch the videos and press a virtual button on the GUI when the bus is seen to enter a roadway segment of interest and when it is seen to exit the roadway segment, and to do so for all sequenced segments that are seen to be traversed in the video clip. Pressing the GUI's virtual button records the video frame number associated with the bus's segment entrance or exit. To "detect" vehicles in the imagery, trained students supported by this project and in course projects (see Section 7) watched the video and pressed a GUI virtual button to record the frame number when a vehicle in the imagery is observed to pass a line superimposed on the imagery perpendicular to the bus direction and approximately midway along the length of the bus. Comparing the recorded frame number of the detected vehicle against the frame numbers indicating the entrance and exit of a bus on a specified roadway segment recorded in the segmenting step allowed a detected vehicle to be associated with a segment-direction and time.

In the context of the project reported here, the clipping and segmenting steps were fully automated. The latitude and longitude coordinates of the beginning and end of each roadway segment-direction along a CABS route are identified. These static coordinates, the video files, the timestamps of the beginnings and ends of the video files, and the Automatic Vehicle Location (AVL) data (which include timestamps and the corresponding bus location coordinates) for the buses on which the videos were recorded are processed by a Python code written by a project team member to automatically identify the sections of the videos that are of interest (i.e., automatic "clipping"), to identify the frame numbers that define the beginning and end of each segment-direction (i.e., automatic "segmenting"), and to determine the time it takes each bus to traverse the segment-direction (which is used in estimating the segment-direction traffic volume from the number of detected vehicles associated with each bus pass). The results of this automation are identical to what was previously done semi-automatically up to the beginning of the "vehicle detection" step, which continued to be applied using the GUI as described above.

In a parallel project, an approach was developed to detect and record vehicles fully automatically in the imagery using machine vision methods (Redmill, et al. 2023). Preliminary results show the promise of developing such algorithms into a software tool that could replace the semi-automatic vehicle detection step with a fully automated approach. However, additional testing, validation, and refinement are needed before the fully automated approach can be considered reliable under a wide set of conditions. In the empirical studies described in this report, the automated clipping and segmenting steps described above were used when processing imagery, and as noted above, vehicles continued to be detected using the previously developed GUI.

For each bus pass over a roadway segment of interest, the output of these three steps are the frame numbers of detected vehicles and the frame numbers associated with bus's entering and exiting segments of interest while traveling in the opposite direction of the detected vehicles. Comparing the frame numbers of the detected vehicles and the frame numbers delineating the entrance and exit of the bus to and from the segment allows an automatic determination of the number of vehicles n detected on each segment-direction of interest for each bus pass over the segment (travelling in the opposite direction). All vehicles detected on the segment after the bus entered the segment (travelling in the opposite direction) and before it exited the segment in a single bus pass are presently considered to be associated with the time the bus entered the segment. An estimate of the times the vehicles were actually detected could be determined using the recorded frame numbers associated with the vehicle detection. However, given the small time for a bus to traverse a segment (one or two minutes at most), the temporal resolution associated with the time the bus entered the segment is sufficient for the volume estimations considered in this research.

3.2 Volume Estimation Methodology

The "modified moving observer" approach presented in McCord, et al. (2020) again forms the basis of the time-of-day volume estimation used in this project, but methodological improvements discussed in Section 3.2.2 were developed, and the empirical results presented in Section 3.2.3 demonstrate the improved quality of the volume estimations obtained. A review of the modified moving observer approach previously used is first presented in Section 3.2.1.

3.2.1 Review of Previously Developed Volume Estimation Approach

The investigators developed the approach described in detail in McCord, et al., (2020) to estimate a traffic volume for a specified time-of-day interval on a given day from vehicle observations obtained from a "moving observer" such as a transit bus in regular service. The approach consists of estimating the equivalent of a traditional traffic volume of short duration from the vehicle detections obtained on an individual bus pass over the roadway segment and then aggregating the estimated traffic volumes obtained from different bus passes occurring during the specified time-of-day interval.

Traffic volumes on a segment are traditionally estimated from a fixed-location sensor or from human observers counting the number of vehicles that pass a point on the segment over the period of interest. Sensors, such as cameras, on mobile sensing platforms traverse the entire road segment and detect vehicles at different locations on the segment at different times. To convert the vehicles observed at different locations on the segment at different times to an estimate of the traditional traffic volume past a fixed location, consider a mobile platform that traverses "Direction 1" (e.g., northbound) of a roadway segment in t_1 time units, and while doing so, "observes" n vehicles travelling in the opposite "Direction 2" (e.g., southbound in this example). For simplicity, the expression "the platform observes the vehicles" is used rather than "vehicles are digitized from the sensed data to produce an identification of vehicle presence."

A hypothetical "virtual vehicle" travelling in Direction 2 (the direction opposite of the platform travel direction and in the direction of the observed traffic) is considered to enter the Direction 2 upstream end of the segment at the instant the platform leaves the segment (travelling in Direction 1) at this location. At this time, which occurs t_1 time unis after the platform enters the segment, the platform stops observing vehicle presence or absence on the segment.

A hypothetical "virtual observer" situated at the Direction 2 downstream end of the segment is considered to begin counting vehicles passing a fixed location in Direction 2 at the instant the platform enters the segment. Assuming that all n Direction 2 vehicles the platforms observes while traversing the segment travel the entire segment (an assumption made when estimating segment volume from vehicles passing a fixed segment location with traditional methods) and that the hypothetical virtual vehicle does not overtake any of the vehicles before it reaches the virtual observer at the downstream end of the segment, the virtual observer would count the n vehicles observed by the platform over a time period $t_1 + t_2$, where t_2 is the time the virtual vehicle would require to traverse the segment in Direction 2. That is, the end of the stationary virtual observer's observation period occurs t_2 time units after the mobile platform leaves the segment, which, as stated above, is t_1 time units after the platform enters the segment, the beginning of the virtual observer's observation period.

The equivalent traffic volume for vehicles traveling in Direction 2 from this individual platform pass is, therefore, n vehicles in $t_1 + t_2$ time units. As discussed in Section 3.1, in this project the n vehicles and time t_1 taken by the platform – i.e., the bus – to traverse the segment are obtained from the segmenting and vehicle detection steps when processing the imagery. The time t_2 that is assumed for the virtual vehicle to traverse the segment could be determined in several ways. Presently, t_2 is set to the length of the segment divided by the posted speed limit.

In this way, each platform pass (traversal) leads to an estimated volume of n vehicles in $t_1 + t_2$ time units for the time interval beginning when the platform enters the segment and ending $t_1 + t_2$ time units after the platform enters the segment. In McCord et al., (2020), the traffic volumes for different bus passes occurring in a given time period were aggregated by expanding each traffic volume to a volume corresponding to the duration of interest – e.g., if $t_1 + t_2$ is measured in minutes and a 60-minute (hourly) volume V^{60} is desired, $V^{60} = 60 \times \frac{n}{t1 + t2}$ – and then taking a simple (arithmetic) average of all the expanded volumes obtained from bus passes that occurred during the specified time-of-day period.

3.2.2 Modifications to Volume Estimation Approach

In this project, modifications were made to the previously developed approach summarized above. These modifications consist of adjusting video volumes for an individual bus pass where unreasonably low or high bus volumes would be estimated and of aggregating the volumes from the individual bus passes differently to provide an estimate of a volume for the specified time-of-day period on the day the bus pass videos were collected.

<u>Modifications to volumes from individual bus passes</u>: When investigating the empirical video volume estimates, it was noticed that some bus passes led to estimates of zero vehicles and that some other bus passes led to estimates that were too high to be reasonable.

It is reasonable that a bus might traverse a segment when no vehicles were travelling in the opposite direction, for example, during a very low volume period or between passage of vehicle platoons. Although it would make sense that some short duration ($t_1 + t_2$) observation periods would in reality result in no vehicles observed, if this observation is to represent a traffic volume for an extended time period, a volume of zero vehicles would be unreasonable. Therefore, it was decided to consider adjusting a bus pass volume of zero to a positive volume. The following adjustments of zeros (AZ) for bus pass volumes were considered:

- AZ1: Replace an empirical video bus pass volume of 0 vehicles by a volume that is the equivalent of a flow of 30 vehicles/hour/lane
- AZ2: Replace an empirical video bus pass volume of 0 vehicles by a volume that is the equivalent of flow of 60 vehicles/hour/lane
- AZ3: Replace an empirical video bus pass volume of 0 vehicles by the average of all other bus pass volumes in the hour (beginning on HH:00) that are greater than 0 and less than the volume corresponding to an estimate of capacity (see below)
- AZ4: Replace an empirical video bus pass volume of 0 vehicles by the average of all other bus pass volumes in the hour (beginning on HH:00) that are greater than 0 and less than the volume corresponding to an estimate of capacity (see below) and one additional volume that is the equivalent of 30 vehicles/hour/lane

For surface streets between intersections, a rough estimate of capacity as 600 vehicles/hour/lane was considered based on TRB (2000). Video volume estimates for some bus passes were greater than an hourly directional volume (summed across lanes) determined by this capacity flow rate. Manual observations of some videos of bus passes that led to these greater-than-capacity volume estimates indicated that these estimated large volumes were a result of including queued vehicles (usually at the downstream intersection where the bus enters a segment) in the number of vehicles counted. Approaches to explicitly handle queued vehicles are presented in Section 3.3. To allow an expedient solution for studies in this project, *ad hoc* adjustments to capacity (AC) of greater-than-capacity video volumes were considered. These adjustments are similar in spirit to the adjustments of zeros made for zero-volume bus passes, but in this case the video volumes are decreased, rather than increased. The following adjustments to capacity (AC) were considered for bus pass volumes that are greater than 600 vehicles per hour per lane:

- AC1: Replace the volume on a bus pass with an equivalent hourly volume greater than that corresponding to a flow of 600 vehicles/hour/lane by a volume that is the equivalent of 600 vehicles/hour/lane
- AC2: Replace the volume on a bus pass with an equivalent hourly volume greater than that corresponding to a flow of 600 vehicles/hour/lane by a volume that is the equivalent of 500 vehicles/hour/lane
- AC3: Replace the volume on a bus pass with an equivalent hourly volume greater than that corresponding to a flow of 600 vehicles/hour/lane by the average of all other bus pass volumes in the hour (beginning on HH:00) that are greater than 0 and less than the equivalent of 600 vehicles/hour/lane
- AC4: Replace the volume on a bus pass with an equivalent hourly volume greater than that corresponding to a flow of 600 vehicles/hour/lane by the average of all other bus pass volumes in the hour (beginning on HH:00) that are greater than 0 and less than the equivalent of 600 vehicles/hour/lane and one additional volume that is the equivalent of 600 vehicles/hours/lane

Iterative, preliminary empirical investigations were conducted with these adjustments (both AZ and AC) by comparing resulting video volumes to road-tube or manual-count volumes (see below), and it was decided to consider the following combinations of adjustments more systematically. These combinations are termed Adjustment Cases.

- Adjustment Case 1: Do not adjust either zero or greater-than-capacity bus pass volumes, i.e., “do nothing” compared to the previously used approach
- Adjustment Case 2: Discard zero or greater-than-capacity bus pass volumes, i.e., consider these volumes as “bad data” that are to be “deleted”
- Adjustment Case 3: Combine AZ1 and AC1
- Adjustment Case 4: Combine AZ2 and AC2
- Adjustment Case 5: Combine AZ3 and AC3
- Adjustment Case 6: Combine AZ4 and AC4
- Adjustment Case 7: Combine AZ1 and AC3

<u>Modifications to aggregation of individual bus pass volumes:</u> As discussed in Section 3.1, individual bus pass volumes were previously aggregated to determine a volume for the time-of-day interval on the day the bus pass video imagery was collected by expanding each individual bus pass volume to a volume for common duration (e.g., one hour), and taking the arithmetic average of all the expanded volumes obtained

from bus passes that entered the segment during the time-of-day interval considered. This approach is referred to as a *Simple Average* aggregation.

A second way considered to aggregate bus pass volumes is the use of a *Weighted Average* aggregation. In this approach, the individual bus pass volumes are again expanded to volumes for a common duration, and the average of all these expanded volumes each weighted by the $t_1 + t_2$ duration of the pass is taken. The time $t_1 + t_2$ represents the duration of time that the virtual observer would conduct the traffic counts (see Section 3.1), and it would seem reasonable to give more weight to volumes obtained from longer observation periods. It can be shown that this weighted average is equivalent to determining the volume as the sum across all bus passes i in the time-of-day interval of the vehicles n_i observed during the bus passes, divided by the sum across the bus passes of the virtual observation periods $(t_1 + t_2)_i$. This equivalent interpretation would represent the total number of vehicles observed during the period associated with the multiple bus passes, divided by the total time of (virtual) observations.

The simple and weighted average approaches consider all bus pass volumes occurring during the time interval for which the volume estimate is being sought, and only those volumes. Doing so can lead to considering volumes further apart in time to be more similar than estimates closer together in time. For example, consider short-duration bus pass volumes beginning at 8:00 am, …, 8:50 am, 9:01 am and an interval between 8:00 am and 9:00. The volume obtained at 8:00 am and 8:50 am would be considered in the averaging procedure for this interval, whereas the volume obtained at 9:01 am would not be considered, and the volume at 8:00 am is implicitly assumed to be representative of the unobserved period after the 8:50 am observation until the end of the hour, whereas the volume at 9:01 am is considered irrelevant.

To address this issue, a third aggregation approach, termed *Flow Rate Integration*, is considered. In this approach, volumes are considered to represent observations of flow rates as a function of continuous time. Specifically, the volume of n vehicles in virtual observation time t_1+t_2 yields a flow rate:

$$q(t) = \frac{n}{t_1+t_2} \tag{3.2.2-1}$$

where the assumed instantaneous time t of the estimated flow rate is set to the time the bus enters the segment. This time could be set at the midpoint, the end, or any other time the bus is on the segment, but compared to other assumptions, this aspect is expected to have little effect on the estimated volume, given the small duration of $t_1 + t_2$. The multiple bus passes provide different $q(t)$ values at different times, which are considered to depict the flow rate as a function of time. The volume V during time interval $[T, T + \Delta T]$ is found by integrating the flow rate function between T and $T + \Delta T$:

$$V[T, T + \Delta T] = \int_T^{T+\Delta T} q(t)dt \tag{3.2.2-2}$$

Presently, linear interpolation is assumed between consecutive $q(t)$ values, although other assumptions could be considered (Charmchi Toosi, 2021).

3.2.3 Empirical Investigation of Modifications to Volume Estimation Approach

Adjustment Cases 1-7 were combined with each of the three aggregation methods to estimate the corresponding video volumes for all segment-direction-hour-days on 10/25/2018, 10/24/2019, and 11/05/2020 for which both video and road tube data are available (see Table A-1 in Appendix A). Denoting the video-based volume estimate for segment-direction by *S.x* (see Section 2), hour *h*, and date *d* as $V^{vid}_{s.x,\ h,\ d}$ and the corresponding road tube volume as $V^{tub}_{s.x,\ h,\ d}$ which is considered the ground truth, the absolute value of the relative "error" ARE is determined as follows:

$$ARE_{s.x,h,d} = \left|\frac{V^{vid}_{s.x,h,d} - V^{tub}_{s.x,h,d}}{V^{tub}_{s.x,h,d}}\right| \tag{3.2.3-1}$$

The ARE represents the magnitude (absolute value) of the error in the video volume estimate (difference between the video and ground truth, road tube volumes), scaled by the ground truth volume to allow similar comparisons across a range of low to high true volumes that would result from different segment-directions (spatial differences in volumes), hours of the day (daily temporal differences in volumes). and days (temporal differences across years, e.g., days during COVID-induced conditions and pre-COVID conditions; see Section 5). The average ARE values, taken across all segment-direction-hour-days by Adjustment Case-Aggregation Method combination are presented in Table 3.2.3-1.

Table 3.2.3-1: Average absolute relative error (average ARE) by Adjustment Case-Aggregation Method combination; Average taken across all segment-direction-hour-days where video and road tube data were available; N is the number of segment-direction-hour-days in the Adjustment Case and is the same for all Aggregation Methods used

	Aggregation Method			
Adjustment Case (AC)	**Simple Average**	**Weighted Average**	**Flow Rate Integration**	**N**
AC1	0.244	0.243	0.238	280
AC2	0.224	0.224	0.213	277
AC3	0.228	0.228	0.220	280
AC4	0.223	0.222	0.214	280
AC5	0.224	0.228	0.215	277
AC6	0.225	0.222	0.216	280
AC7	0.216	0.215	0.207	277

From Table 3.2.3-1, it is seen that using Adjustment Case 7 with the Flow Rate Integration method leads to the lowest average ARE of all Adjustment Case-Aggregation Method combinations. Moreover, for each Aggregation Method (column) Adjustment Case 7 results in lowest average ARE, and for each Adjustment Case (row), the Flow Rate Integration method results in lowest average ARE. Therefore, in Sections 4 onward, Adjustment Case 7 is used with the Flow Rate Integration method to estimate video volumes for specified time-of-day intervals from a series of bus pass video volumes on a given day.
It is noted that the averages were taken across all segment-direction-hour-days where video and road tube volumes are available, not just segment-direction-hour-days that contain bus passes whose video volumes were subject to an Adjustment Case. Moreover, even for segment-direction-hour-days that contain bus passes with adjusted volumes, the hourly volume was determined by integrating over multiple flow rate estimates, most of which are determined from volumes that did not need to be adjusted. Therefore, the

improvements seen in Table 3.2.3-1 as a result of the adjustments would underestimate the improvements offered for any individual bus pass that was adjusted.

3.3 Explicitly Handling Queued Vehicles in Estimation Methodology: Promising Extensions

As discussed in Section 3.2.2, unreasonably large (“greater-than-capacity”) video volume estimates were derived from the imagery on some bus passes over some segment-directions. The videos for a subset of bus passes that led to these larger-than-capacity volumes were reexamined and seen to contain vehicles queued at a downstream intersection where the bus enters the segments that were included in the vehicle count for the bus pass. These vehicles would have much lower spacing when queued than when in the nonqueued state and would, therefore, increase the overall vehicle count per time of bus observation. This increased count per time would then result in an increased flow rate estimate for the bus pass when using Equation (3.2.2-1). In the previous section, *ad hoc* downward adjustments of the volumes (flow rates) of these greater-than-capacity bus pass volumes improved the resulting volume estimates. In this section, preliminary approaches to explicitly address queued vehicles are described and evaluated. Empirical results show that these approaches are promising.

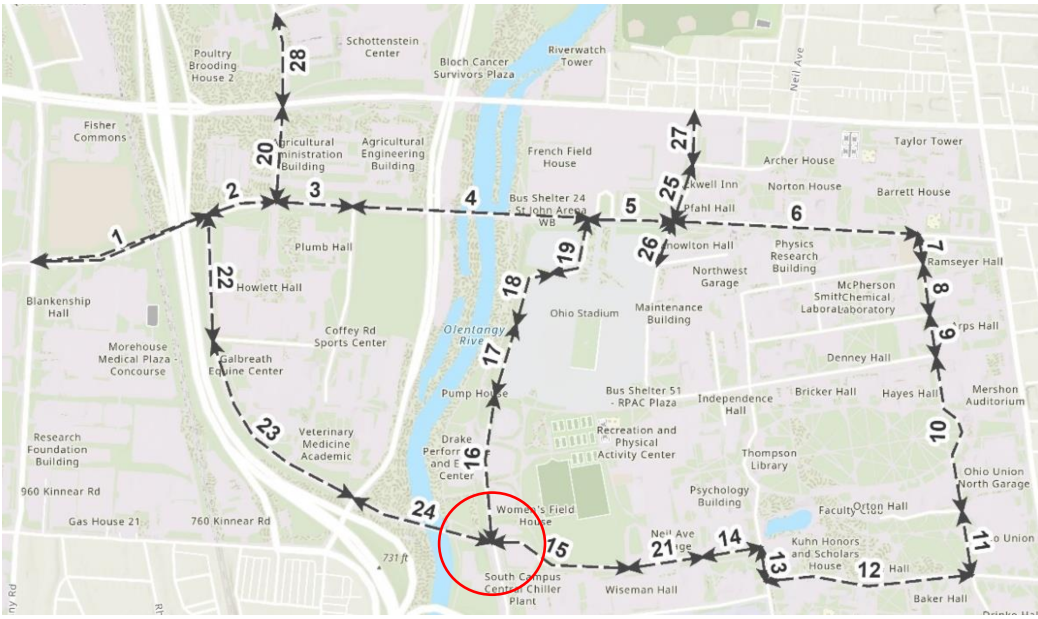
In the video imagery observed, the queues occurred at the downstream traffic end of the segment-direction, i.e., at the downstream intersection. The following two approaches were developed and evaluated to determine better volume estimates in the presence of queued vehicles.

<u>Queue Approach 1</u>: In this approach, the portion of the segment-direction that contains the queued vehicles is eliminated from consideration to form a “shortened” segment. Specifically, the number of queued vehicles n_q is subtracted from the number of vehicles n previously recorded on the bus pass to determine the number of nonqueued vehicles n' observed on the shortened segment, the time t_1' incurred by the bus in traversing the shortened segment is determined, and the time t_2' for the virtual vehicle to traverse the shortened segment is determined. Then, Equation (3.2.2-1) is used to calculate the segment-direction flow rate on the bus pass as $n' / (t_1' + t_2')$.

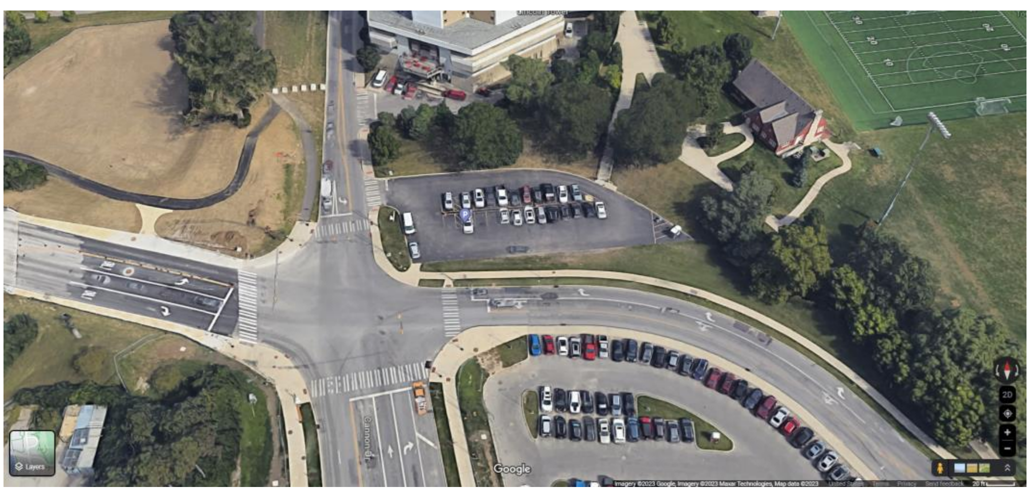
<u>Queue Approach 2</u>: This approach assumes that the queued vehicles would have already departed the segment when the bus entered the segment. That is, if the traffic signal had been green when the vehicles arrived at the intersection, they would not have been observed on this segment by the entering bus. Therefore, the number of nonqueued vehicles n' determined as in Queue Approach 1 is used with the original bus traversal time t_1 and virtual vehicle time t_2 with Equation (3.2.2-1) to determine the segment-direction flow rate on the bus pass as $n' / (t_1 + t_2)$.

In the empirical investigations conducted, the queues were manually observed in the imagery, and the numbers $n_{q\text{-}l}$ of long vehicles (buses and trucks) and $n_{q\text{-}s}$ of short vehicles (passenger cars, motorcycles) in the queue were manually counted. The sum $n_q = n_{q\text{-}l} + n_{q\text{-}s}$ results in the number of queued vehicles, which is the only additional input needed for Queue Approach 2, and is also needed as one input for Queue Approach 1. For Queue Approach 1, lengths of 50 feet for long vehicles and 20 feet for short vehicles were assumed to calculate a total queue length ql for the longest lane queue observed. The bus traversal time t_1' and virtual vehicle time t_2' on the shortened segment were then estimated assuming that the times are proportional to the segment lengths: $t_1' = t_1 \times (length_{seg} - ql) / length_{seg}$, and $t_2' = t_2 \times (length_{seg} - ql) / length_{seg}$, where $length_{seg}$ is the entire length of the (original) segment.

To assess the potential of the two Queue Approaches, segment-direction-hour-days with ARE (see Equation 3.2.3-1) on 10/25/2018, 10/24/2019, 11/05/2020 that are greater than 0.5 were identified. The video volumes were obtained using Adjustment Case 7 (see Section 3.2). The segment-directions all correspond to approaches to an intersection between segments 15 and 24. In Figure 3.3-1, the location of this intersection with respect to the supernetwork of Figure 2-1 and an overhead view of the intersection are presented. All bus pass videos during the segment-direction-hour-day were visually inspected for queues. Select video frames from the bus pass videos depicting queues are shown in Figure 3.3-2.



(a) Location of the intersection on supernetwork of Figure 2-1



(b) Aerial image of intersection (source: Google Maps accessed 06/10/2023)

Figure 3.3-1: Intersection between segments 15 and 24 where large overestimation by video volumes were observed that were seen to be associated with queues

Figure 3.3-2: Screen shots from 11/05/2020 video imagery showing queued vehicles at downstream end of segment-direction 24.1 at 14:06:57 (from bus 1903) on left and at downstream end of segment-direction 15.2 at 14:17:35 (from bus 1706) on right

The flow rates corresponding to bus passes where queues were observed were recalculated using Queue Approach 1 and Queue Approach 2, and the hourly volumes were recalculated using the revised bus pass flow rates and the flow rates of the other bus passes aggregated by the Flow integration Method. In Table 3.3-1, the segment-direction-day-hours used in this empirical evaluation are listed, along with the estimated video hourly volumes and ARE values obtained when using *ad hoc* "Adjustment Case 7" from Section 3.2.2 and when using Queue Approaches 1 and 2 from this section. The road-tube hourly volumes, considered as ground truth, are also listed.

Table 3.3-1: Hourly volumes and ARE values obtained in empirical investigation of approaches to explicitly address queued vehicles in determining video-based volumes

			Hourly volume obtained from				ARE when using		
Segment-Direction	**Day**	**Hour**	**Road Tube**	**Video with ad hoc adjust't[1]**	**Video with QA1[2]**	**Video with QA2[3]**	**Video with ad hoc adjust't[1]**	**Video with QA1[2]**	**Video with QA2[3]**
24.1	10/24/2019	12	221.5	360.66	291.46	246.36	0.63	0.32	0.11
24.1	10/24/2019	15	252.5	402.79	377.25	360.13	0.60	0.49	0.43
15.2	11/05/2020	9	114	209.86	166.12	161.09	0.84	0.46	0.41
15.2	11/05/2020	14	202	330.92	261.22	236.50	0.64	0.29	0.17
24.1	11/05/2020	13	134.5	205.99	119.09	114.17	0.53	0.11	0.15
24.1	11/05/2020	14	148	267.38	155.07	150.33	0.81	0.05	0.02

[1]Adjustment Case 7 from Section 3.2
[2]Queue Approach 1
[3]Queue Approach 2

The results in Table 3.3-1 demonstrate that the approaches developed to explicitly address queued vehicles when estimating bus pass flow rates greatly improved the estimated hourly volumes compared to those resulting from the improvements offered by the *ad hoc* adjustments presented in the previous section. Both Queue Approaches 1 and 2 show substantial improvement for every segment-direction-hour-day considered, with Queue Approach 2 leading to lower ARE than Queue Approach 1 for all but one segment-direction-hour-day. Once again, the estimated hourly video volumes were obtained from multiple bus passes, some of which would not be subject to these modifications. Therefore, the improvement that would be obtained on an individual bus pass would be underestimated.

The empirical results demonstrate the promise of improving video-based volume estimation by explicitly addressing queued vehicles. The GUI used to record data for volume estimation could be modified to allow semi-automatic determination of the number of long and short queued vehicles in the queue for use in Approach 1, or simply the total number of queued vehicles for use in Queue Approach 2. The GUI could also be modified to allow identification of the frame number associated with the end of the queue, which would lead to a better determination of t_1' for use in in Queue Approach 1. Recording these values would, however, increase the time required for the semi-manual processing of the imagery. It is also noted that Queue Approach 2 would need to be reconsidered for queues that occur other than at the downstream traffic end of the section, for example, queues that result from pedestrian crossings or from bus stops without pullouts.

Since large quantities of imagery were already processed before these Queue Approaches were evaluated, it was not feasible to reprocess all the imagery for the empirical studies of this report. Therefore, the subsequent empirical studies are based on video volumes determined from the *ad hoc* adjustments of the previous section which were easily programmed for automatic adjustments of already processed data. It is also noted that the promise of being able to automatically detect vehicles in the imagery discussed in Section 3.2 is encouraging because all the values needed for Queue Approach 1, Queue Approach 2, or other related approaches could eventually be determined automatically.

4 Evaluation of Time-of-day Volume Estimation for a Specific Day

Hourly video volumes were estimated on multiple segments of the supernetwork of Figure 2-1 between 8 am and 6 pm on 10/25/2018, 10/24/2019, and 11/05/2020 (see Table A-1). On these days, hourly volumes were also determined from road tube data over the 10-hour period for small subsets of segment-directions and from manual traffic counts for various segment-direction (see Table A-1). The "road tube volumes" and "manual volumes" are considered as ground truth for comparison with the "video volumes" estimated on these days. (As stated at the end of Section 3.3, video volumes in this and subsequent sections are estimated using the *ad hoc* Adjustment Case 7 and Flow Rate Integration aggregation method described in Section 3.2.2) Paired (video-vs.-road tube or video-vs.-manual) segment-direction-day-hour volumes are pooled across the three days and across the use of either road tube volumes or manual volumes as the ground truth, and the absolute value of the relative error ARE is computed using the equivalent of Equation (3.2.3-1) with either road-tube or manual volume substituting for $V_{s.x,h,d}^{tub}$ as the ground truth. Values of ARE are also determined for comparisons of 10-hour video volumes to 10-hour road tube volumes for the segments where road tube data are available. Recall that manual volumes are only available for at most a few hours on a given day. The empirical cumulative distribution functions (ecdfs) of the 1-hour and 10-hour volumes are presented in Figure 4.1, and summary statistics of the distributions are presented in Table 4.1.

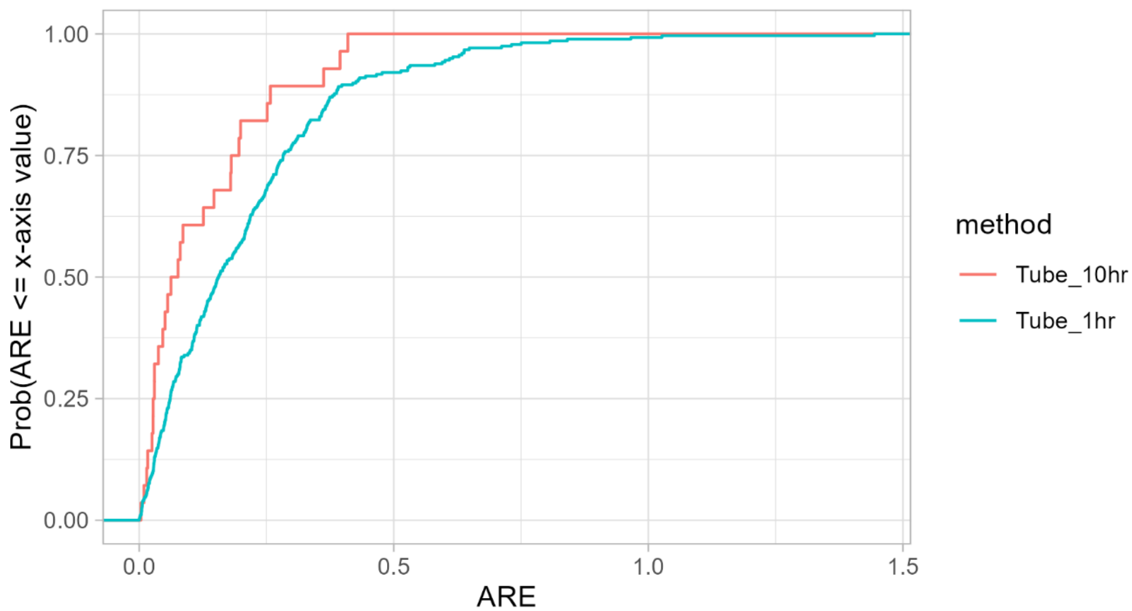


Figure 4.1: Ecdfs of ARE values obtained when comparing hourly or 10-hour video volumes estimated on 10/25/2018, 10/24/2019, and 11/05/2020 to ground truth

Table 4.1: Summary statistics of distributions from Figure 4.1

Statistic	**Hourly Volume ARE**	**10-hour Volume ARE**
Mean	0.273	0.121
Standard Deviation	0.280	0.121
Min	0.000	0.003
25%-ile	0.080	0.029
50%-ile	0.203	0.069
75%-ile	0.355	0.185
Max	1.730	0.410

Not surprisingly, the distributions indicate that the 10-hour video volume estimates are much closer to the ground truth volumes than are the hourly volumes. All the 10-hour percentile ARE values are less than the corresponding hourly percentile values, with the mean (median) decreasing from an approximate 27% (20%) error to an approximate 12% (7%) error. As expected, the longer 10-hour estimation period allows the mix of the over- and under-estimation errors to "balance out" in the more aggregate estimation. As also expected, the standard deviation associated with the 10-hour ARE values (0.121) is less than that of the hourly ARE values (0.280). Both distributions contain ARE values taken across the same multiple segment-directions and the same multiple days, but the hourly distribution also contains ARE values taken across the additional dimension of hour of the day.

There are additional contributing factors to the nature of the 10-hour and 1-hour distributions of the ARE values. The distributions of 10-hour ARE values are determined only from comparison between video and road tube volumes, since manual traffic counts were only taken for an hour or so on the data collection days, while the distributions of hourly ARE values are determined from comparisons between video volumes and either road tube or manual volumes. Volumes from road tubes and manual counts would be subject to different types of errors. Perhaps more importantly, road tubes were placed on segments of particular interest to the Mid-Ohio Planning Commission, which serves as the Metropolitan Planning

Organization for the area, whereas the manual counts were scheduled to "cover" the other segments in the network. As such, the road tube and manual count segments would likely not be homogeneous in terms of characteristics that are likely to contribute to the quality of estimating traffic volumes from video imagery. Indeed, as seen in Figures 4.2 and 4.3 and Table 4.2 and 4.3, the road tube segments generally have larger volumes and longer lengths. Moreover, from Figure 4.4 and Table 4.4, it is seen that the ARE values obtained when using manual volumes as the ground truth are noticeably larger than those obtained when using road tube volumes as the ground truth.

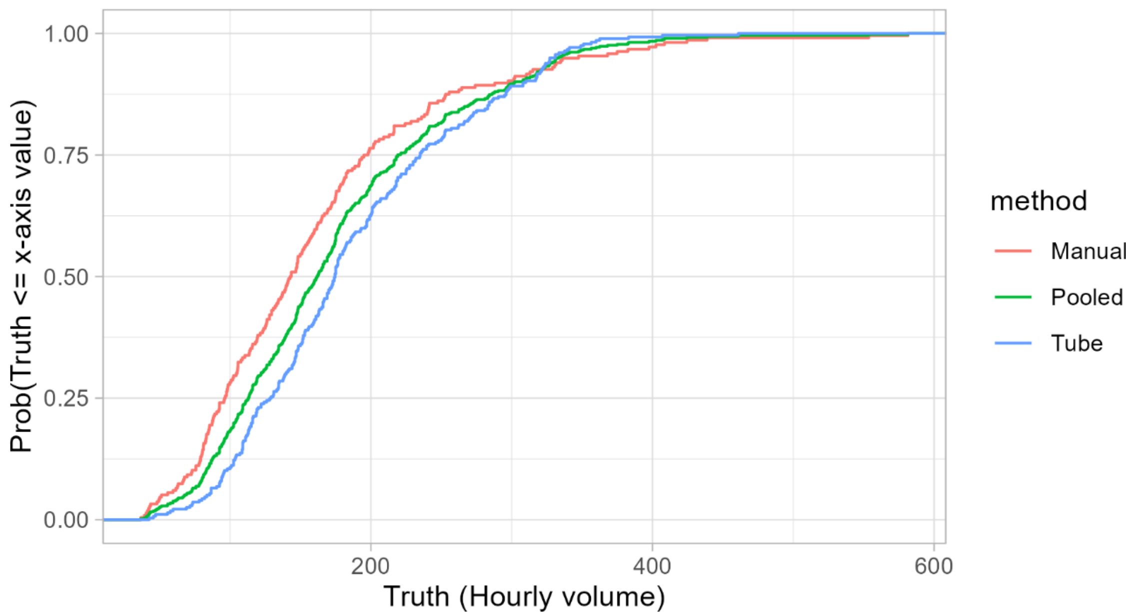


Figure 4.2: Ecdfs of "true" hourly traffic volumes on segments with true volumes determined from manual traffic counts, from road tube data, and the pooled distribution across the two types of data collection; Data collected on 10/25/2018, 10/24/2019, and 11/05/2020

Table 4.2: Summary statistics of distributions from Figure 4.2

	Data Serving as Ground Truth		
Statistic	**Road Tube**	**Manual**	**Pooled Road Tube and Manual**
Mean	187.6	161.9	176.3
Standard Deviation	78.1	92.4	85.5
Min	42.5	36.6	36.6
25%-ile	129.0	96.4	113.0
50%-ile	174.5	143.0	161.8
75%-ile	235.0	195.8	219.0
Max	461.0	581.5	581.5

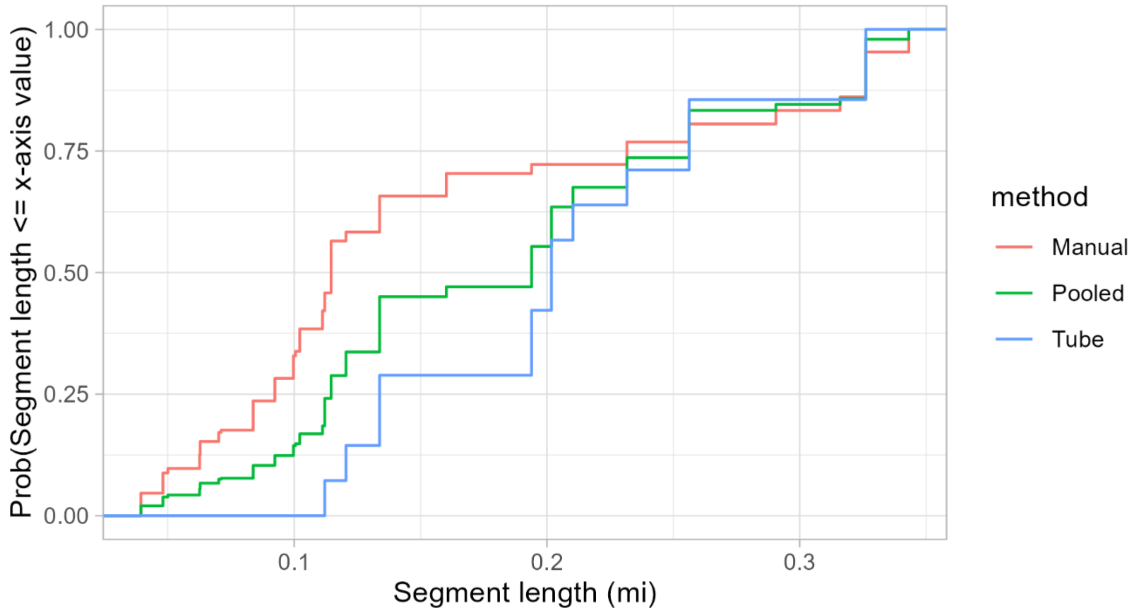


Figure 4.3: Ecdfs of segment lengths, in miles, of segments with volumes determined from manual traffic counts, from road tube data, and the pooled distribution across the two types of data collection; Data collected on 10/25/2018, 10/24/2019, and 11/05/2020

Table 4.3: Summary statistics of distributions from Figure 4.3

	Data Serving as Ground Truth		
Statistic	**Road Tube**	**Manual**	**Pooled Road Tube and Manual**
Mean	0.21	0.16	0.21
Standard Deviation	0.06	0.10	0.09
Min	0.11	0.04	0.11
25%-ile	0.13	0.09	0.13
50%-ile	0.21	0.12	0.20
75%-ile	0.26	0.23	0.26
Max	0.33	0.34	0.33

The volume comparisons comprising the hourly ecdf in Figure 4.1 are decomposed to form separate distributions based on using road tube or manual volumes as the ground truth. The resulting ecdfs are presented in Figure 4.4 along with the pooled distribution from Figure 4.1. Summary statistics are presented in Table 4.4.

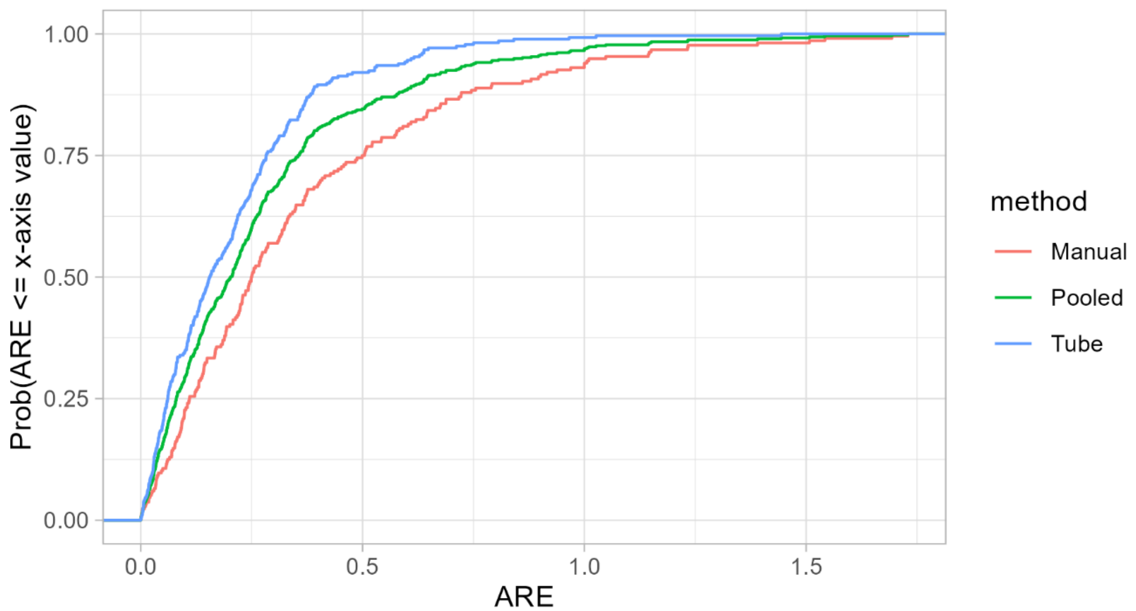


Figure 4.4: Ecdfs of ARE values obtained when comparing hourly video volumes estimated on 10/25/2018, 10/24/2019, and 11/05/2020 to road tube, manual, and pooled ground “true” volumes

Table 4.4: Summary statistics of distributions from Figure 4.4

	Data Serving as Ground Truth		
Statistic	**Road Tube**	**Manual**	**Pooled Road Tube and Manual**
Mean	0.207	0.357	0.273
Standard Deviation	0.197	0.338	0.278
Min	0.000	0.000	0.000
25%-ile	0.061	0.110	0.080
50%-ile	0.156	0.250	0.203
75%-ile	0.282	0.500	0.354
Max	1.444	1.730	1.730

From Figure 4.4 and Table 4.4, it is seen that the ARE values obtained when using manual volumes as the ground truth are noticeably larger than those obtained when using road tube volumes as the ground truth. To investigate the possibility that the difference in the overall ARE values obtained when using road tube volumes or manual volumes as ground truth are partially a result of different volumes and segment characteristics in the two groups, the ARE values for video volume-vs.-true volume comparisons *i* are regressed against the corresponding true hourly volumes Vol_i^{tru} (as determined from either the road tube volume or manual volume) for the comparisons and lengths of the segment-directions Len_i in the comparison using the following model specification:

$$ARE_i \; = \; \beta_0 + \; \beta_1 Vol_i^{tru} + \beta_2 Len_i \qquad (4\text{-}1)$$

The regression estimation results, presented in Table 4.5, show very low p-values for the coefficients of the two explanatory variables (as well as for the intercept). The negative sign of the estimated β_2 coefficient indicates that, all else equal, longer segments would tend to have lower ARE than shorter segments. This indication is reasonable, since longer segments would be associated with longer equivalent observation times t_1+t_2 for individual bus passes. Moreover, the impacts of any queued vehicles (see Section 3.3) would tend to be diminished on longer segments.

Table 4.5: Summary regression results using specification (4-1) investigating the association of the true volume and segment length with ARE value in hourly estimates when pooling data from *all comparisons* between video volumes and either road tube or manual volumes on 10/25/2018, 10/24/2019, and 11/05/2020

Variable	**Coefficient Estimate**	**Std. Error**	**t-stat**	**p-value**
Intercept	0.559	0.037	14.930	< 2e-16
Manual (True) Volume, Vol^{tru}	-0.001	0.000	-4.827	1.86e-06
Segment Length, Len	-0.915	0.139	-6.589	1.14e-10
$R^2 = 0.119$ N = 493				

The very significant (p-value =1.86E-06) associated with the estimated $\beta_1$coefficient may be surprising at first. The scaling of the difference between the estimated video volume and the true volume by the magnitude of the true volume in the ARE metric (see Equation (3.2.2-1)) is motivated by allowing comparisons of estimation errors across segment-direction-day-hours involving volumes of various magnitudes. As such, little if any effect of volume on this metric is originally expected. A scatter plot of the ARE values as a function of the true volume (either road tube or manual volume) is presented in Figure 4.5.

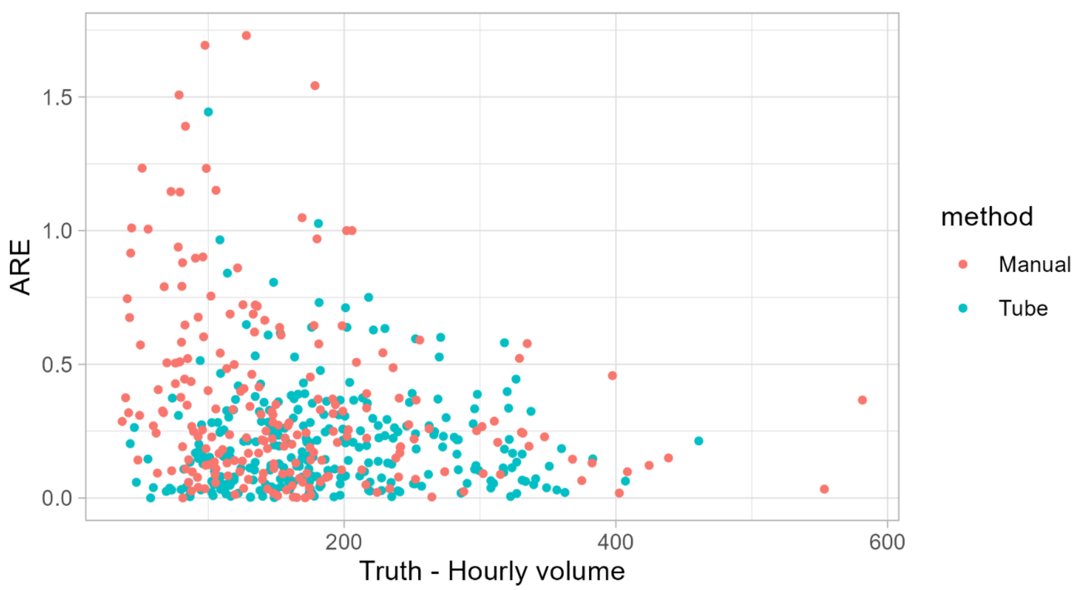


Figure 4.5: Scatter plot of ARE values versus true volume involved in the comparison associated with the ARE value; Comparison with manual volumes in red and with road tube volumes in blue

Figure 4.5 indicates a much larger proportion of large ARE values at low values of volume than at higher values of volume, which would explain the negative slope (negative value of β_1) in the ARE-vs.-volume relation. From the discussion in Section 3.3, larger ARE values are generally believed to be associated with queued vehicles during some of the bus passes used in estimating the video volume. Queued vehicles can be observed during times of either high or low true volume, but since the true volumes are used in the denominator of the ARE metric, the ARE value would tend to be higher when queues occur at times of low true volumes (smaller denominator), compared to when queues occur at times of high true volumes (larger denominator). Very large ARE values, defined to be greater than 0.5 and which are likely to be associated with observations involving queued vehicles, are not considered in a subsequent regression where the remaining data are used again with the specification in Equation (4.1). The results, presented in Table 4.6, show that the effect of the segment length is still negative ($\beta_2 < 0$) and very significant (p-value = 0.000796), but that the p-value associated with the coefficient associated with the true volume (β_1) increases to 0.753, indicating that it would be likely to observe the empirical relation between ARE and true volume if there really was no volume effect, and where no effect of true volume on ARE partially motivates the use of the ARE metric.

It is also seen in Figure 4.2 and Figure 4.5 that the comparisons between video volumes and manual volumes appear to be overrepresented, relative to the comparison between video volume and road tube volumes, for lower values of true volumes. As discussed above, road tubes were placed on segments of relative interest to the Mid-Ohio Regional Planning Commission (MORPC). Such segments would tend to be higher volume segments. Since the lower volume comparisons appear to have larger ARE values, this overrepresentation of comparisons with manual volume at lower volumes could explain the greater ARE values in the manual distributions than in the road tube volumes seen in Figure 4.4 and Table 4.4. Moreover, longer length segments, which are statistically associated with lower ARE values according the negative and highly significant estimated values of β_2 in both Table 4.5 and Table 4.6, would tend to be segments of more interest to MORPC.

Table 4.6: Summary regression results using specification (4-1) investigating the association of the true volume and segment length with ARE value in hourly estimates when pooling data from comparisons between video volumes and either road tube or manual volumes on 10/25/2018, 10/24/2019, and 11/05/2020 with ARE values less than 0.5

Variable	**Coefficient Estimate**	**Std. Error**	**t-stat**	**p-value**
Intercept	0.227	2.01e-02	11.298	< 2e-16
Manual (True) Volume, Vol^{tru}	-1.99e-05	6.33e-05	-0.315	0.753
Segment Length, Len	-0.243	7.34e-02	-3.310	0.001
R^2 = 0.026 N = 417				

To investigate the hypothesis that the larger ARE values seen in the empirical manual distribution are partially a result of overrepresentation of segments that have smaller true volumes and shorter segment lengths, the true volumes and segment lengths involved in each segment-direction-day-hour comparison are used in Equation (4-1) with the estimated coefficient values presented in Table 4.5 to determine "model-predicted" ARE values. The "model-predicted" ARE values determined in this way are plotted as to whether the video volume was compared to a manual or road tube volume in the empirical distributions of Figure 4.4 and Table 4.4. The ecdfs plotted in Figure 4.6 and the corresponding summary statistics presented in Table 4.7 indicate that the empirical comparisons comprising the manual distributions of Figure 4.4 and Table 4.4 would be expected to result in larger ARE values than the comparisons comprising the road tube distributions because of differences in true volumes and segment lengths in the segment-direction-day-hours for which comparison were made in the two distributions.

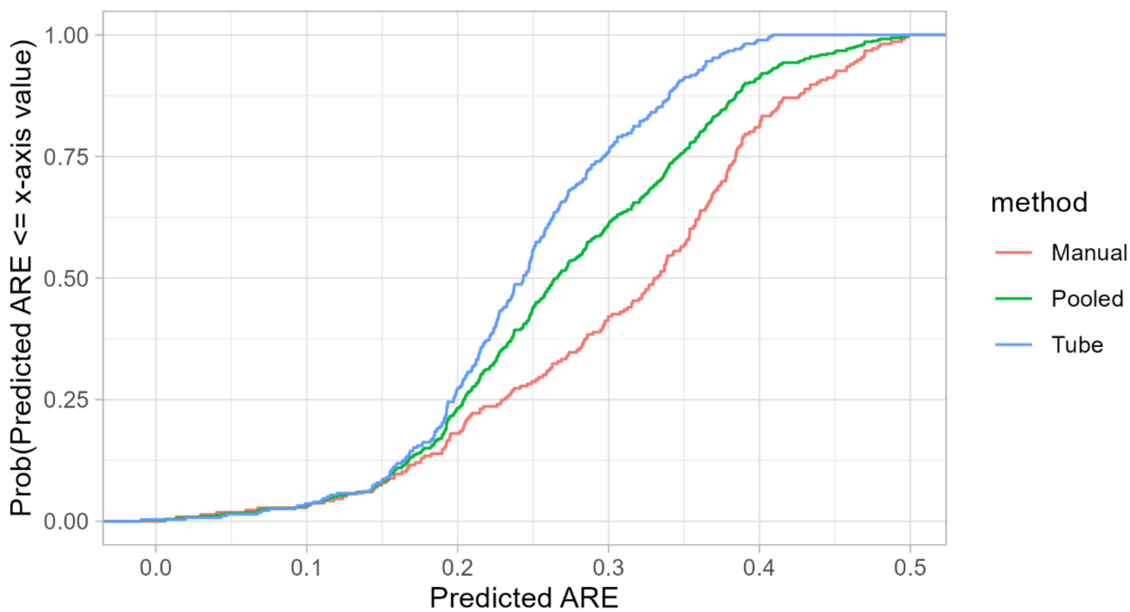


Figure 4.6: Ecdfs of "model-predicted" ARE values, using Equation (4.1) and Table 4.5, for segment-direction-day-hours considered in Figure 4.4 and Table 4.4

Table 4.7: Summary statistics of distributions from Figure 4.6

	Data Serving as Ground Truth		
Statistic	**Road Tube**	**Manual**	**Pooled Road Tube and Manual**
Mean	0.245	0.309	0.273
Standard Deviation	0.076	0.106	0.096
Min	---[1]	0.006	---[1]
25%-ile	0.197	0.231	0.204
50%-ile	0.2446	0.331	0.266
75%-ile	0.297	0.384	0.346
Max	0.408	0.499	0.499

[1] A negative minimum value resulted from applying Equation 4-1; since ARE values cannot be negative by definition, the negative minimum value output from the model is not reported

The model-based results presented in Figure 4.6 and Table 4.7 support the statistical results seen in Table 4.5 that higher volumes and longer length segments are associated with lower ARE values. The very low R^2 values when using all the data (Table 4.5) and when attempting to avoid comparisons where queues may be responsible for particularly large ARE values (Table 4.6) indicate that other factors likely have a large effect on the quality of the video-based volume estimation. Determining these factors would be helpful both in providing clues to improve the estimation methodology and in indicating the degree of confidence one would have in a specific estimate. Investigating these other factors would be an interesting topic of future research.

5 Estimation and Monitoring of Vehicle Miles Traveled

5.1 Vehicle Miles Traveled

Vehicle distance traveled is arguably the most fundamental metric of network-wide vehicular travel (Kumapley and Fricker, 1997; Fricker and Kumapley, 2002; Roess et al., 2004; FHWA, 2022; Williams et al., 2016). By definition, vehicle distance traveled is the sum, over all vehicles traveling on the network during a specified time period, of the distance traveled by each vehicle on the network during the time period. Distances are usually considered in kilometers or miles, leading to measures of Vehicle Kilometers Traveled (VKT) or Vehicle Miles Traveled (VMT). VMT is used in this report.

It is impractical to track the travel of all vehicles on a network over a time period, and there have been various proposals to estimate VMT (Kumapley and Fricker, 1997; Fricker and Kumapley, 2002; Roess et al., 2004; FHWA, 2022; Williams et al., 2016; Fan et al., 2019). The most common approach based on direct measurements, and that which has proven practical for both statewide and "smaller" roadway networks (Roess et al., 2004; FHWA, 2022), disaggregates the roadway network into segments and sums, across all segments, the vehicle miles traveled on each segment during the time period. Denoting the traffic volume on segment *i* during the time period by V_i and the length of the segment (in miles) by L_i, the vehicle miles traveled on segment *i* during the time period is $L_i \times V_i$, and the network VMT during the time period is therefore:

$$VMT \;=\; \sum_{\forall segments,i} L_i \times V_i \qquad (5.1\text{-}1)$$

Accurate, static segment lengths are readily available in public roadway databases. Therefore, the accuracy of estimated VMT depends largely on the accuracy of the estimated traffic volumes during the specified time period, and the ability to monitor or update VMT estimates depends on the ability to readily obtain traffic volumes. The ability to estimate accurate volumes on an ongoing basis using available bus-based video imagery is the focus of the research covered in this report, and in this section empirical investigations of the accuracy in determining VMT from the volumes estimated using the methodology of Section 3 are presented.

5.2 Empirical Comparisons of Video-based and LBS-based VMT to Road-tube VMT

Ten-hour VMT, between 8:00 am and 6:00 pm, is estimated for 10/25/2018, 10/24/2019, and 11/05/2020 across "subnetworks" of segment-directions on the day. (These are the three days of data on which road tube data were collected.) These subnetworks are subsets of the supernetwork presented in Section 2 and consist of the (unconnected) segment-directions on which road-tube data were collected on the day. The segments included in the subnetworks, the lengths of the networks, and the numbers of bus passes obtained over the ten hours can be obtained from Table A.1 in Appendix A (data table), but this information is summarized in Table 5.2-1 for convenience. VMT is estimated separately from segment-direction volumes obtained from video, road-tube, and Location Based Service (LBS) data (see Section 2) collected on the day.

Table 5.2-1: Segments comprising road tube-equipped subnetworks and number of bus-passes on day of VMT estimation

Day	Segment numbers[1] (No. of bus passes obtained for 10-hr video estimation)	Total Network Length of Segment-directions [mi]
10/25/2018	1(35/35), 4(90/91), 10(51/33), 15(53/26); 19(36/42)	2.240
10/24/2019	5(39/65); 16(20/47); 20(38/39); 24(32/29)	1.333
11/05/2020	1(86/88); 4(94/161); 15(88/106); 20(118/61); 24(47/43)	2.224

[1]Volumes obtained on both directions of the segments

The 10-hour volumes obtained from the video, LBS, and road tube data are used with segment lengths to determine the 10-hour VMT by each data source for the road-tube equipped subnetwork. These VMT values are presented in Table 5.2-2. The video-based VMT values are seen to be much closer to the road-tube VMT values than are the LBS-based VMT values. Note that because the road-tubes were placed on different segments in the different years, the VMT values are not comparable across years. To quantify differences from the ground truth, the absolute relative errors (ARE) between the VMT determined from either video- or LBS-based volumes (indicated by superscript *data*) and the VMT determined from road-tube volumes (considered as ground truth and indicted by *tub*)

$$ARE(VMT^{data}) = \left|\frac{VMT^{data} - VMT^{\mathrm{tub}}}{VMT^{tub}}\right| \tag{5.2-1}$$

are calculated for each day. These ARE values, also presented in Table 5.2-2, indicate that using volumes derived from the video imagery to estimate VMT leads to differences from the ground truth, road-tube-based VMT of at most 10% and as low as 0.2%, whereas using LBS-based volumes leads to differences greater than 36% in all cases and over 123% on one day.

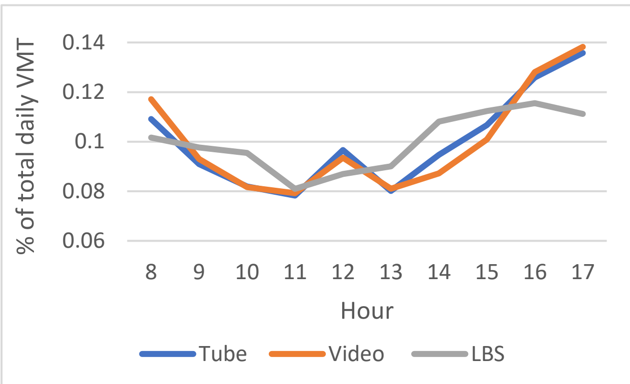
Table 5.2-2: Ten-hour VMT on road-tube subnetworks when using video, LBS, and road-tube data by day, and corresponding absolute relative errors (ARE) in VMT estimates compared to road-tube VMT

Day	Video VMT	LBS VMT	Tube VMT	ARE(VMT^{vid})	ARE(VMT^{LBS})
10/25/2018	7,592	13,445	7,610	0.23%	76.68%
10/24/2019	5,570	6,914	5,054	10.21%	36.80%
11/05/2020	5,210	11,039	4,929	5.72%	123.96%

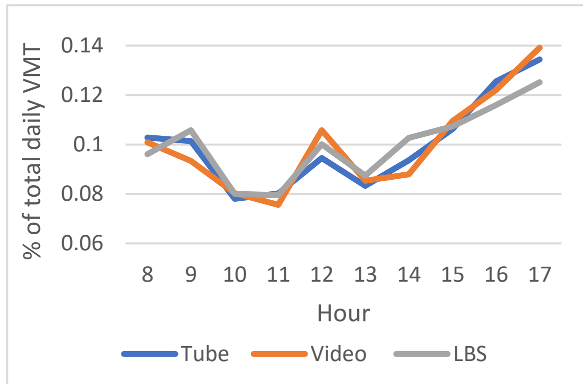
In addition to determining the 10-hour VMT, VMT time-of-day patterns are determined using volumes from each of the sets of video, LBS, and road tube data. Specifically, the VMT across the road-tube network is determined from each hour *h* of the 10-hour period on day *d* using Equation (5.1-1) with static segment-direction lengths and volumes determined with *data* in *h* of *d* for segments on which road-tubes were placed in the year. Denoting the hourly VMT as $VMT_{h,d}^{data}$, the proportion $P_{h,d}^{data}$ of the 10-hour VMT in hour *h* and day *d* with respect to the 10-hour VMT is determined as:

$$P_{h,d}^{data} = \frac{VMT_{h,d}^{data}}{\sum_{\forall \xi} VMT_{\xi,d}^{data}} \tag{5.2-2}$$

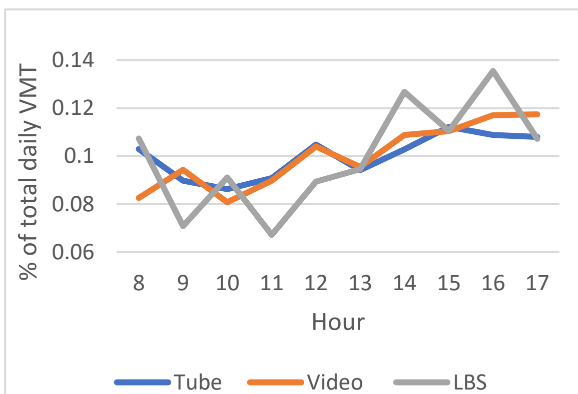
The $P_{h,d}^{data}$ values for the 10/25/2018, 10/24/2019, and 11/05/2020 "road-tube networks" are graphed by data source in Figure 5.2-1.



(a) 10/25/2018



(b) 10/24/2019



(c)11/05/2020

Figure 5.2-1: Proportion of 10-hour road-tube network VMT carried in each hour as determined when using video, LBS, and road-tube data by day

In Figure 5.2-1, the time-of-day VMT patterns obtained when using video volumes appear to be more similar to the patterns obtained when using the ground truth road-tube volumes than do the patterns obtained when using LBS volumes. To quantify the differences in the patterns, the absolute value of the differences between the $P_{h,d}^{data}$ determined when using either the video or LBS volumes (i.e., *data* = *vid* or *LBS*) and that determined when using the road-tube volumes (i.e., $P_{h,d}^{tub}$) are determined for each hour on the day of estimation, and the average of the absolute value of the differences across the 10 hours of the day $AAD(P_d^{data})$ is taken:

$$AAD(P_d^{data}) = \frac{\sum_{\forall h} |P_{h,d}^{data} - P_{h,d}^{tub}|}{10} \quad (5.2\text{-}3)$$

These average absolute value of time-of-day pattern differences from the road-tube patterns in each year are presented in Table 5.2-3. The AAD values obtained when using road-tube data are approximately one-half the AAD values obtained when using LBS data, indicating that the time-of-day patterns determined when using video data are much closer to those determined using road-tube data than are the time-of-day patterns determined when using LBS data, regardless of the year. Recall that different "road-tube-networks" are present in the different years.

Table 5.2-3: Average absolute value of differences (AAD) from road-tube VMT time-of-day patterns of VMT time-of-day patterns on road-tube networks determined when using video- and LBS-based VMT

Day	**AAD(P^{vid})**	**AAD(P^{LBS})**
10/25/2018	0.0054	0.0104
10/24/2019	0.0027	0.0052
11/05/2020	0.0059	0.0121

5.3 Empirical Comparisons of Video-based VMT and LBS-based VMT on Expanded Networks

Ten-hour VMT, between 8:00 am and 6:00 pm, is also estimated for 10/25/2018, 10/24/2019, 11/05/2020, and 11/04/2021 on an "expanded" network, consisting of segments where both video and LBS data were obtained for all four days. This common expanded network consists of the segments listed in Table 5.3-1, where also are listed the static lengths of the segments and numbers of bus passes used to estimate video-based volumes for the segment-direction during the 10-hour period. VMT is again estimated separately from segment-direction volumes obtained from video and from LBS data collected on those days. The 10-hour VMT values for the expanded networks are presented in Table 5.3-2. The LBS-based VMT values are seen to be very different from the video-based values.

When considering VMT estimated for the expanded network, there is no ground truth value to which the estimated VMT values can be compared. However, the days on which the VMT is estimated are all Thursdays at approximately the same time of the academic term. Therefore, patterns in the estimated VMT over the years (represented by the VMT for the late October/early November dates) can be compared to *a priori* expectation of how traffic changed over these years. Therefore, in Table 5.3-2, and subsequent tables and figures for the expanded network, the designation of the days on which the VMT is estimated is replaced by a designation of the year corresponding to late October/early November day. The 2018 and 2019 days correspond to what are called "pre-pandemic conditions." The 2020 day corresponds to "full pandemic" conditions, when almost all classes were conducted remotely and discretionary travel to campus was discouraged. The 2021 day corresponds to "recovering" conditions, when most classes were back to being offered in person, but when pandemic awareness (e.g., mandatory mask wearing indoors on campus) was strong and many meetings were still conducted remotely.

Table 5.3-1: Segments, segment lengths, and number of and number of bus-passes of expanded network by year (date) of VMT estimation

Segment Number	Segment Length [mi]	No. of bus passes for 10-hour video estimation: Segment-direction s.1/s.2[1]			
		10/25/2018	10/24/2019	11/05/2020	11/04/2021
1	0.256	35/35	79/78	86/88	142/143
2	0.100	36/37	48/47	40/41	47/47
3	0.111	90/89	88/83	96/163	130/131
4	0.326	90/91	84/84	94/161	130/132
5	0.120	36/53	39/65	56/102	45/83
6	0.343	32/53	42/49	58/38	49/92
7	0.039	56/36	44/38	36/58	82/45
8	0.070	56/36	45/42	38/60	82/48
9	0.063	53/34	45/38	37/60	84/45
10	0.232	51/33	44/18	40/60	87/51
11	0.092	50/36	45/19	38/100	85/47
12	0.291	48/34	47/19	40/60	35/50
13	0.048	36/32	18/43	60/39	47/80
14	0.084	55/37	45/20	40/60	80/46
15	0.194	53/26	74/47	88/106	174/140
16	0.210	33/56	20/47	59/39	46/85
17	0.102	37/53	18/47	59/39	46/81
18	0.101	37/56	18/46	60/39	45/82
19	0.112	36/42	18/46	60/39	45/81
20	0.134	51/56	38/39	118/61	83/80
21	0.115	56/33	45/19	40/60	81/46

[1]Direction s.1 refers to EB or NB traffic direction; direction s.2 refers to WB or SB traffic direction

Table 5.3-2: Ten-hour VMT on expanded networks determined from video- and LBS-based volumes, derived growth factors, and ODOT growth factors, using 2018 as reference

Year[1]	Video VMT	LBS VMT	Video GF	LBS GF	ODOT GF
2018	18,268	34,269			
2019	18,303	38,230	1.00	1.12	1.02
2020	9,431	32,883	0.52	0.96	0.92
2021	14,378	37,322	0.79	1.09	0.98

[1]Video and LBS 10-hour VMT are obtained on one Thursday in late October or early November in the indicated year, namely, 10/25/2018, 10/24/2019, 11/05/2020, 11/04/2021

"Growth factors" (Jiang et al., 2006; FHWA 2022) representing the ratio of VMT values in year *y* to the VMT in 2018 as determined from video- or LBS-based VMT (designated by *data)* are given by:

$$GF_y^{data} = \frac{VMT_y^{data}}{VMT_{2018}^{data}} \tag{5.3-1}$$

The calculated growth factor (*GF*) values are also presented in Table 5.3-2. In addition, the annual growth factors with respect to 2018 travel as determined from Ohio Department of Transportation (ODOT) state-wide traffic monitoring statistics for urban collector/local roads (ODOT, 2022) are presented.

There were no major demographic, infrastructure, or transportation-related policy changes on the OSU campus that would substantially affect overall vehicular traffic between 2018 and 2019. In Table 5.3-2, the video-based 2019 growth factor (1.00) is quite remarkable in reflecting this expectation. This video-based 2019 growth factor is also close the 2019 ODOT growth factor (1.02). The small difference between the two growth factors may be a result of more stability in campus traffic from year to year than in general statewide traffic on the same functional class of roadways. The LBS-based 2019 growth factor (1.12) gives a very different, and erroneous, indication of difference in travel on the campus between 2018 and 2019. There is no causal reason that traffic would have increased by 12% between 2018 and 2019, and observations by those regularly experiencing campus traffic on weekdays in autumn semester in the in the two years would rule out a 12% difference.

The 2020 VMT is estimated for conditions when the pandemic greatly affected travel to and from the OSU campus, what is considered the "full pandemic" condition. Therefore, the 2020 VMT is expected to be much less than the 2018 VMT. The 2020 video-based growth factor (0.52) in Table 5.3-2 indicates that there was approximately half as much travel in 2020 (i.e., after the onset of the pandemic) compared to 2018. This video-based 2020 growth factor is much less than the 2020 ODOT factor (0.92), which is expected. Statewide traffic monitoring factors are based on travel over the entire year. The first few months of 2020 were before the pandemic changed travel patterns and, therefore, the 2020 annual ODOT factor would reflect a combination of pre-pandemic and during pandemic conditions. Moreover, the change to remote instruction for the OSU campus in autumn 2020 severely affected almost all academic campus travel, an impact that would be expected to be greater than the impact on general, statewide urban collector/local roads travel during these "full pandemic" conditions. The 2020 LBS-based growth factor (0.96) indicates a decrease in travel during the full pandemic condition ($GF_{2020} < 1$), but much less of a decrease than that indicated by the video-based factor and even less than the decrease indicated by the ODOT growth factor for traffic on urban collector/local roads across the entire state and during both pre-pandemic and pandemic conditions in 2020. Recall that the LBS data-based volumes are specific to the dates on which video imagery data were collected, specifically the "full pandemic" conditions in 2020. In short, the video-based growth factors are in line with *a priori* expectations, whereas the LBS-based factors contradict these expectations.

Similarly, the 2021 video-based growth factor (0.79) is much more reasonable than the 2021 LBS-based factor (1.09). Based on familiarity with local conditions, there was more roadway traffic in the 2021 "recovering" conditions – when most, but not all classes were in person – than under the "full pandemic" conditions of 2020, but still noticeably less traffic than in 2018. In autumn 2021, in-class attendance was noticeably reduced compared to 2018, and many meetings were still held remotely. The 2021 video-based growth factor (0.79) is still noticeably less than 1.00 but also noticeably greater than the 2020 video-based factor (0.52). Again, the video-based 2021 factor is less than the ODOT 2021 factor (0.98), supporting the expectation that campus traffic was still affected by pandemic conditions more than general, statewide travel on urban collector/local roadways. Conversely, the 2021 LBS-factor (1.09) unreasonably indicates that 2021 VMT was greater than 2018 VMT and that campus travel was proportionately higher than statewide travel in 2021.

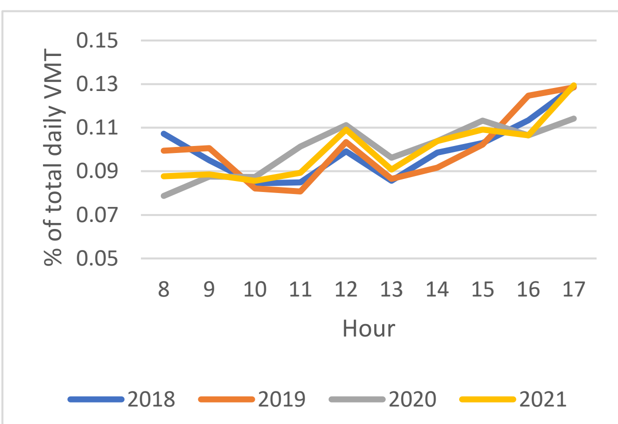
Time-of-day patterns obtained from the video- and LBS-based VMT are again determined for each year using the $P_{h,d}^{data}$ metric of Equation (5.2-2) but when considering VMT for the expanded network. These values are plotted for the various years in Figures 5.3-1 when using video- and LBS-based data. As discussed above, there were no factors that would be expected to affect campus travel patterns between 2018 and 2019. Therefore, the time-of-day pattern would be expected to be similar in these two years and more similar than when the pandemic substantially affected class-related and discretionary travel in 2020. The plots in Figure 5.3-1(a) appear to support this expectation. To quantify the differences in the time-of-day patterns across years, a metric analogous to the Equation (5.2-3) average absolute difference in hourly proportions is used, but this time considering difference in time-of-day proportions across consecutive years as follows:

$$AAD(P_{y,y+1}^{data}) = \frac{\sum_{\forall h} |P_{h,y+1}^{data} - P_{h,y}^{data}|}{10} \tag{5.3-2}$$

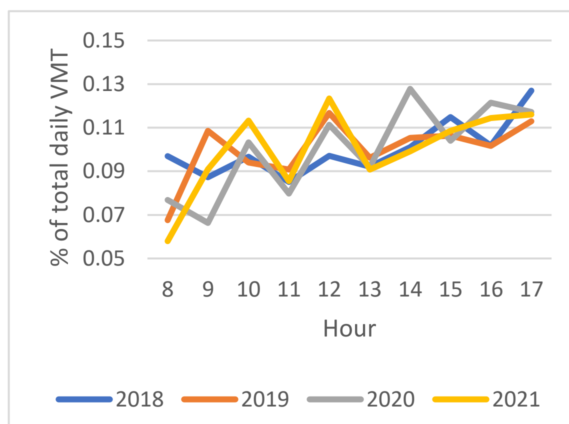
The absolute average differences obtained when using video- and LBS-based VMT values are presented in Table 5.3-3.

When using video-based VMT, the much smaller AAD value (0.0044) determined from comparing 2018 and 2019 time-of-day patterns than that (0.0132) determined from comparing 2019 and 2020 patterns is consistent with expectations, whereas the similarity in the values (0.0110 for 2018-2019 and 0.0130 for 2019-2020) obtained when using LBS-based VMT is not. Moreover, the 2018-2019 AAD value is much smaller when using video data than when using LBS data (0.0044 vs. 0.0110), indicating that the LBS data are leading to much larger differences in the temporal patterns between two years where the patterns are expected to be similar.

The comparisons of the 2018 and 2019 plots to the 2020 plot in Figure 5.3-1(a) indicate lower percentages of travel in the traditional morning commute time (8-9 am) and higher percentage of travel in the lunchtime and midday periods (11am – 4 pm) during the 2020, "full pandemic" conditions than during the 2018 and 2019 pre-pandemic conditions. Although no strong hypotheses were formed for these trends beforehand, they make *ex post* sense after seeing the patterns where travel to campus did not follow the conventional commute hours. These trends are not apparent when looking at the LBS-based time-of-day patterns in Figure 5.3-1(b).



(a) Video-based VMT



(b) LBS-based VMT

Figure 5.3-1: Proportion of 10-hour expanded network VMT in each hour by year as determined when using video- and LBS-based VMT

Table 5.3-3: Average absolute value of differences (AAD) in time-of-day patterns for consecutive years determined when using video- and LBS-based VMT

Year, Year + 1	Video AAD	LBS AAD
2018-2019	0.0044	0.0110
2019-2020	0.0132	0.0130
2020-2021	0.0051	0.0114

Similarly, no *a priori* hypotheses were formed about the time-of-day patterns during the "recovering" 2021 conditions. Indeed, investigating such patterns is one motivation for the type of regular monitoring presented here. When using the video-based VMT values, the 2020-2021 AAD value (0.0051) is much smaller than the 2019-2020 value (0.0132) and similar to the value (0.0044) obtained when comparing what are believed to be steady-state pre-pandemic 2018 and 2019 time-of-day patterns. That is, it appears that the time-of-day pattern under the "recovering" 2021 conditions is similar to that under the "full pandemic" conditions. The AAD values obtained when using LBS-based VMT values are also smaller when comparing 2018 and 2019 and 2020 and 2021 patterns than when comparing 2019 and 2020 patterns. However, the differences in the values are smaller, and the large difference in the patterns represented by the much larger 2018-2019 value would not make this observation apparent.

6 Average Day Volume Estimation

The time-of-day vehicle volumes used in the studies reported in previous sections are all volumes for specified time intervals on a single day, the day on which the data used to estimate the volumes were collected. Although off-line estimates of traffic volumes on a specific day could be useful in some instances, the purpose of general traffic monitoring is to determine traffic volumes on a typical day, where measures such as Average Annual Daily Traffic (AADT) or Average Daily Traffic (ADT) (FHWA, 2022) are sought. Since transit buses cover the same road segments on a daily basis, the video imagery available from daily coverage by transit buses would be particularly attractive for estimating time-of-day volumes on a typical day. In Section 6.1 the data collection design and the data collected for the purpose of estimating traffic volume for a typical day are described. In Section 6.2, an empirical study is presented that illustrates how averaging multiple volume estimates for a given time-of-day period yields very good estimates of the average of the actual volumes on the sampled days for that time-of-day period. In Section 6.3, it is recognized that the average of sample volumes, even if error free, is only an estimate of the true underlying average day volume. An analytical framework is presented to investigate the differences between estimating the average day volume for a time-of-day period from video volumes compared to sampling true volumes. In addition, empirical results are obtained using this framework and empirical data.

6.1 Data Collection

Segment-direction 4.1 (see Figure 2.1) was considered for the empirical study. This segment-direction is 0.326 miles long and has two traffic lanes, with a traffic signal at the downstream traffic end of the segment. At approximately 75% of the distance along this segment-direction (in the direction of traffic flow), vehicles can turn left, crossing segment-direction 4.2, into a small parking lot. Vehicles exiting this parking lot can turn left, after crossing segment-direction 4.2, onto segment-direction 4.1. There are no other "vehicle leakage" points along the segment. Near the small parking lot there is a pedestrian cross-walk that is not heavily used. Approximately 85% of the distance along this segment direction, there is a bus stop that does not have a pullout, with buses stopping in the right lane of the two directional travel lanes.

The segment is used by commuting traffic and caries a large amount of inbound traffic in the morning and, to a lesser extent, at the end of the lunch hour. Based on video-based volumes, Segment 4.1 had the 11th, 9th, and 4th highest segment-direction 10-hour volume on the "non-pandemic affected" days of 10/25/2018, 10/24/2019, and11/01/2022, respectively. Interestingly, Segment 4.1 had the 38th and 33rd largest 10-hour segment-direction volumes on the "full pandemic" and "recovering" days of 11/05/2020 and 11/04/2021 (see Section 5.3).

Students associated with the research project conducted manual data counts on segment-direction 4.1 throughout Spring and Autumn academic semesters in 2022. Attempts were made to conduct counts on two different days of the week during the same two hours on each day in both semesters, but course schedules did not allow implementation of this desired design. After accommodating student schedules, the day-hour-semesters indicated in Table 6.1-1 were settled upon.

Table 6.1-1: Data collection schedule for average day volume studies

Day of week	Spring 2023	Autumn 2023
Monday	11:30-12:30	13:00-14:00
Wednesday	9:30-10:30	9:30-10:30
Thursday	9:30-10:30 11:30-12:30	9:30-10:30 13:00-14:00

The manual counts were to be collected during the day-hour on a weekly basis unless some reason, such as inclement weather or last-minute data collector illness, resulted in cancelling or reducing the data collection period. Manual data were collected using the short-break method (see Section 2.2) with counts taken for four minutes followed by a one-minute break. All counts were taken in the eastbound traffic direction given the focus of this study on one direction. Expanding the four-minute counts, as described in Section 2.2, allowed determination of five-minute and, subsequently, hourly "manual volumes". These manual values are considered as ground truth in the empirical studies reported in this study.

Video imagery was obtained from the OSU transit buses traversing Segment 4.2 (westbound direction) to allow observation of vehicles travelling in the eastbound 4.1 direction. The bus-based imagery was used with the estimation methodology described in Section 3. Bus passes were obtained during the hour of data collection and for at least 15 minutes before and 15 minutes after the hour to allow for use of the Flow Integration method (see Section 3.2.2) to estimate hourly "video volumes" from the flow rates determined from the individual bus passes. The empirical hourly and video volumes by date, day-of-week, and hour are presented in Table A-2, in Appendix A. The numbers of bus passes used to estimate the hourly volumes are also shown.

6.2 Sampled Average Video vs. Sampled Average Manual Volumes

Data were collected during the eight semester-day-of-week(dow)-hour periods of Table 6.1-1. The average hourly volumes obtained from the daily video-estimates $V_{sem-dow-hr}^{vid,avg}$ and the average hourly volumes obtained from the average manual data $V_{sem-dow-hr}^{man,avg}$ are presented in Table 6.2-1. The differences *DifAvg* between these two averages

$$DifAvg_{sem-dow-hr} = V_{sem-dow-hr}^{vid,avg} - V_{sem-dow-hr}^{man,avg} \quad (6.2\text{-}1)$$

and absolute relative errors *ARE*(*DifAvg*) in the average video volumes, relative to the average manual volumes

$$ARE(DifAvg)_{sem-dow-hr} = \left|\frac{V^{vid,avg}_{sem-dow-hr} - V^{man,avg}_{sem-dow-hr}}{V^{man,avg}_{sem-dow-hr}}\right| \quad (6.2\text{-}2)$$

are also presented. In addition, for all days *d* during the semester-dow-hr period on which data were collected, the absolute relative error of the video volumes relative to the manual volumes

$$ARE(Day)_{sem-dow-hr,d} = \left|\frac{V^{vid}_{sem-dow-hr,d} - V^{man}_{sem-dow-hr,d}}{V^{man}_{sem-dow-hr,d}}\right| \quad (6.2\text{-}3)$$

are calculated. The average *Avg*(*ARE*(*Day*)) of these values is also presented in the table for each period. Note that the average of the daily differences between the video and manual volumes when not taking absolute value would equal the difference between the average video and average manual volumes *DifAvg*).

Table 6.2-1: Average hourly manual ($V^{man,avg}$) and video ($V^{vid,,avg}$) volumes, difference in average volumes (DifAVG), absolute relative error of the average volumes (ARE(DifAvg)), and average of daily absolute relative errors (Average(ARE(Day)), assuming manual volume as ground truth; N is the number of days on which data are available for the sem-dow-hr period

Sem-Dow-Hr	**N**	$\mathbf{V^{man,avg}}$	$\mathbf{V^{vid,avg}}$	**DifAvg**	**ARE (DifAvg)**	**Average ARE(Day)**
SP-Th-9:30	6	173.75	156.28	– 17.47	0.10	0.14
SP-We-9:30	6	185.52	179.94	– 5.58	0.03	0.11
SP-Mo-11:30	11	160.51	154.53	– 5.98	0.04	0.12
SP-Th-11:30	8	154.77	145.26	– 9.51	0.06	0.09
AU-Th-9:30	8	160.66	173.76	13.09	0.08	0.13
AU-We-9:30	5	209.46	202.25	– 7.21	0.03	0.10
AU-Mo-13:00	12	154.73	164.69	9.96	0.06	0.13
AU-Th-13:00	6	145.05	148.74	3.69	0.03	0.21

The results in Table 6.2-1 show that, as expected, the magnitude of the error (ARE) between the average volumes *ARE*(*DifAvg*) is less than the average of the daily ARE values *Average ARE*(*Day*). However, the results also show that the magnitude of the error between the average volumes is *substantially* less than the average of the daily error magnitudes for all sem-dow-hr periods, and less than 10% in all periods – and much less than 10% in most periods – except the SP-Th-9:30 period, where the *ARE*(*DifAvg*) is 10%.

In determining volumes for a time period on a typical day, different groups of days are often combined. For example, weekdays may be combined and treated separately than weekends. The different semester-dow-hour periods of Table 6.2-1 are investigated for grouping into sets of periods similar in volume. Given the consistency in course schedules across semesters at OSU, it was expected that that the volumes in the same day-of-week and hour would be similar in the two semesters. Therefore, t-tests of differences in means were first conducted between the manual volumes for the SP-Th-930 and

AU-Th-930 periods and between the manual volumes for the SP-We-930 and AU-We-930 periods. The null hypothesis underlying these tests, and the subsequent tests in this section, is that the difference in means of the manual volumes (assumed to represent the true volumes) in the two periods is zero. The degrees of freedom and the p-values resulting from these tests are presented in Table 6.2-2. Consistent with expectations, one could not reject the equality of the Spring semester and Autumn semester means in the Thursday 9:30 hour (p-value = 0.38). Therefore, it was decided to group these two periods. However, the p-value of 0.09 associated with the comparison in the Wednesday 9:30 hour in the two semesters is surprising. The test shows a significant difference (at the 10% level) between the two means, with the Autumn semester mean being noticeably larger than the SP semester mean as seen in Table 6.2-1. No explanation for this difference has yet been identified, but it was decided not to group the Wed-:930 period across the two semesters.

Grouping for the same hour across different days of the week is investigated next. Prior expectations are not as strong on these investigations. Monday and Wednesday course schedules are different than Tuesday and Thursday course schedules, but vehicular traffic on this segment at these time periods would be only partially affected by course schedules. To investigate a day-of-week difference at the 9:30 hour, the data from the Spring and Autumn Thursday 9:30 periods are pooled as a result of the previous "across semester" test and compared to the Spring Wednesday 9:30 hour, which is not pooled with the Autumn Wednesday 9:30 hour based on the previous "across semester" test. Based on the 0.18 p-value, it was decided to group these periods into a group that consisted of SP-Th-9:30, AU-Th-9:30, and SP-We-9:30. The pooled Autumn and Spring Thursday 9:30 data were tested against the Autumn Wednesday 9:30 data. The AU-We-9:30 mean volume is considered statistically different (p-value = 0.088) from the SP/AU-Th-9:30 mean volume and greater than the mean volumes at 9:30 for the other semester-dows (see Table 6.2-1). The means of the Spring 11:30 volumes on Thursday and Wednesday are not statistically different (p-value 0.5914), and it was decided to group the 11:30 period across the days of week. Similarly, the p-value (0.1965) resulting from the tests of means of the Autumn 13:00 volumes on Thursday and Monday was large enough that it was decided to group these two periods.

Table 6.2-2: P-values and degrees of freedom for tests of means between manual volumes in different data collection periods

Periods Compared		**Degrees of Freedom**	**P-value**	**Grouping Decision**
SP-Th-9:30	AU-Th-9:30	11.778	0.3805	Group periods
SP-We-9:30	AU-We-9:30	7.1698	0.0835	Do not group periods
Th-9:30 , SP and AU combined	SP-We-9:30	9.7269	0.1710	Group periods
Th-9:30 , SP and AU combined	AU-We-9:30	15.863	0.0002	Do not group periods
SP-Th-11:30	SP-Mo-11:30	14.379	0.5914	Group periods
AU-Th-13:00	AU-Mo-13:00	8.3084	0.1965	Group periods
9:30, SP-Th, AU-Th, SP-We comb.	SP-11:30, Th and Mo combined	35.754	0.0881	Do not group periods
9:30, SP-Th, AU-Th, SP-We combined	AU-13:00, Th and Mo combined	27.829	0.0062	Do not group periods
SP-11:30, Th and Mo combined	AU-13:00, Th and Mo combined	29.953	0.2720	Do not group periods[1]

[1] Decision not to group based on a combinator of factors as explained in text

It is expected that the mean volumes would be different in the different hours of the day, reflecting time-of-day variability in demand that is recognized in general transportation systems. The p-values in the second and third last rows of Table 6.2-2 (0.0881 and 0.0062, respectively) are sufficiently supportive of this expectation, whereas the p-value in the final row (0.2720) does not lend strong support for the difference in the mean 11:30 and 13:00 volume. However, because of the usual approach of considering volumes by time of day to differ, the recognition that not rejecting the null hypothesis does not imply that it should be accepted, and the strong support for treating the other two time-of-day periods separately, it was decided to maintain three separate time-of-day periods rather than combine the 11:30 and13:00 hours in the subsequent studies.

From these grouping decisions, four distinct periods are identified. These periods, along with the corresponding average hourly volume and differences measures similar to those in Table 6.2-1, are presented in Table 6.2-3. The fourth period in Table 6.2-3 consists of the AU-We-9:30 period presented in Table 6.2-1 when considering the most disaggregate sem-dow-hr periods. As explained above, the tests of means did not lead to grouping this period with any other. It is presented in Table 6.2-3 for completements, but because of the small number of days, it is not considered in the empirical analyses of Section 6.3. The results in Table 6.2-3 confirm the results in Table 6.2-1, namely, that the error between the average video and manual volumes ($ARE(AvgDif)$) for the hourly period is much less than the average of the daily errors ($Avg(ARE(Day))$. In Table 6.2-3, it is seen that the error between the average volumes is not larger than 5%. The increased number of days in the sample improves the correspondence between the average video volumes and average manual volumes.

Table 6.2-3: Average hourly manual ($V^{man,avg}$) and video ($V^{vid,,avg}$) volumes by grouped period, differences in average volumes (DifAVG), absolute relative error of the average volumes (ARE(DifAvg)), and average of daily absolute relative errors (Average(ARE(Day)), assuming manual volume as ground truth; N is the number of days on which data are available for the sem-dow-hra in the group

Grouped Period Indicator	**Grouped Period**	**N**	$\boldsymbol{V^{man,avg}}$	$\boldsymbol{V^{vid,avg}}$	**DifAvg**	**ARE(DifAvg)**	**Average ARE(Day)**
1	9:30: AU-Th, SP- Th, SP-We	20	172.05	170.37	– 1.68	0.01	0.13
2	11:30: : SP-Thu, SP-Mo	19	158.09	150.63	– 7.47	0.03	0.10
3	13:00: AU-Th, AU-Mo	18	151.51	159.38	7.87	0.05	0.15
4	9:30: AU-We	5	209.46	202.25	– 7.21	0.03	0.10

6.3 Video Volumes vs. Average Day Volume

The results in the previous section show that the averages of the multiple days of hourly volume estimates obtained from video imagery for a given time-of-day period when using the approach developed in this project are very close to the averages of the hourly volumes obtained from the ground truth manual counts for the same time-of-day periods on the same days. As expected, the results also show that the ARE (magnitude of error) between the average video-based average and manual average is markedly less than the average of the daily ARE values between the video-based and ground truth manual volumes. As mentioned above, in typical traffic monitoring, one would be interested in the hourly volume on the "average day". Even if there is no measurement or estimation error in the manual counts, the average of the finite number of volumes obtained from manual counts would not necessarily represent the true average day volume because of day-to-day variability in traffic volumes.

To investigate the ability of the average video volumes to estimate the true average day volume, let μ_X represent the true average day volume on the segment-direction during the time-of-day period considered and V_i and X_i, respectively, represent the video and true volumes obtained on day i during this time-of-day period. Of interest is how the sample mean $Avg[V;Nv]$ of the video volumes over Nv days approximates the true average day volume μ_X and how this approximation compares to the approximation to μ_X offered by the sample mean $Avg[X;Nx]$ of the true volumes over the same or a different number of days Nz.

A difference $d_i = V_i - X_i$ between the video and true volume on day i during the hour of interest is considered so that:

$$V_i = X_i + d_i(X_i) \tag{6.3-1}$$

where the difference d_i is indicated as possibly depending on the value of the true volume X_i. For example, the use of relative error when summarizing errors across different segment-directions and time-of-day periods is motivated by the hypothesis that it would be more likely to have a large difference between video and true volumes when the segment-direction-hour volume is large than when it is small.

By definition, the expected value of the true values $E[X_i]$ equals the true mean, that is $E[X_i] = \mu_X$. Since $E[V_i] = E[X_i] + E[d_i(X_i)]$ (the expectation of a sum equals the sum of the expectations), one can write:

$$E[V_i] = E[X_i] + E[d_i(X_i)] = \mu_X + E[d_i(X_i)] \tag{6.3-2}$$

It is assumed that the manual count on day i during the hour considered leads to an error-free volume X_i on the day-hour (i.e., the ground truth for that day). That is, it is assumed that there is no important measurement error when manually counting vehicles and no important estimation error associated with expanding the four-minute counts obtained with the short-break method to five-minute volumes (see Section 2.2). Therefore, the manual and true volumes on day-hour i can be used interchangeably, and one can investigate differences $d_i = V_i - X_i$ between video and true volumes by investigating empirical differences between video and manual volumes on the day-hours. To investigate the impact of the true volume X_i on the difference between video and true volumes d_i, differences are formed on each day and hour for which video and manual volumes were obtained, and the manual volumes on the day and hour are regressed against the difference in the same day and hour as follows:

$$di = \beta_o + \beta_1 X_i \tag{6.3-3}$$

The regression estimation results are provided in Table 6.3-1.

Table 6.3-1: Summary regression results using specification (6.3-3) investigating the effect of true volume on difference between video and true volumes for ranges of values in empirical study

Variable	Coefficient Estimate	Std. Error	t-stat	p-value
Intercept	25.164	20.475	1.229	0.224
Manual (True) volume X	-0.160	0.123	-1.300	0.199
Number of Observations: 62 R^2 : 0.0274				

The results indicate that, at least for the range of volumes obtained on segment-direction 4.1 during the days and hours investigated, one cannot reject the null hypothesis that the difference between the video and true (manual) hourly volumes does not depend on the true volume. Not rejecting the null hypothesis does not imply that it should be accepted, but because of a lack of evidence of a dependence, to proceed, Equation (6.3-1) is rewritten as follows:

$$V_i = X_i + d_i \tag{6.3-4}$$

and Equation (6.3-2) is rewritten as follows:

$E[V_i] = \mu_X + E[d_i]$ (6.3-5)

To investigate $E[d_i]$ for the empirical study conducted in this project, the empirical d_i values are pooled across all days in the first three periods indicated in Table 6.2-3. (As discussed near the end of Section 6.2, the fourth period indicated is not considered in the empirical study of this section because of the small sample size. A t-test indicates that the means of the differences are not significantly different from zero (p-value = 0.726). Again, not rejecting the null hypothesis does not imply that it should be accepted, but without evidence to the contrary it is assumed that $E[d_i] = 0$, and Equation (6.3-5) can be written as follows:

$$E[V_i] = \mu_X \tag{6.3-6}$$

That is, the expected value of the video volumes would equal the true volume mean, i.e., the true average day volume.

Even though $E[V_i] = \mu_X$ – the expected value of the video volumes equals the true average day volume – sampling over a finite number of days Nv would generally not lead to a sample mean of the video volumes $Avg[V;Nv]$ equal to μ_X because of the variance σ_V^2 in the V_i volumes that results from day-to-day variation in the true daily volumes – i.e., because of variance σ_X^2 in the true day-to-day volumes – and because of variance in the video-based measurement and estimation error – i.e., because of σ_d^2. Specifically, $\sigma_V^2 = \sigma_X^2 + \sigma_d^2 + 2\sigma_{X,d}^2$, where $\sigma_{X,d}^2$ is the covariance between the true volumes X and the differences d between the video and true volumes. The assumed independence of d_i on X_i resulting from the regression results using specification (6.3-3) would imply $\sigma_{X,d}^2 = 0$, and the variance of the video volume on day i would therefore be given by the following:

$$\sigma_V^2 = \sigma_X^2 + \sigma_d^2 \tag{6.3-7}$$

Since different average volumes are considered for the periods in Table 6.2-3, different μ_X values are considered for each period. F-tests of equality of variances in the true volumes σ_X^2 among the periods lead to rejecting the null hypothesis of equality of σ_X^2 between Periods 1 and 3 and between Periods 2 and 3 in Table 6.2-3, but not between Periods 1 and 2 in the table. Again, Period 4 is not considered in the empirical study in this section because of the small number of daily volumes in the periods. Because of the difference in variances in two of the three combinations of compared periods and because different means μ_X are considered for each of the three periods, different σ_X^2 are also considered for each period. Based on the regression estimation results of Table 6.3-1, the d_i values are assumed not to depend on the Xi values. Therefore, a single σ_d^2 value, which is estimated to be 596.07, is considered for each period. The resulting estimated means and variances of a volume on a given day for each of the three periods are presented in Table 6.3-2. In the table, the estimated video variance σ_V^2 in the period is calculated as the sum of the variance in the true volumes σ_X^2 and the variance in the difference of the video volume from the true volume σ_d^2 based on Equation (6.3-7).

Table 6.3-2: Means and variances of individual day true (X) and video (V) hourly volumes and differences (d) by period estimated from empirical data

<table>
<tr><th>Grouped Period Indicator</th><th>Grouped Period</th><th>E[Xi] = E[Vi] = μ_X</th><th>σ_X^2</th><th>$\sigma_d^{2(1)}$</th><th>$\sigma_V^{2(2)}$</th></tr>
<tr><td>1</td><td>9:30: AU-Th, SP- Th, SP-We</td><td>172</td><td>769.01</td><td rowspan="3">596.07</td><td>1365.08</td></tr>
<tr><td>2</td><td>11:30: SP-Thu, SP-Mo</td><td>158</td><td>473.37</td><td>1069.44</td></tr>
<tr><td>3</td><td>13:00: AU-Th, AU-Mo</td><td>152</td><td>174.87</td><td>770.95</td></tr>
</table>

[1]Variance of differences estimated from data pooled across periods
[2]σ_V^2 calculated as $\sigma_X^2 + \sigma_d^2$ from Equation (6.3-7)

As stated above, the interest is in how the sample mean $Avg[V;Nv]$ of the video volumes over Nv days approximates the true average day volume μ_X and how this approximation compares to the approximation to μ_X offered by the sample mean $Avg[X;Nx]$ of the true (manual) volumes as a function of the number of days Nx on which volumes are obtained. The expectation of the average is equal to the average of the expectations. Therefore, the following holds:

$$E[Avg[X;Nx]] = Avg[E[X;Nx]] = Avg[\mu_X] = \mu_X \qquad (6.3\text{-}8a)$$

and using Equation (6.3-6), the following can be written:

$$E[Avg[V;Nv]] = Avg[E[V;Nv]] = Avg[\mu_X] = \mu_X \qquad (6.3\text{-}8b)$$

That is, the expectations of the average true (X) and video (V) volumes from a sample of N days are equal to the true average volumes.

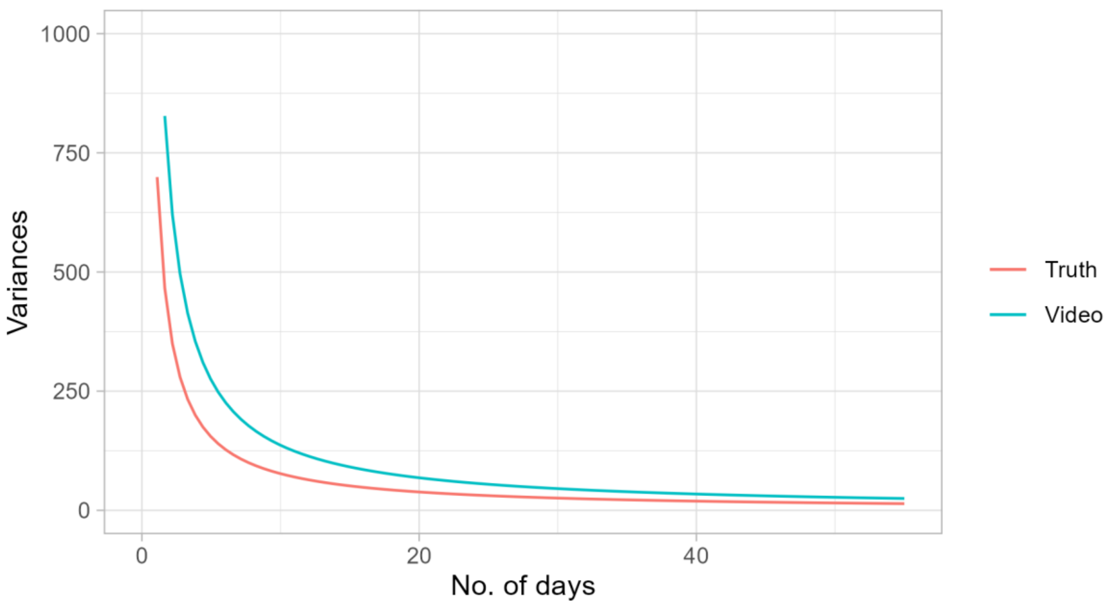
The variance of an average of N independent and identically distributed observations, the following is obtained:

$$Var[Avg[X;Nx]] = Var[X_i] / Nx = \sigma_X^2 / Nx \tag{6.3-9a}$$

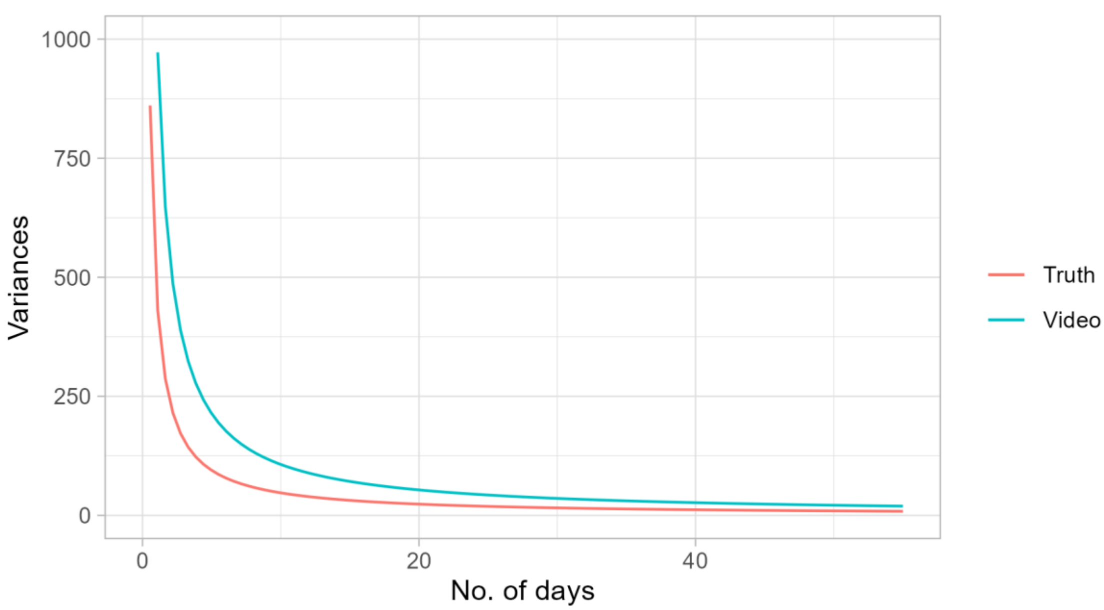
and

$$Var[Avg[V;Nv]] = Var[V_i] / Nv = \sigma_V^2 / Nv \tag{6.3-9b}$$

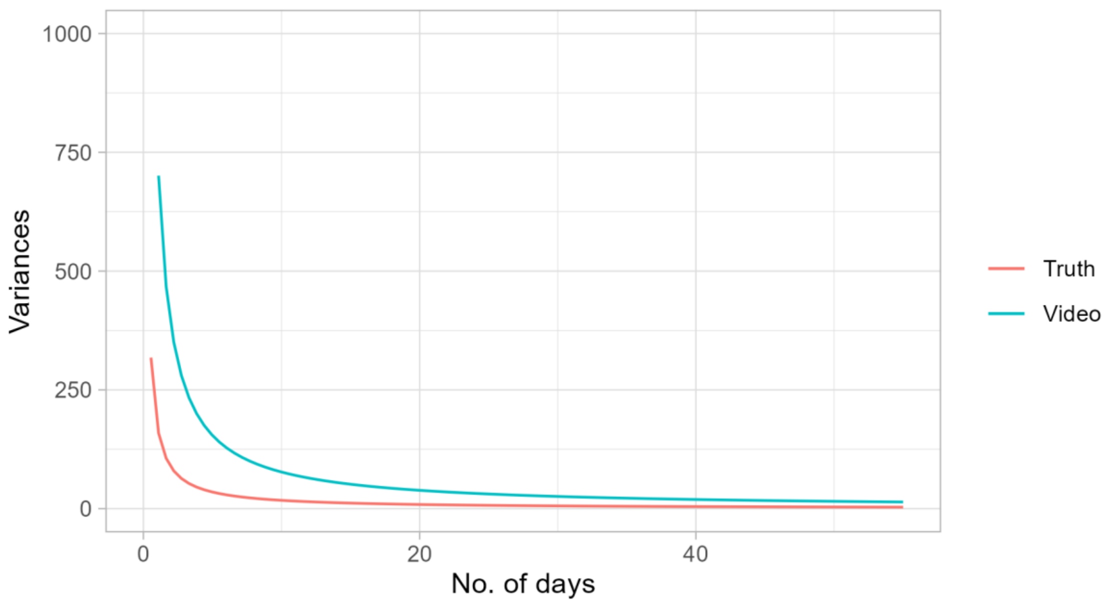
The variances of the average true and average video volumes – *Var*[*Avg*[*X*;*Nx*]] and *Var*[*Avg*[*V*;*Nv*]], respectively – for each period can, therefore, be calculated as a function of the number of days *N* using Equations (6.3-9a) and (6.3-9b) and the values from Table 6.3-2. Graphs of these variances as a function of the number of days sampled are presented for each period in Figure 6.3-1.



(a) Period 1, 9:30 – 10:30 Wednesday and Thursday



(b) Period 2, 11:30 – 12:30 Monday and Thursday



(c) Period 3, 13:00 – 14:00 Monday and Thursday

Figure 6.3-1: Variance of average hourly volumes taken across number of days sampled as a function of number of days sampled for true (manual) and video volume samples for specified time-of-day periods

The video volume functions in Figure 6.3-1 are all above the corresponding true volume functions, indicating that for a sample of $Nx = Nv$ days, the video volume sample average has larger variance than the true volume sample average. The larger variance of the video volume average results from the added single day variance associated with the accuracy of the video estimation, as represented by σ_d^2, when determining the single-day variance σ_V^2 compared to the true single day true variance σ_X^2. For a given number of days N (for both video and true samples) of sampled hourly volumes, Equations (6.3-7) and (6.3-8), the vertical distance between the two curves is $\sigma_V^2 / N - \sigma_X^2 / N = \sigma_d^2 / Nv$.

For all three time-of-day periods – depicted by Figures 6.3-1 (a), (b), and (c) – both the video and true volume functions show that the variance decreases rapidly with an increase in the number of days sampled when the number of days is small, but then levels off after a few days. The “bends” in the functions occur between approximately 5 and 15 days for the video volume functions and between 2 and 7 days for the true volume functions. The 2 to 7 day range of the true volume functions is interesting, since this is typically the range of “short-term” or “coverage” sample counts taken in traditional practice (see, e.g., FHWA 2022).

The video volume curves can also be considered to lie to the right of the true volume functions, indicating that compared to the number of days of true hourly volumes required to obtain a given variance value, additional days of sample video hourly volumes are required. The additional number of video sample days required, represented by the horizontal distance between the functions, depends on the value of variance (y-axis) and on the time-of-day period considered (Figures 6.3-1 (a), (b) and (c)), with the 13:00-14:00 Monday and Thursday period (Figure 6.3-1(c)) requiring the greatest increased number of days. This makes sense, since σ_d^2 is considered to be constant across the three time-of-day periods, while σ_X^2 (representing the daily variation in true volumes) is smallest for this period (see Table 6.3-2).

Although the functions allow one to determine the increased numbers of days of video hourly volumes to be sampled compared to the number of days of manual hourly volumes sampled, the motivation for using bus-based video imagery is that this imagery is available, whereas manual data collection requires special effort and costs. Therefore, the number of true and video volume days required to obtain equal variance are not directly comparable based on the effort and cost involved.

To provide a more meaningful interpretation of the relation between the number of days for which the time-of-day period volumes are obtained and the ability to represent the true average day volume, the probability of obtaining an average volume that is within a specified interval of the true average day volume μ_X is considered as a function of the number of days sampled. Specifically letting

$$ARE_{Nx} = \left| \frac{Avg[Xi;Nx] - \mu_X}{\mu_X} \right| \tag{6.3-9a}$$

and

$$ARE_{Nv} = \left| \frac{Avg[Vi;Nv] - \mu_X}{\mu_X} \right| \tag{6.3-9b}$$

represent the absolute value of the relative error of the sample average with respect to the true average day volume when the average is obtained, respectively, with *Nx* true daily volumes and *Nv* video volumes, the probability P' that the sample averages are less than a specified ARE (denoted ARE') can be written as follows:

$$\begin{aligned} P'(X,Nx) &= \text{Prob}\{\left|\frac{Avg[Xi;\, Nx] - \mu_X}{\mu_X}\right| < \text{ARE}'\} = \text{Prob}\{-\text{ARE}' < \frac{Avg[Xi;\, Nx] - \mu_X}{\mu_X} < \text{ARE}'\} \\ &= \text{Prob}\{(1 - ARE')\,\mu_X \le \text{Avg}[Xi, Nx] \le (1 + \text{ARE}')\mu_X\} \end{aligned} \tag{6.3-10a}$$

and

$$\begin{aligned} P'(V,Nv) &= \text{Prob}\{\left|\frac{Avg[Vi;Nv] - \mu_X}{\mu_X}\right| < \text{ARE}'\} = \text{Prob}\{-\text{ARE}' < \frac{Avg[Vi;\, Nv] - \mu_X}{\mu_X} < \text{ARE}'\} \\ &= \text{Prob}\{(1 - ARE')\,\mu_X \le \text{Avg}[Vi, Nv] \le (1 + \text{ARE}')\mu_X\} \end{aligned} \tag{6.3-10b}$$

Tests of normality on the true daily volumes X_i and the differences d_i lead to p-values of 0.3014 and 0.1545, respectively, indicating that there is not sufficient evidence to reject the null hypothesis that these values are normally distributed. Therefore, these variables are assumed to be normally distributed, and since the sum of normally distributed variables is normally distributed, $V_i = X_i + d_i$ is also assumed to be normally distributed. Moreover, since the average of normally distributed variables is normally distributed, $Avg[X_i;Nx]$ and $Avg[V_i;Nv]$ are assumed to be normally distributed. Subtracting the mean and dividing by the standard deviation in the inequalities of Equations (6.3-10), the equations can be written as:

$$\begin{aligned} P'(X,Nx) &= Prob\{\frac{(1-ARE')\mu_X - \mu_X}{[\sigma_x^2/Nx]^{0.5}} \le \frac{Avg[Xi;Nx] - \mu_X}{[\sigma_x^2/Nx]^{0.5}} \le \frac{(1+ARE')\,\mu_X - \mu_X}{[\sigma_x^2/Nx]^{0.5}}\} \\ &= Prob\{\frac{-\mu_X\, ARE'}{[\sigma_x^2/Nx]^{0.5}} \le \frac{Avg[Xi;Nx] - \mu_X}{[\sigma_x^2/Nx]^{0.5}} \le \frac{\mu_X\, ARE'}{[\sigma_x^2]/Nx]^{0.5}}\} \end{aligned} \tag{6.3-11a}$$

and

$$P'(V,Nv) = Prob\{\frac{(1-ARE')\,\mu_X - \mu_X}{[\sigma_v^2/Nv]^{0.5}} \le \frac{Avg[Vi;Nv] - \mu_X}{[\sigma_v^2/Nv]^{0.5}} \le \frac{(1+ARE')\,\mu_X - \mu_X}{[\sigma_v^2/Nv]^{0.5}}\}$$

$$= \ Prob\{\frac{-\mu_X \ ARE'}{[\sigma_v^2/Nv]^{0.5}} \leq \frac{Avg[Vi;Nv] \ -\mu_X}{[\sigma_v^2/Nv]^{0.5}} \ \ \leq \ \frac{\mu_X \ ARE'}{[\sigma_v^2/Nv]^{0.5}}\} \qquad (6.3\text{-}11b)$$

where $\frac{Avg[Xi;Nx] \ -\mu_X}{[\sigma_x^2/Nx]^{0.5}}$ and $\frac{Avg[Vi;Nv] \ -\mu_X}{[\sigma_v^2/Nv]^{0.5}}$ are now standard normal random variable. Equations (6.3-11) can then be written as follows:

$$P'(X, Nx) = \Phi\left(\frac{\mu_X ARE'}{[\sigma_x^2/Nx]^{0.5}}\right) - \Phi\left(\frac{-\mu_X ARE'}{[\sigma_x^2/Nx]^{0.5}}\right) = \Phi\left(\frac{\mu_X ARE'}{[\sigma_x^2/Nx]^{0.5}}\right) - \left(1 - \Phi\left(\frac{\mu_X ARE'}{[\sigma_x^2/Nx]^{0.5}}\right)\right)$$

$$= \ 2\ \Phi(\frac{\mu_X ARE'}{[\sigma_x^2/Nx]^{0.5}}) \ - 1 \qquad (6.3\text{-}12a)$$

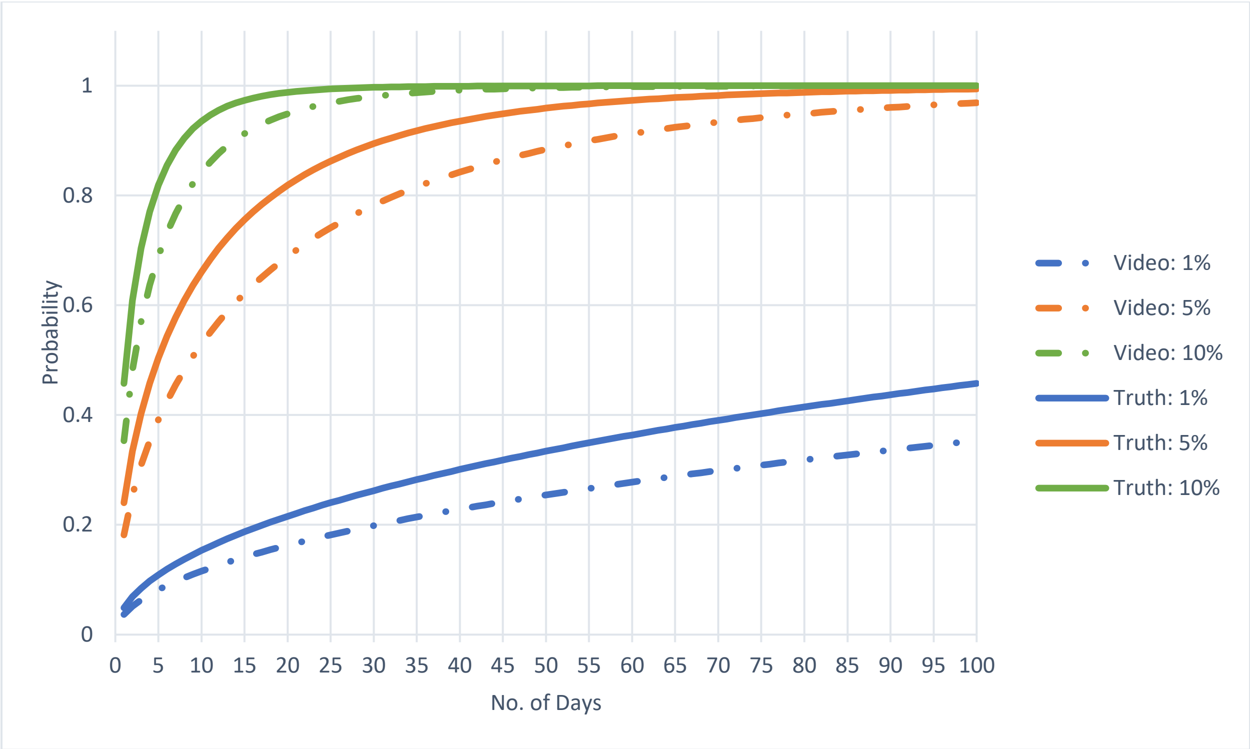
and

$$P'(V,Nv) = \Phi\left(\frac{\mu_X ARE'}{[\sigma_v^2/Nv]^{0.5}}\right) - \Phi\left(\frac{-\mu_X ARE'}{[\sigma_v^2/Nv]^{0.5}}\right) = \Phi\left(\frac{\mu_X ARE'}{[\sigma_v^2/Nv]^{0.5}}\right) - \left(1 - \Phi\left(\frac{\mu_X ARE'}{[\sigma_v^2/Nv]^{0.5}}\right)\right)$$

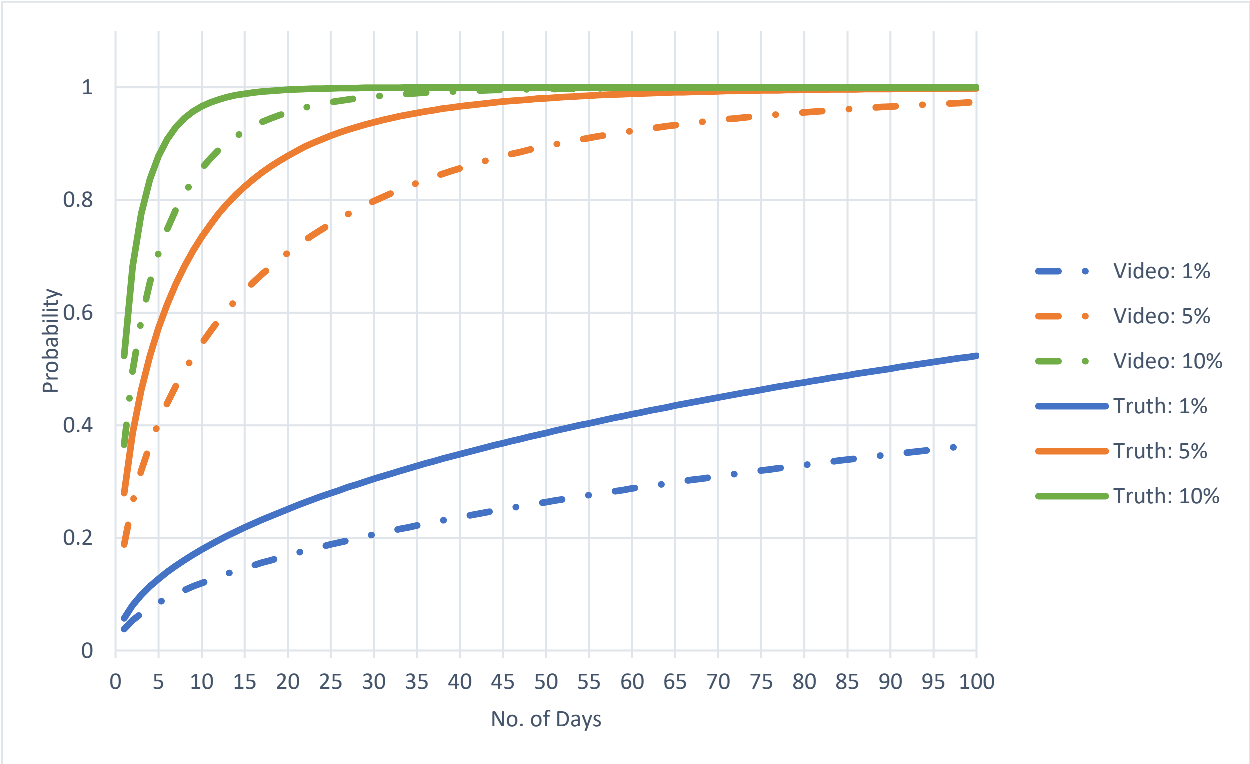
$$= \ 2\ \Phi(\frac{\mu_X ARE'}{[\sigma_v^2/Nv]^{0.5}}) \ - 1 \qquad (6.3\text{-}12b)$$

where $\Phi(\cdot)$ is the cumulative standard normal function.

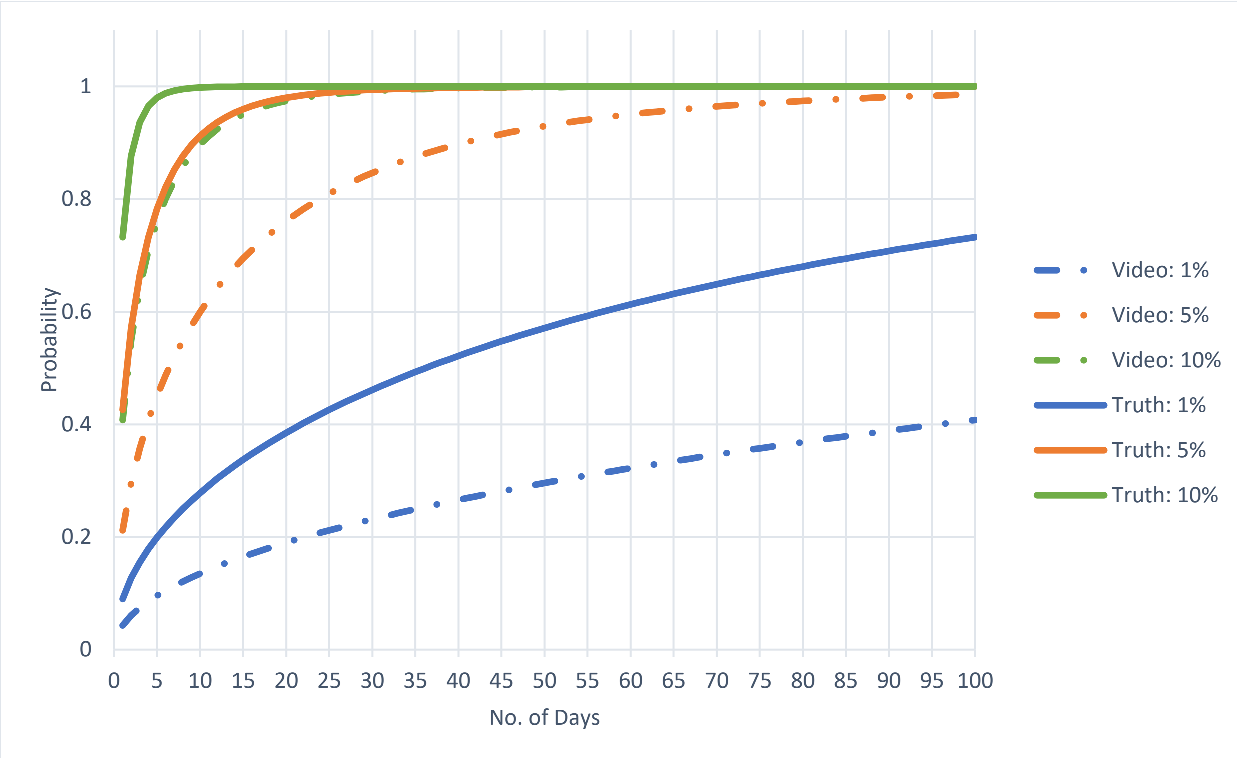
These relations can be evaluated using the estimated means and variances from Table 6.3-2 in the expression of the argument of the cumulative standard normal function. Since the empirical variances are estimated from relatively small sample size data sets (i.e., *N* is not greater than 20 – see Table 6.2-3), the cumulative standard normal distribution is replaced by the cumulative t-distribution with N – 1 degrees of freedom. The probabilities P'(*X*,*Nx*) and P'(*V*,*Nv*) as functions of the number of days sampled are plotted for ARE' = 0.10 (10% error), ARE' = 0.05 (5%) error, and ARE' = 0.01 (1% error) in Figure 6.3-2 for each of Periods 1, 2, and 3 from Table 6.2-3.



(a) Period 1, 9:30 – 10:30 Wednesday and Thursday



(b) Period 2, 11:30 – 12:30 Monday and Thursday



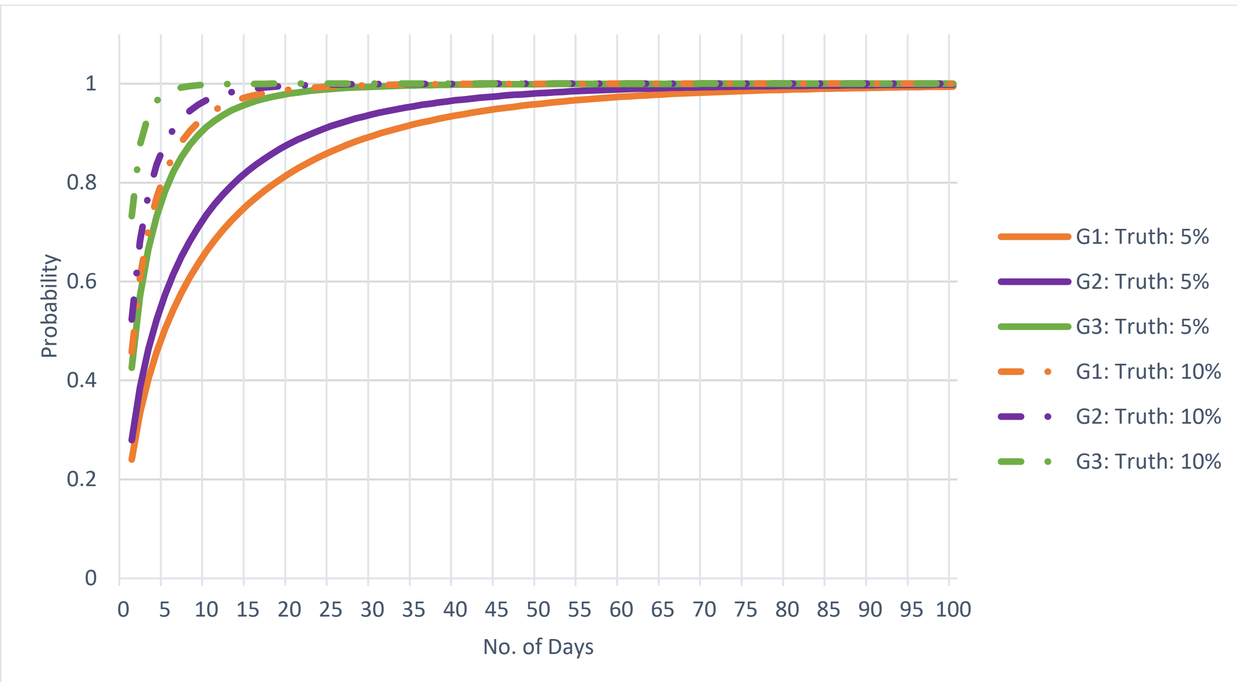
(c) Period 3, 13:00 – 14:00 Monday and Thursday

Figure 6.3-2: Probability P' of the sample average hourly volume being within +/– ARE' of the true average hourly volume as a function of the number of days N in which hourly volumes are sampled when volumes are determined from video imagery and from true (manual) counts

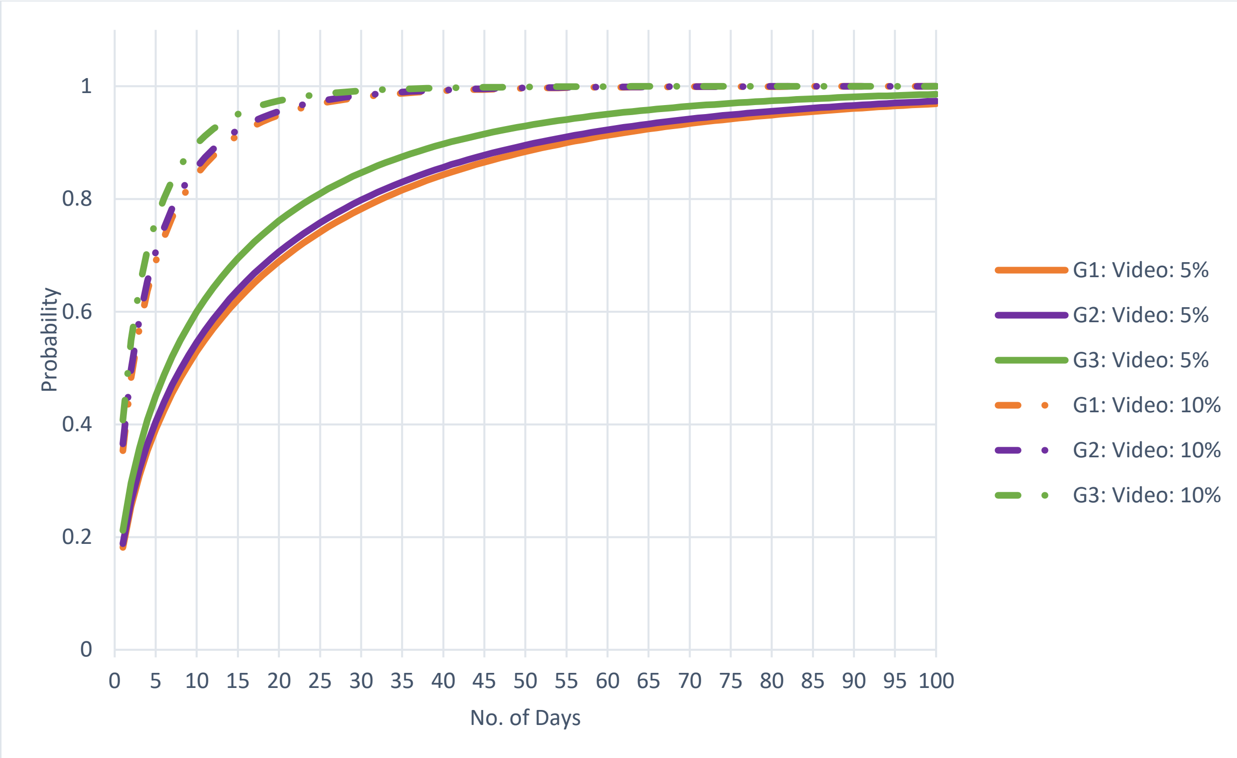
The plots for all the time-of-day periods (i.e., each of Figures 6.3-2 (a)-(c)) show that even at a very large number of days sampled (N = 100 in the plots) the probability of obtaining a sample average volume with error less than 1% (ARE'< 0.01) is small, even when true volumes are sampled. Specifically, the probability is approximately 0.75 at N = 100 days for the 13:00-14:00 Monday and Thursday period (Figure 6.3-2(c)) when sampling true volumes and less than 0.52 at N = 100 days when sampling true volumes in the other periods and when sampling video volumes for all three periods. Targeting 10% or perhaps 5% error (ARE' level) is much more reasonable than targeting 1% error. As mentioned above, traffic counts are traditionally taken to sample volumes on a few days at most. For true volume samples of seven days, the probabilities of obtaining a 5% error (ARE' = 0.05) is approximately 0.60 and 0.65 in Figures 6.3-2(a) and (b), respectively, and even though greater, the probability is only approximately 0,85 in Figure 6.3-2(c). These results would tend to support the 10% error target typically considered in traffic monitoring (see, e.g., FHWA 2022).

As in Figure 6.3-1, the video volume curves in Figure 6.3-2 are to the right of the true volume curves, indicating in this case an increased number of daily hourly video volumes that must be sampled to obtain the same probability P' level and targeted error ARE'. Compared to the number of true days sampled, the additional number of video days that must be sampled to obtain an equivalent probability P' of obtaining a specified error ARE' level is represented by the horizontal distance between the solid and dashed curves of the same color (ARE' value). From the figures, it is seen that the additional number of days increases for higher P’ levels and for lower ARE’ levels. As in Figure 6.3-1, the additional number of days required is greatest for the 13:00-14:00 Monday and Thursday period (Figure 6.3-2(c)). Again, this largest increase is because this period has the lowest daily variation in true volumes σ_x^2 and because the additional component of variance σ_d^2 included in the determination of video volume variance σ_v^2 is determined to be constant among the periods.

Analogous to the pattern seen in Figure 6.3-1, where the variance decreases rapidly with numbers of days sampled for small number of days sampled and then levels off, in Figure 6.3-2 the probably of obtaining a specified error level (ARE’) increases rapidly with number of days sampled for small number of days sampled and then levels off. To provide an easier representation of the number of sample days of hourly volumes required to obtain a probability P’ of at most a specified error ARE’ of 0.05 and 0.10, the corresponding curves are reorganized by combining all three time-of-day periods in the same plot and separating by whether true volumes (Figure 6.3-3(a)) or video volume (Figure 6.3-3(b)) are sampled.



(a) True volume samples



(b) Video volume samples

Figure 6.3-3: Probability P’ of the sample average hourly volume being within +/- ARE’ of the true average hourly volume as a function of the number of days N in which hourly volumes are sampled for different time-of-day periods

Both the true (Figure 6.3-3(a)) and video (Figure 6.3-3(b)) volume plots illustrate relatively tight clustering of the three time-of-day period curves for 10% error and more spread in the 5% error curves. The differences in the time-of-day period curves for a given ARE’ result from difference in the true average day hourly volume and the true day-to-day variations, which would not be known beforehand and must be estimated from samples. The tight clustering of the curves for the 10% errors indicates that a general range of prescribed number of days to sample might be available for this level of error, which as mentioned above is a typical error considered in practice. Specifically, the true volumes curves (Figure 6-3.3(a)) imply required sampling approximately in the 2 to 7 day range mentioned above to achieve a probability P’ = 0.90 to achieve at most a 10% specified error (ARE’ = 0.10). To achieve P’ = 0.90 with ARE’ = 0.10 when sampling video volumes, Figure 6-3.3(b) indicates that approximately 10 to 15 days of hourly video volumes must be sampled. Again, the 10 to 15 days of imagery required for the sampling of video volumes is already available from buses in tegular transit service, whereas the 2 to 7 days of true sampling requires additional deployment costs.

7 Education and Outreach

The manual and video data collections on 10/25/2018, 10/24/2019, 11/05/2020, 11/04/2021, and 11/01/2022 were undertaken in conjunction with an annual term project in CIVILEN 5720: Transportation Engineering Data Collection Studies. The term projects in 2018 and 2019 were reported on in McCord et al. (2020), but these two projects are referenced in this report to illustrate the continuity and evolution of the projects.

CIVILEN 5720 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 investigators of the project covered in this report and is taken by Civil Engineering undergraduate students and by Civil Engineering graduate students and City and Regional Planning graduate students specializing in transportation. Semester enrollments by undergraduate and graduate student status are presented in Table 7-1.

Table 7-1: Enrollments in CIVILEN 5720 by semester, 2018-2022

Semester	Undergraduate Students	Graduate Students	Total Students
Autumn 2018	27	3	30
Autumn 2019	24	8	32
Autumn 2020	25	2	27
Autumn 2021	26	3	29
Autumn 2022	25	3	28

A major component of the technical content of this course relates to traffic volume data collection and analysis across small, regional, and statewide roadway networks. In addition to lecture materials, field data collections are used as laboratory type exercises to reinforce technical concepts and to offer practical empirical experience. Before 2018, students would use traditional data collection techniques to estimate traffic volumes on three or four OSU campus roadway segments for an hour or two to gain field experience with manual data collection and processing. They would then analyze the estimated segment volumes and vehicle miles traveled (VMT) for the very small network of segments and limited time period of data collection. The research project summarized in McCord et al. (2022), which led to the research project document in this report, inspired the co-instructors of the course to add a term project involving estimating hourly volumes for an extended period of times (12 hours for the data collection day in 2018, 6 hours for the data collection in 2020, and 10 hours each for the data collection days in 2019, 2021, and 2022) over an extended network of campus roadway segments using both traditional methods and the video-based estimation methods being developed in the effort documented in this report. The segments of the supernetwork of Figure 2-1 and Table 2-1 considered in each semester (year) were modified slightly throughout the different semester (yearly) offerings of the course, but data from previous semesters were also used to investigate changes in traffic over time on a common network, namely the “semester network” of 2018. The segments of the supernetwork considered in each year are presented in Table 7-2.

In the context of each semester term project, students conducted manual traffic counts with the short-break, alternating count method (see Section 2.2) and converted the manually collected counts to segment-direction hourly volumes. The students also used the Graphical User Interface (see Section 3.1) to record vehicle detections in the video imagery received from TTM (see Section 2.1) during the semester. In the 2018-2020 semesters, the students used the processed manual and video data for the day on which they collected data. In some term project tasks, they also used data processed in previous semesters for comparison purposes. Because of the time needed to collect and process both manual and video data, beginning in 2021 the instructors designed the term projects so that student would analyze only data collected and processed in the previous semesters. However, students would still collect and process manual and video data in the concurrent semester for use in term projects in following semesters. As explained in Section 2.3, the Mid-Ohio Regional Planning Commission also placed road tubes on a few segments in 2018, 2019, and 2020 (see Appendix A).

Table 7-2: Segments comprising “semester networks” considered in CIVILEN 5720 term projects

Semester	Segments [1,2]	Total Segment-direction Network Miles
Autumn 2018[3]	1-21	6.3
Autumn 2019	1-24; 26.1	7.7
Autumn 2020	1- 28 (only 25.2, 27.2)	8.0
Autumn 2021	1-24; 28	7.7
Autumn 2022	1-11; 13-15; 20-21;	4.7

[1]Segment-directions illustrated in Figure 2-1 and described in Table 2-1

[2]Volumes on both directions of segments were considered unless otherwise noted

[3]Autumn 2018 was network used for comparisons through the years

The term project tasks were modified each semester. The descriptions and tasks of the term projects for each semester are presented in Appendix B. In general, the focus of each project was on estimating segment volumes by hour of day using volumes estimated from traditional traffic counts and again from bus-based video imagery. In addition, the students also used the estimated hourly volumes to determine network vehicle miles travelled. As in practice, the traditional traffic count approach used in the projects requires sampling (“covering”) segment-direction-hours across space and time because of limited personnel and equipment, whereas the bus-based video approach provides comprehensive spatial and temporal coverage. Graduate students associated with the overall research project covered in this report prepared the video imagery obtained from campus buses operating on the data collection day so that the students in the course could conduct the vehicle detection step during class time and as an additional out-of-class assignment. The students were trained during class time on the logic and protocols associated with this vehicle detection step. The techniques associated with estimating volumes from both the traditional and mobile sensing platform, video-based approaches were previously presented as fundamental course content, where the video-based approaches in Section 3.2.1 are those presented in the course. The methodological developments presented in Section 3.2.2 were made relatively recently, and the subtleties of the developments are considered to be beyond what the general population of students in this fundamental course could understand without sacrificing too much coverage of other topics.

The following changes to scope involving estimation of volumes from videos were made from one semester to the next:

- Autumn 2019: Given the success of the first project in 2018, additional roadway segments were included in Autumn 2019, compared to Autumn 2018, although the 12-hour data collection period was reduced to a 10-hour period. Volumes obtained in Autumn 2018 and Autumn 2019 were considered samples of volumes on two days of homogeneous traffic volume periods.
- Autumn 2020: In Autumn 2020, course instruction took place online because of COVID pandemic lockdown-related policies, although manual data collection was possible because of the outdoor setting and large physical distances separating data collectors. In part because of the online instruction, video-based volumes were only processed and analyzed during online class time for a total of six hours, consisting of three two-hour time-of-day periods representing what would typically be morning, midday, and afternoon peak periods. (Video volumes for the remaining hours were processed after the course was finished by students funded by the overall research project covered in this report. For the term project, the students calculated differences in video-based volumes from ground truth (road tube or manually collected) hourly volumes and differences in six-hour vehicle miles travelled (VMT), with the intent of indicating that

differences in more aggregated traffic measures (VMT) would tend to be smaller than differences in the more disaggregated hourly volumes. In addition, VMT estimated using video volumes for the same six-hour period but for the semester network used in Autumn 2018 were determined for 2018, 2019, and 2020. The students compared these VMT values to indicate the ability of the video-based estimates to clearly show the reduction in travel associated with the 2020 COVID pandemic-related restrictions on campus.

- Autumn 2021: As discussed above, video and manual data were collected and processed in conjunction with the term project, but analysis was conducted only using processed data from Autumn 2018, Autumn 2019, and Autumn 2020. Changes in video-based segment-direction volumes and in network VMT from 2018 to 2019 and from 2019 to 2020 were calculated by the students to highlight the ability of the video-based volumes to show stability between 2018 and 2019 network-wide motorized travel and COVID pandemic-induced decreases in this travel from 2019 to 2020. In addition, these changes were compared to "subjective estimates" in growth factors previously elicited from the students to indicate the concept of quantification of what could be considered "general domain knowledge". In addition, the students calculated differences between video-based and ground truth volumes and VMT and compared the results to "errors" associated with network volume estimation using traditional methods that they quantified using empirical data collected and analyzed in the semester before the term project was assigned. Doing so allowed the students to appreciate ways to meaningfully assess the magnitudes of errors associated with new sensing technologies.
- Autumn 2022: Video-based growth factors obtained using the video volumes were compared to Ohio Department of Transportation-published growth factors, which were discussed previously in the semester. Differences between video and ground truth volumes were again quantified by the students and then used as a basis for the students to discuss the relative potential of using video data to accurately depict hourly volumes, longer-term (10-hour) volumes, network VMT, and qualitative changes in motorized travel over the years.

Although the video vehicle detection tasks were conducted individually, as was manual data collection beginning in Autumn 2020, the analysis and writing of the term project reports were conducted in groups of four to six students. Periodic oral updates on project progress were also made by the groups or by a randomly selected imember of each group. The term project written reports documented approaches, assumptions, results, and interpretations using technical communication techniques emphasized in the course.

The technical focus of the course relates to traditional and new approaches to data collection, processing, estimation, and analysis, and interpretation of empirically determined travel patterns over space and time. This focus was also at the center of the term projects. However, the term projects also incorporated more general objectives that have been increasingly emphasized in engineering programs, namely, working in teams, effectively communicating technical materials, and analyzing complex laboratory data, where in this case the laboratory comprises the actual campus roadways. 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 and relatable to the students. No formal evaluation of the students' satisfaction with the term project was conducted. However, students seemed more engaged in the term project than in other aspects of the course.

In addition to the research covered in this report forming the basis of the CIVILEN 5720 term project, the annual estimates (as calculated by the research project team, not by the course students) of vehicle miles travelled (VMT) determined across the campus roadways on a "typical weekday while the semester is in session" (see Section 6) were provided to The Ohio State University's Transportation and Traffic Management (TTM). As mentioned previously, 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. While the OSU community is surveyed through the use of questionnaires that ask for socioeconomic and travel information, these are the only in situ traffic flow estimates available to TTM for the roadways on and around the OSU campus.

8 Summary and Conclusions

This project focused on investigating the potential to use video imagery available from transit buses in regular service to accurately estimate time-of-day traffic volumes across urban networks. Transit buses regularly cover most major roadways of the urban network, so there would be no additional cost associated with deploying the sensing bus platform. Since video cameras are now regularly installed on buses in many transit fleets for safety, security, and liability reasons, there would also be no additional cost associated with deploying the camera sensors. And, since fleets of transit buses repeatedly cover the same roadways several times per hour, many hours per day, and day after day, the repeated observations obtained could lead to very good estimates of time-of-day traffic volumes and monitoring of these volumes.

A method previously developed by the investigators was modified and applied in multiple empirical studies using video imagery obtained from transit buses operating in regular service on the campus of The Ohio State University (OSU), a large campus with multiple land uses that serves as a living lab representative of urban areas. Concurrent data were obtained from manual traffic counts, road tubes, and a presently popular Location Based Service (LBS) data aggregator for comparative purposes. Descriptions of the data sets and the roadway network were presented in Section 2.

In Section 3, the methodology previously developed to estimate traffic volumes from a mobile platform, such as a bus, that repeatedly passes roadway segments was presented. Improvements made to the software-based implementation of the methodology during this project are then described, and modifications to the estimation methodology are proposed. The modifications consist of adjusting excessively low-volume or excessively high-volume estimates from an individual bus pass in what is considered an *ad hoc* manner and changing the approach to aggregating the volume estimates from multiple bus passes into a volume estimate for a specific time-of-day interval. Empirical comparisons of the estimates obtained with these modifications to traffic volumes obtained from road tube data demonstrate the improvements offered by the modifications.

The imagery associated with many of the bus passes that led to excessively large volume estimates were seen to contain queued vehicles at intersections, and two approaches were subsequently developed to explicitly address queued vehicles. Limited empirical comparisons with volumes determined from road tube data demonstrate greatly improved accuracy compared to the *ad hoc* modifications. At this point, these results are considered preliminary, and the approaches to addressing queued vehicles would require additional effort in implementation on a large-scale basis. Therefore, the *ad hoc* adjustments are used for the subsequent empirical studies in this report.

Distributions of errors associated with estimating time-of-day volumes using bus-based imagery are presented in Section 4. The errors were assessed by comparing the volume estimates to volumes obtained from road tube or manual count data. A mean error on the order of 27% was observed for hourly volume estimates, but the mean error was approximately 12% for 10-hour volume estimates. The median errors were smaller, approximately 20% and 7% for hourly and 10-hour estimates, respectively. A few very large errors could increase the mean error with respect to the median error. As noted in Section 3, it is likely that many of these large errors are a result of including queued vehicles in the volume estimates, and the approaches developed to address queued vehicles could eventually greatly reduce these large errors.

Moreover, it was seen that very different error distributions occurred when decomposing the comparisons as to the whether the video-based volumes were compared to volumes obtained from road tubes or to volumes obtained from manual traffic counts. The road tube volumes were associated with higher volumes and longer segments than were the manual count volumes. When considering only the errors determined from comparisons with volumes obtained from road tubes, which are generally placed on roads of more interest to transportation agencies, the mean and median errors in the hourly volumes are only 20% and 15%, respectively, rather than the 27% and 20% mentioned above for the pooled comparisons involving tube and manual data. These results indicate that video-based estimation of a specific hourly volume would be better on more important roadway segments, namely, segments that are longer and carry higher volumes. A 20% average error associated with estimating a specific hourly estimate on a specific day may still be unacceptable, but the potential to reduce this average error by addressing queued vehicles is noteworthy. Moreover, the substantially better accuracy observed in 10-hour volume estimates and observed in the applications of Sections 5 and 6 indicate that even the present volume estimation approach could be useful in multiple applications.

In Section 5, video-based volume estimates were used to estimate 10-hour, network-level vehicle miles traveled (VMT) on a typical weekday over four consecutive years. On subnetworks equipped with road tubes, the difference in video-based VMT estimates and road tube-based VMT estimates range from less than 1% to 10%. By comparison, differences in VMT estimates obtained when using volumes from a popular Location Based Services (LBS) data aggregator to road-tube based VMT estimates range from 35% to 124%. In addition, differences in VMT time-of-day patterns derived from video and road tube volumes are less than half the differences in VMT time-of-day patterns derived from LBS and road tube volumes. VMT and VMT time-of-day patterns are also determined for larger networks, where many segments were not equipped with road tubes. The absence of road tubes on many segments does not allow comparisons to ground truth results for these expanded networks. However, comparisons were made with respect to local knowledge of traffic changes over the years, which involved greatly reduced traffic as a result of COVID pandemic restrictions and increasing, but not "back to normal", traffic when pandemic restrictions were eased. Comparisons were also made with Ohio Department of Transportation (ODOT) factors representing yearly changes in statewide traffic. The results obtained when using video volumes were consistent with local knowledge and published ODOT factors, whereas those obtained when using LBS volumes were not. Based on these results, it appears that using video volumes for estimation of network level VMT, monitoring of VMT changes, and determination of network level time-of-day patterns can produce very good results, whereas using volumes from a presently popular data aggregator and provider cannot, at least for the types of networks that formed the basis of these empirical investigations.

The empirical studies of Sections 3, 4, and 5 all consider estimating a time-of-day traffic volume for the day on which the data were collected. A great advantage of using transit buses for traffic volume estimation is the ability to obtain data on the same large number of roadway segments on many days. These many repeated estimates would allow estimating an "average" time-of-day volume, which is typically of more interest in off-line traffic monitoring than is an estimate of a time-of-day volume on a specific day. The improved accuracy of average day estimation was addressed in Section 6. An extensive data collection effort was implemented, where concurrent bus-based imagery and manual traffic counts were obtained for one segment-direction over two academic semesters for multiple hours on multiple days. The differences in sample average hourly video and manual volumes were between 1% and 5% for the four different time-of-day periods considered. These values can be compared to the average error for a specific day that was seen to be on the order of 20% in Section 4.

The average of hourly volumes obtained over a finite number of multiple days, even if they are error-free representations of the true volumes occurring on the day of collection, would not necessarily represent the true average hourly volume because of day-to-day variability in traffic volumes. Therefore, an analytical framework was also presented to investigate the ability to provide good estimates of the true average day hourly volume when obtaining sample hourly volumes over a specified number of days. The empirical data were used to estimate input values for this analytical framework, and it is seen that, for the time-of-day periods covered in the empirical data collection, good results could be obtained with only a few days of video-based bus volumes.

In addition to the methodological developments and empirical demonstrations associated with the research component of this project, this project also included important education and outreach aspects. In Section 7, the use of the research concept in term projects for an annually offered OSU course on transportation data collection was described, as well as how the term project addressed multiple important pedagogical objectives of increasing interest in engineering education. In Section 7, it was also described that the annual VMT estimates across the OSU campus network are regularly provided to university transportation planners and operators as the only *in situ* data-driven source of motorized travel across the campus network.

In general, it appears that estimating an hourly traffic volume for a specific hour of a specific day from bus-based video imagery leads to relatively large errors at this time. However, the accuracy appears to be sufficiently good for practice when estimating volumes over longer aggregation periods (e.g., ten hours), when using the estimated volumes to determine estimates of network vehicle miles traveled, and when determining an average hourly volume, rather than an hourly volume for a specific day. Moreover, it was seen that many of the large errors associated with estimating hourly volumes on a specific day result from including queued vehicles in the data used for estimation. Preliminary evaluation of approaches developed to address queued vehicles demonstrates very good performance, which would imply that much improved estimation accuracy could be obtained with additional research. Moreover, the magnitudes of the errors were seen to be statistically associated with segment length, which can be observed in practice. However, the model relations developed are not sufficiently precise to provide useful predictions of whether specific estimates would be more or less accurate. It would be helpful to conduct additional research to determine other factors that are associated with the quality of a video-based volume estimate and to possibly develop a quantitative model that could be used in practice to indicate the degree of confidence to be attributed to specific estimates. Discovering the factors associated with good or bad quality estimates would also be helpful in improving the estimation methodology. In addition to research on developments in the estimation methodology, it would be useful to provide more evidence of the very good results seen in the empirical studies conducted in this research project by replicating the studies and extending them to other urban networks covered by transit buses operated by different agencies.

Even though additional methodological developments and empirical studies would be helpful, the results presented in this report, especially when compared to those obtained from a presently popular data aggregator and provider, indicate that existing imagery captured from cameras on transit buses in regular operation could be a low cost, accurate approach to traffic volume estimation.

The focus of the research was on improving the estimation methodology and evaluating performance of the estimated volumes in various applications and not on developing a software package that could be used in practice. Nevertheless, it is noted that other than vehicle detection, the steps involved with implementing the present estimation approach are fully automated. Based on approximate calculations, the process, including the semi-automated vehicle detection step used in the empirical studies, required approximately 10 minutes of human time on average for every segment-direction-day-hour of volume estimation for the types of segments and number of bus passes used in the empirical studies. Human traffic counters obtain counts on both directions of a segment (although with decreased accuracy compared to counting in one direction). Therefore, present human data collection would require approximately 30 minutes per segment-direction-day-hour, that is, approximately three times the human vehicle detection time involved with the video-based estimation. These estimates of time required do not consider the time to download video from buses, which can be automated, or the time for manual data collectors to travel to and from the data collection locations and the set-up time involved. In short, the present video-based approach appears very time-competitive with manual data collection. Of course, portable automatic sensors can avoid much of the human time involved with some traffic counts, but as emphasized in the motivation to this research, these automatic sensors can only collect data on a limited number of segments and on an infrequent basis. Moreover, recent results (Redmill, et al., 2023) indicate the promise of automating the vehicle detection step with additional research, which would further reduce the already competitive time requirements of estimating volume estimates from transit bus-based imagery on a regular basis.

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Appendix A: Summary of Empirical Data Obtained for Use in Empirical Studies

Table A-1: Data collected on data collection days, 10/25/2018, 10/24/2019, 11/05/2020, 11/04/2021, 11/01/2022; Numbers in parentheses in "Video" column refer to the number of bus passes from which video data were collected during the corresponding time period

	Oct. 25, 2018				Oct. 24, 2019				Nov. 05, 2020				Nov. 04, 2021			Nov. 01, 2022	
Seg_dir	Video	LBS	Manual	Road Tube	Video	LBS	Manual	Road Tube	Video	LBS	Manual	Road Tube	Video	LBS	Manual	Video	Manual
1.1	7:00-19:00 (42)	24-hour	11:00-12:00	24-hour	7:00-19:00 (94)	24-hour	8:00-9:00; 11:00-13:00		7:00-19:00 (98)	24-hour		24-hour	7:00-19:00 (171)	24-hour	11:30-12:30	7:00-19:00 (116)	11:15-12:15
1.2	7:00-19:00 (41)	24-hour	11:00-12:00	24-hour	7:00-19:00 (91)	24-hour	8:00-9:00; 11:00-13:00		7:00-19:00 (103)	24-hour		24-hour	7:00-19:00 (171)	24-hour	11:30-12:30	7:00-19:00 (125)	11:15-12:15
2.1	7:00-19:00 (42)	24-hour	11:00-12:00		7:00-19:00 (56)	24-hour	8:00-10:00; 11:00-12:00		7:00-19:00 (48)	24-hour	11:15-12:15		7:00-19:00 (56)	24-hour	11:30-12:30	7:00-19:00 (70)	11:15-12:15
2.2	7:00-19:00 (44)	24-hour	11:00-12:00		7:00-19:00 (54)	24-hour	8:00-10:00; 11:00-12:00		7:00-19:00 (49)	24-hour	11:15-12:15		7:00-19:00 (57)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
3.1	7:00-19:00 (106)	24-hour	11:00-12:00		7:00-19:00 (104)	24-hour	11:00-12:00; 17:00-18:00		7:00-19:00 (111)	24-hour	11:15-12:15		7:00-19:00 (154)	24-hour	11:30-12:30	7:00-19:00 (122)	11:15-12:15
3.2	7:00-19:00 (107)	24-hour	11:00-12:00		7:00-19:00 (97)	24-hour	11:00-12:00; 17:00-18:00		7:00-19:00 (188)	24-hour	11:15-12:15		7:00-19:00 (155)	24-hour	11:30-12:30	7:00-19:00 (125)	11:15-12:15
4.1	7:00-19:00 (105)	24-hour	8:00-9:00; 11:00-13:00; 15:00-17:00	24-hour	7:00-19:00 (100)	24-hour	8:00-9:00; 11:00-14:00		7:00-19:00 (110)	24-hour	11:15-12:15	24-hour	7:00-19:00 (152)	24-hour	11:30-12:30	7:00-19:00 (123)	11:15-12:15
4.2	7:00-19:00 (109)	24-hour	8:00-9:00; 11:00-13:00; 15:00-17:00	24-hour	7:00-19:00 (100)	24-hour	8:00-9:00; 11:00-14:00		7:00-19:00 (186)	24-hour	11:15-12:15	24-hour	7:00-19:00 (158)	24-hour	11:30-12:30	7:00-19:00 (125)	11:15-12:15
5.1	7:00-19:00 (44)	24-hour	11:00-12:00		7:00-19:00 (46)	24-hour		24-hour	7:00-19:00 (64)	24-hour	11:15-12:15		7:00-19:00 (52)	24-hour	11:30-12:30	7:00-19:00 (122)	11:15-12:15
5.2	7:00-19:00 (64)	24-hour	11:00-12:00		7:00-19:00 (76)	24-hour		24-hour	7:00-19:00 (122)	24-hour	11:15-12:15		7:00-19:00 (102)	24-hour	11:30-12:30	7:00-19:00 (126)	11:15-12:15
6.1	7:00-19:00 (39)	24-hour	11:00-12:00		7:00-19:00 (49)	24-hour	8:00-9:00; 11:00-12:00		7:00-19:00 (67)	24-hour	11:15-12:15		7:00-19:00 (56)	24-hour	11:30-12:30	7:00-19:00 (121)	11:15-12:15
6.2	7:00-19:00 (63)	24-hour	11:00-12:00		7:00-19:00 (58)	24-hour	8:00-9:00; 11:00-12:00		7:00-19:00 (46)	24-hour	11:15-12:15		7:00-19:00 (110)	24-hour	11:30-12:30	7:00-19:00 (126)	11:15-12:15
7.1	7:00-19:00 (66)	24-hour	11:00-12:00		7:00-19:00 (52)	24-hour	8:00-9:00; 11:00-13:00		7:00-19:00 (43)	24-hour	11:15-12:15		7:00-19:00 (99)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
7.2	7:00-19:00 (44)	24-hour	11:00-12:00		7:00-19:00 (45)	24-hour	8:00-9:00; 11:00-13:00		7:00-19:00 (67)	24-hour	11:15-12:15		7:00-19:00 (52)	24-hour	11:30-12:30	7:00-19:00 (121)	11:15-12:15
8.1	7:00-19:00 (66)	24-hour	11:00-12:00		7:00-19:00 (53)	24-hour			7:00-19:00 (45)	24-hour	11:15-12:15		7:00-19:00 (99)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
8.2	7:00-19:00 (44)	24-hour	11:00-12:00		7:00-19:00 (50)	24-hour			7:00-19:00 (69)	24-hour	11:15-12:15		7:00-19:00 (55)	24-hour	11:30-12:30	7:00-19:00 (121)	11:15-12:15
9.1	7:00-19:00 (63)	24-hour	11:00-12:00		7:00-19:00 (53)	24-hour	11:00-12:00		7:00-19:00 (43)	24-hour	11:15-12:15		7:00-19:00 (101)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
9.2	7:00-19:00 (42)	24-hour	11:00-12:00		7:00-19:00 (45)	24-hour	11:00-12:00		7:00-19:00 (69)	24-hour	11:15-12:15		7:00-19:00 (52)		11:30-12:30	7:00-19:00 (121)	11:15-12:15
10.1	7:00-19:00 (60)	24-hour	11:00-12:00	24-hour	7:00-19:00 (52)	24-hour	8:00-9:00; 10:00-12:00		7:00-19:00 (47)	24-hour	11:15-12:15		7:00-19:00 (107)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
10.2	7:00-19:00 (41)	24-hour	11:00-12:00	24-hour	7:00-19:00 (22)	24-hour	8:00-9:00; 10:00-12:00		7:00-19:00 (69)	24-hour	11:15-12:15		7:00-19:00 (59)	24-hour	11:30-12:30	7:00-19:00 (122)	11:15-12:15
11.1	7:00-19:00 (60)	24-hour	11:00-12:00		7:00-19:00 (53)	24-hour	10:00-13:00		7:00-19:00 (46)	24-hour	11:15-12:15		7:00-19:00 (102)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
11.2	7:00-19:00 (42)	24-hour	11:00-12:00		7:00-19:00 (23)	24-hour	10:00-13:00		7:00-19:00 (117)	24-hour	11:15-12:15		7:00-19:00 (53)	24-hour	11:30-12:30	7:00-19:00 (121)	11:15-12:15
12.1	7:00-19:00 (58)	24-hour	7:00-8:00		7:00-19:00 (55)	24-hour	12:00-13:00		7:00-19:00 (48)	24-hour	11:15-12:15		7:00-19:00 (46)	24-hour	11:30-12:30		11:15-12:15
12.2	7:00-19:00 (40)	24-hour	7:00-8:00		7:00-19:00 (25)	24-hour	12:00-13:00		7:00-19:00 (69)	24-hour	11:15-12:15		7:00-19:00 (55)	24-hour	11:30-12:30		11:15-12:15
13.1	7:00-19:00 (43)	24-hour			7:00-19:00 (23)	24-hour	8:00-9:00; 11:00-12:00; 16:00-18:00		7:00-19:00 (69)	24-hour	11:15-12:15		7:00-19:00 (52)	24-hour	11:30-12:30	7:00-19:00 (71)	11:15-12:15
13.2	9:00-13:00; 14:00-16:00 (32)	24-hour			7:00-17:00; 18:00-19:00 (50)	24-hour	8:00-9:00; 11:00-12:00; 16:00-18:00		7:00-19:00 (48)	24-hour	11:15-12:15		7:00-19:00 (97)	24-hour	11:30-12:30	7:00-19:00 (72)	11:15-12:15
14.1	7:00-19:00 (65)	24-hour	7:00-10:00; 16:00-19:00		7:00-19:00 (52)	24-hour			7:00-19:00 (49)	24-hour			7:00-19:00 (97)	24-hour	11:30-12:30	7:00-19:00 (72)	11:15-12:15
14.2	7:00-19:00 (44)	24-hour	7:00-10:00; 16:00-19:00		7:00-19:00 (24)	24-hour			7:00-19:00 (69)	24-hour			7:00-19:00 (52)	24-hour	11:30-12:30	7:00-19:00 (72)	11:15-12:15
15.1	7:00-19:00 (63)	24-hour	7:00-8:00	24-hour	7:00-19:00 (90)	24-hour			7:00-19:00 (103)	24-hour	11:15-12:15	24-hour	7:00-19:00 (208)	24-hour	11:30-12:30	7:00-19:00 (46)	11:15-12:15
15.2	7:00-15:00; 18:00-19:00 (33)	24-hour	7:00-8:00	24-hour	7:00-19:00 (57)	24-hour			7:00-19:00 (121)	24-hour	11:15-12:15	24-hour	7:00-19:00 (163)	24-hour	11:30-12:30	7:00-19:00 (46)	11:15-12:15
16.1	7:00-19:00 (41)	24-hour			7:00-19:00 (24)	24-hour		24-hour	7:00-19:00 (66)	24-hour	11:25-12:25		7:00-19:00 (52)	24-hour	11:30-12:30		11:15-12:15
16.2	7:00-19:00 (66)	24-hour			7:00-19:00 (56)	24-hour		24-hour	7:00-19:00 (47)	24-hour	11:25-12:25		7:00-19:00 (101)	24-hour	11:30-12:30		11:15-12:15
17.1	7:00-19:00 (45)	24-hour	8:00-10:00; 16:00-18:00		7:00-19:00 (22)	24-hour			7:00-19:00 (67)	24-hour	12:45-13:45		7:00-19:00 (52)	24-hour	11:30-12:30		11:15-12:15
17.2	7:00-19:00 (64)	24-hour	8:00-10:00; 16:00-18:00		7:00-19:00 (56)	24-hour			7:00-19:00 (47)	24-hour	12:45-13:45		7:00-19:00 (96)	24-hour	11:30-12:30		11:15-12:15
18.1	7:00-19:00 (44)	24-hour			7:00-19:00 (22)	24-hour			7:00-19:00 (68)	24-hour	14:45-15:45		7:00-19:00 (51)	24-hour	11:30-12:30		11:15-12:15
18.2	7:00-19:00 (67)	24-hour			7:00-19:00 (55)	24-hour			7:00-19:00 (47)	24-hour	14:45-15:45		7:00-19:00 (97)	24-hour	11:30-12:30		11:15-12:15
19.1	7:00-19:00 (44)	24-hour		24-hour	7:00-19:00 (22)	24-hour	8:00-9:00; 11:00-13:00		7:00-19:00 (68)	24-hour	11:15-12:15		7:00-19:00 (51)	24-hour	11:30-12:30		11:15-12:15
19.2	7:00-19:00 (49)	24-hour		24-hour	7:00-19:00 (56)	24-hour	8:00-9:00; 11:00-13:00		7:00-19:00 (47)	24-hour	11:15-12:15		7:00-19:00 (96)	24-hour	11:30-12:30		11:15-12:15
20.1	7:00-19:00 (60)	24-hour	7:00-9:00; 10:00-15:00		7:00-19:00 (46)	24-hour		24-hour	7:00-19:00 (136)	24-hour	12:30-13:30	24-hour	7:00-19:00 (97)	24-hour	11:30-12:30	7:00-19:00 (53)	11:15-12:15
20.2	7:00-19:00 (65)	24-hour	7:00-9:00; 10:00-15:00		7:00-19:00 (46)	24-hour		24-hour	7:00-19:00 (69)	24-hour	12:30-13:30	24-hour	7:00-19:00 (93)	24-hour	11:30-12:30	7:00-19:00 (52)	11:15-12:15
21.1	8:00-19:00 (62)	24-hour	8:00-19:00		8:00-19:00 (49)	24-hour			7:00-19:00 (48)	24-hour	11:15-12:15		7:00-19:00 (98)	24-hour	11:30-12:30	7:00-19:00 (72)	11:15-12:15
21.2	7:00-16:00; 17:00-19:00 (40)	24-hour	8:00-19:00		7:00-19:00 (23)	24-hour			7:00-19:00 (69)	24-hour	11:15-12:15		7:00-19:00 (52)	24-hour	11:30-12:30	7:00-19:00 (73)	11:15-12:15
22.1					7:00-19:00 (35)	24-hour	8:00-10:00; 12:00-13:00; 16:00-17:00		7:00-19:00 (54)	24-hour	15:15-16:15		7:00-19:00 (110)	24-hour	11:30-12:30	7:00-19:00 (49)	11:15-12:15
22.2					7:00-19:00 (37)	24-hour	8:00-10:00; 12:00-13:00; 16:00-17:00		7:00-18:00 (54)	24-hour	15:15-16:15		7:00-19:00 (109)	24-hour	11:30-12:30	7:00-19:00 (47)	11:15-12:15
23.1					7:00-19:00 (35)	24-hour	11:00-12:00; 17:00-18:00		7:00-19:00 (54)	24-hour	11:15-12:15		7:00-19:00 (106)	24-hour	11:30-12:30	7:00-19:00 (48)	11:15-12:15
23.2					7:00-19:00 (37)	24-hour	11:00-12:00; 17:00-18:00		7:00-19:00 (55)	24-hour	11:15-12:15		7:00-19:00 (110)	24-hour	11:30-12:30	7:00-19:00 (47)	11:15-12:15
24.1					7:00-19:00 (38)	24-hour		24-hour	7:00-19:00 (54)	24-hour		24-hour	7:00-19:00 (109)	24-hour	11:30-12:30	7:00-19:00 (47)	11:15-12:15
24.2					7:00-19:00 (35)	24-hour		24-hour	7:00-19:00 (51)	24-hour		24-hour	7:00-19:00 (113)	24-hour	11:30-12:30	7:00-19:00 (48)	11:15-12:15
25.1							11:00-13:00			24-hour	11:15-12:15				11:30-12:30		11:15-12:15
25.2							11:00-13:00		7:00-19:00 (79)	24-hour	11:15-12:15				11:30-12:30		11:15-12:15
26.1					7:00-15:00; 16:00-18:00 (24)	24-hour	11:00-13:00; 16:00-18:00		7:00-19:00 (75)	24-hour	11:15-12:15				11:30-12:30		11:15-12:15
26.2						24-hour	11:00-13:00; 16:00-18:00		7:00-19:00 (78)	24-hour	11:15-12:15				11:30-12:30		11:15-12:15
27.1											11:15-12:15				11:30-12:30		11:15-12:15
27.2									7:00-19:00 (77)	24-hour	11:15-12:15				11:30-12:30		11:15-12:15
28.1									7:00-19:00 (130)	24-hour	11:15-12:15		7:00-19:00 (98)	24-hour	11:30-12:30	7:00-19:00 (54)	11:15-12:15
28.2									7:00-19:00 (66)	24-hour	11:15-12:15		7:00-19:00 (101)	24-hour	11:30-12:30	7:00-19:00 (53)	11:15-12:15

Table A-2: Manual and video hourly volumes used in average day study of Section 6; Numbers in parenthesis are the number of bus passes used to estimate the video volume in the hour

Date	Hour	Day	Semester	Video Vol (# bus passes)	Man Vol
2-16-22	9:30	Wed	Spring	179.71 (10)	191.88
3-2-22	9:30	Wed	Spring	173.49 (14)	146.88
3-10-22	9:30	Thu	Spring	150.68 (11)	162.50
3-24-22	9:30	Thu	Spring	186.76 (13)	189.38
3-30-22	9:30	Wed	Spring	232.62 (13)	213.13
4-6-22	9:30	Wed	Spring	150.59 (8)	203.13
4-7-22	9:30	Thu	Spring	201.65 (4)	184.38
4-13-22	9:30	Wed	Spring	183.04 (10)	199.38
4-14-22	9:30	Thu	Spring	121.86 (11)	184.38
4-21-22	9:30	Thu	Spring	181.99 (14)	193.13
4-27-22	9:30	Wed	Spring	160.17 (8)	158.75
5-5-22	9:30	Thu	Spring	94.7 (4)	128.75
9-15-22	9:30	Thu	Fall	147.67 (8)	165.88
9-22-22	9:30	Thu	Fall	184.35 (11)	164.69
9-29-22	9:30	Thu	Fall	215 (8)	165.50
10-13-22	9:30	Thu	Fall	106.86 (7)	93.13
10-27-22	9:30	Thu	Fall	195.37 (11)	185.06
11-10-22	9:30	Thu	Fall	207.4 (9)	186.06
12-1-22	9:30	Thu	Fall	154.99 (12)	168.88
12-8-22	9:30	Thu	Fall	178.41 (6)	156.13
9-21-22	9:30	Wed	Fall	205.97 (8)	215.94
9-28-22	9:30	Wed	Fall	206.22 (6)	210.50
10-5-22	9:30	Wed	Fall	163.95 (8)	208.06
10-12-22	9:30	Wed	Fall	180.36 (9)	190.63
12-7-22	9:30	Wed	Fall	254.74 (5)	222.19
2-7-22	11:30	Mon	Spring	145.73 (13)	155.63
2-10-22	11:30	Thu	Spring	156.26 (15)	155.00
2-14-22	11:30	Mon	Spring	171.11 (10)	146.88
2-21-22	11:30	Mon	Spring	191.55 (10)	164.38
2-28-22	11:30	Mon	Spring	138.54 (12)	154.38
3-7-22	11:30	Mon	Spring	113.66 (12)	155.00
3-10-22	11:30	Thu	Spring	148.82 (12)	145.00
3-21-22	11:30	Mon	Spring	144.8 (8)	164.38
3-24-22	11:30	Thu	Spring	164.95 (12)	181.25
3-28-22	11:30	Mon	Spring	181.96 (11)	197.50
4-4-22	11:30	Mon	Spring	180.74 (10)	176.88
4-7-22	11:30	Thu	Spring	129.5 (6)	160.63
4-11-22	11:30	Mon	Spring	183.35 (7)	166.88

Table A-2 (continued): Manual and video hourly volumes used in average day study of Section 6; Numbers in parenthesis are the number of bus passes used to estimate the video volume in the hour

Date	Hour	Day	Semester	Video Vol (# bus passes)	Man Vol
4-14-22	11:30	Thu	Spring	173.51 (11)	187.50
4-21-22	11:30	Thu	Spring	140.28 (11)	156.25
4-25-22	11:30	Mon	Spring	153.68 (5)	172.50
4-28-22	11:30	Thu	Spring	151.89 (8)	138.13
5-2-22	11:30	Mon	Spring	94.72 (12)	111.25
5-5-22	11:30	Thu	Spring	96.86 (4)	114.38
9-12-22	13:00	Mon	Fall	132.33 (13)	135.25
9-15-22	13:00	Thu	Fall	186.46 (8)	149.25
9-19-22	13:00	Mon	Fall	193.05 (12)	152.00
9-26-22	13:00	Mon	Fall	144.53 (13)	147.63
9-29-22	13:00	Thu	Fall	112.45 (7)	140.94
10-3-22	13:00	Mon	Fall	114.79 (10)	148.81
10-6-22	13:00	Thu	Fall	136.02 (7)	162.06
10-10-22	13:00	Mon	Fall	204.24 (7)	146.63
10-20-22	13:00	Thu	Fall	163.59 (10)	124.88
10-24-22	13:00	Mon	Fall	168.2 (14)	154.06
10-27-22	13:00	Thu	Fall	158.47 (12)	133.44
10-31-22	13:00	Mon	Fall	170.89 (13)	173.75
11-7-22	13:00	Mon	Fall	208.54 (11)	171.44
11-10-22	13:00	Thu	Fall	135.48 (10)	159.75
11-14-22	13:00	Mon	Fall	169.01 (9)	168.81
11-21-22	13:00	Mon	Fall	147.79 (15)	160.13
11-28-22	13:00	Mon	Fall	157.04 (12)	154.00
12-5-22	13:00	Mon	Fall	165.88 (6)	144.31

Appendix B: CIVILEN 5720 Term Project Statements by Semester

The Ohio State University **Autumn 2018**
CIVILEN 5720 Transportation Engineering Data Collection Studies
Department of Civil, Environmental, and Geodetic Engineering

Date Handed Out: Tuesday, 6 November 2018
Date Due: Thursday, 6 December 2018, by noon[1]

Term Project (Grade will be considered equal to one exam grade): Estimating Campus VMT with Multiple Data Sources

Keep a copy of your project report. Work on your project in the assigned groups. Turn in one project report per group. Place all names of the group on the report.

~~You may be asked to orally present your projects as well.~~

We will solicit specific information on how group members contributed.

For all parts, we are expecting good technical communication. You should consider the "clients" to be the instructors of this course. That is, you should assume our knowledge level and do not need to describe basic principles covered in class. However, you should be specific, but concise on approaches used and assumptions made, and illustrate with example calculations if appropriate. The reader should be able to determine quickly the main points. Long tables that support points should be placed in appendices.

Data in the form of collected counts, tube counts, parking garage entries and exists, and vehicle flows determined from video images by cameras mounted on CABS transit buses will be made available.

1. Use the hourly volumes obtained from the manual data collections effort on 23 and 25 October to estimate VMT on a typical Thursday across all the segments considered between 7:00 am and 7:00 pm. Based on your VMT estimate, estimate the amount of fuel consumed from travel on these segments during this time period.

2. How might you use any combination of the road tube data, parking garage data, and traffic volumes estimated from the bus-based video count data to either improve your VMT estimate or to obtain a VMT estimate of similar quality with fewer manual counts? This question is intentionally open-ended. We are looking for thoughtful, creative, and rigorous engineering analyses, supported by numerical investigations, perhaps even leading to revised estimates of VMT.

3. ~~Assume that parking and bus-video data will be available in future at minimal marginal cost to transportation engineers and planners. How might these sources of data be helpful in monitoring or producing new estimates of VMT in future, both for campus and in general? We are again looking for thoughtful, creative, and rigorous analyses. We do not have a right or wrong answer in mind, but we expect your proposal to be defensible.~~

[1] In *both* electronic form via email to both instructors (mccord.2 *and* mishalani.1) and hard-copy form hand-delivered to either of the instructors in their offices 491D or 483E, or in their mailboxes in HI 423 if you don't find them in their offices.

Project Groups

Group 1	Group 2	Group 3
Abdul Latif, Muhammad	Ahmad Shukri, Suraya	Billisits, Ethan
Fauzi, Ahmad	Ahmat, Nurul	Brickner, Nathan
Hamid, Tuah	Mohamad Rodzai, Danial	Lifke, Claire
Mohamad Shahrizal, Syahril	Mohamad, Nazrul	Miller, Skyler
Muhamad Luqmanul Hakim	Mohd Nasir, Sofiya	Wasielewski, Grant
Group 4	Group 5	Group 6
Becht, Henry	Ma, Yingyu	Abdulkadir, Afrah
Suib, Muhammad	Moody, John	Brown, Molly
Syed Ismail, Dani	Pelfrey, Amanda	Joshi, Ashish
Travis, Michael	Summer, Sonja	Sanor, Jerry
Tury, Richard	Wang, Taoyu	Willis, Aaron

UPDATE 2

The Ohio State University **Autumn 2019**
CIVILEN 5720 Transportation Engineering Data Collection Studies
Department of Civil, Environmental, and Geodetic Engineering

Date Handed Out: Tuesday, 29 October 2019
Date Due: Thursday, 5 December 2019, by noon[1]

Term Project (Grade will be considered equal to one exam grade): Estimating Campus Segment Volumes and VMT with Multiple Data Sources

Keep a copy of your project report. Work on your project in the assigned groups indicated on the next page. Turn in one project report per group. Place all names of the group on the report.

~~You may be asked to orally present your projects as well.~~

We will solicit specific information on how group members contributed.

For all parts, we are expecting good technical communication. You should consider the “clients” to be the instructors of this course. That is, you should assume our knowledge level and do not need to describe basic principles covered in class. However, you should be specific, but concise, on approaches used and assumptions made, and you should illustrate with example calculations if appropriate. The reader should be able to determine quickly the logic and main points. Long tables and supporting information should be placed in appendices.

Data in the form of manually collected counts, tube counts, and vehicle flows determined from video images by cameras mounted on CABS transit buses will be made available.

1. Consider all segments for which either manual or road tube data were collected on 22 or 24 October 2019. For these segments, use manually collected and road tube data to estimate the following for a typical Thursday in Autumn 2019:

   - Hourly segment flows between 8:00 am and 6:00 pm
   - 10-hour VMT aggregated across the set of segments specified above

   You should consider the data collected on Tuesday 22 October, 2019 to be representative of data that would have been collected on Thursday 24 October, 2019.

2. Consider the union of segments for which either manual or road tube date were collected this year or last year (October 2018). Use the manual and road tube data collected this year (i.e., the data used in part 1) and estimated volumes for a typical Thursday in Autumn 2019 using manual and road tube data collected last year (October 2018) to estimate the following for a typical Thursday in Autumn 2019:

   - Hourly segment flows between 7:00 am and 7:00 pm
   - 12-hour VMT aggregated across the extended set of segments

[1] In *both* electronic form via email to both instructors (mccord.2 *and* mishalani.1) and hard-copy form hand-delivered to either of the instructors in their offices 491D or 483E, or in their mailboxes in HI 423 if you don’t find them in their offices.

UPDATE 2

~~Again, you should consider the data collected on Tuesday 23 October, 2018 to be representative of data that would have been collected on Thursday 25 October, 2018.~~

Assume that the volumes you estimated for Thursday Oct 24 are representative of volumes on an average weekday when OSU classes are in sessions during Autumn and Spring semesters. Estimate the following:

- Total 12-hour VMT across this campus network and all days when classes are in session during Autumn and Spring semesters
- Total fuel consumed across the same network and period

3. Consider **only** the hourly volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 24 October 2019. These volumes are determined by applying the moving observer method assuming $t_2 = t_1$ for each bus pass and averaging across the estimates from each pass. Estimate the following for a typical Thursday in Autumn 2019:

   - Hourly segment flows between 7:00 am and 7:00 pm
   - 12-hour VMT aggregated across the extended set of segments

4. Compare the results from questions 2 and 3 for the following:

   - Hourly segment flows between 7:00 am and 7:00 pm
   - Daily segment follows between 7:00 am and 7:00 pm
   - 12-hour VMT aggregated across the extended set of segments

   In doing so, think of single indicator *summary* metrics to calculate and use to compare the results from questions 2 and 3.

   Are your comparison results similar or different when considering hourly segment flows, daily segment flow, and 12-hour VMT? Explain the similarities or differences that you note.

Term Project Groups

Group 1	Group 2	Group 3	Group 4
Bresciani, Jeremy	Brosnahan, John	Cottingim, Josh	Dittoe, Austin
Insley, Chris	Liu, Ziming	Foster, Abby	Schenken, Mark
Jackson, Trey	Roy, Raj	Neiderhouser, Jacob	Stefanek, Sydney
Watson-Ables, Julie	Sullivan, Mark	Russell, Matthew	Thompson, Nate
	Wang, Norman	Scholz, Eric	Yoder, Neil

Group 5	Group 6	Group 7
Dobson, Abraham	El Asmar, Paul	Faist, Cody
Schanzlin, Eric	Ferzli, Stephanie	Haubert, Alex
Simons, Tyler	Galdino, Diego	Lai, Welton
Slade, Connor	Gaus, Greg	Reategui, Chris
Wilson, Logan		

The Ohio State University **Autumn 2020**
CIVILEN 5720 Transportation Engineering Data Collection Studies
Department of Civil, Environmental, and Geodetic Engineering

Date Handed Out: Tuesday, 3 November 2020
Update 2 (fourth bullet of part 3 and parts 4-7): Tuesday, 1 December 2020
Date Due: Tuesday, 8 December 2020 at noon

Term Project (25% of course grade): Estimating Campus Segment Volumes and VMT Using Data from Multiple Sources

Work on your project in the assigned groups indicated below. Submit one project report per group. Place all names of the group on the report. Additional submission instructions will be provided.

Any team member may be asked to defend aspects of the project individually. That is, although we expect different team members to take the lead on different aspects, we expect all team members to understand all components of the project.

We will also solicit specific information on how group members contributed using a peer- and self-evaluation questionnaire.

For all parts of the PowerPoint slides based "report", we are expecting good technical communication. You should consider the "clients" to be the instructors of this course. That is, you should assume our knowledge level and do not need to describe basic principles covered in class. However, you should be specific, but concise, on approaches used and assumptions made, and you should illustrate with example calculations if appropriate. The audience should be able to determine quickly the logic and main points. Long tables and supporting information should be placed in appendices after the set of slides you would typically present. Summary tables and information that directly support your results and conclusions should be part of the main slides. Of course, only use tables when they help summarize multiple numerical values or items.

Data in the form of manually collected counts, tube counts, and vehicle flows determined from video images by cameras mounted on CABS transit buses are made available at different stages of the term project.

1. Consider only the segments for which data were collected on 25 October 2018. For these segments use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 25 October 2018 and 24 October 2019 to estimate the following:

    - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 10/25/2018
    - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 10/24/2019
    - 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 10/25/2018
    - 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 10/24/2019

2. Quantify the differences between 2018 and 2019 volumes for common segment-direction-hours and in 12-hour VMT. Compare the differences and discuss whether you believe they might reflect a systematic change in VMT between 2018 and 2019 or if the difference could be attributable to day-to-day variation in campus travel.

3. Consider **all** segments for which either manual or road tube data were collected on 5 November 2020. For these segments, use manually collected and road tube data to estimate the following for 11/5/2020:

    - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval
    - 12-hour (7:00 am to 7:00 pm) segment-direction-volumes
    - 12-hour VMT between 7:00 am and 7:00 pm aggregated across the set of segments specified above
    - 6-hour VMT over the **combined** periods 7:00 am to 9:00 am, 11:00 am to 1:00 pm, and 4:00 pm to 6:00 pm aggregated across the set of segments specified above

4. Consider **all** segments for which either manual or road tube data were collected on 5 November 2020, however, now only consider the following six hours: 7:00 am to 9:00 am, 11:00 am to 1:00 pm, and 4:00 pm to 6:00 pm. For these segments and hours, use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 5 November 2020 to estimate the following for 11/5/2020:

    - Volumes for each segment-direction-hour for the six hours noted above
    - 6-hour VMT over the **combined** periods 7:00 am to 9:00 am, 11:00 am to 1:00 pm, and 4:00 pm to 6:00 pm and aggregated across the set of segments specified above

5. Quantify the differences between the 2020 manual- and tube-based volume estimates and the 2020 video-based volume estimates for common segment-direction-hours and for 6-hour VMT. Compare the differences and **briefly** comment (e.g., a few bullets in a PowerPoint slide) whether you believe video-based estimates could complement or replace manual- and tube-based volume estimates in the future.

6. Consider only the segments for which data were collected on 25 October 2018. For these segments use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 25 October 2018, 24 October 2019, and 5 November 2020 to estimate the following:

    - 6-hour VMT aggregated across the set of segments specified above over the **combined** periods 7:00 am to 9:00 am, 11:00 am to 1:00 pm, and 4:00 pm to 6:00 pm for Thursday, 10/25/2018
    - 6-hour VMT aggregated across the set of segments specified above over the **combined** periods 7:00 am to 9:00 am, 11:00 am to 1:00 pm, and 4:00 pm to 6:00 pm for Thursday, 10/24/2019
    - 6-hour VMT aggregated across the set of segments specified above over the **combined** periods 7:00 am to 9:00 am, 11:00 am to 1:00 pm, and 4:00 pm to 6:00 pm for Thursday, 11/05/2020

7. Quantify the differences between 2018, 2019, and 2020 6-hour VMT based on volumes estimated from video imagery. Compare the differences and discuss whether you believe the differences might reflect systematic changes in VMT between any pair of years 2018, 2019, and 2020 or if the differences could be attributable to day-to-day variation in campus travel.

Term Project Groups

Group 1		Group 3
Matt Allshouse		Nicholas Bernhard
Josh Bals		Shahrzad Charmchi Toosi
Alyssa Meurer		Anthony Collinger
Kayla Saggio		Katherine Coggins
Leiana Yates		Collin Walsh

Group 4	Group 5	Group 6
Josh Banaszak	Aaron Drewes	Matthew Friedman
Jason Leonhardt	Tyler Dubbs	Max Hartman
Jacob Mengelkamp	Frannie Severding	Sara Lemanski
Nathan Scranton	Pedro Tokushiro	Jake O'Donnell
Mingfei Yan	Chandrika White	Ben Peters

The Ohio State University **Autumn 2021**
CIVILEN 5720 Transportation Engineering Data Collection Studies
Department of Civil, Environmental, and Geodetic Engineering

Date Handed Out: Thursday, 21 October 2021
Update 1 (new part to question 2 and questions 3-6): Thursday, 18 November 2021
Date Due: Monday, 13 December 2021 at noon

Term Project (30% of course grade): Estimating Campus Segment Volumes and VMT Using Data from Multiple Sources

Work on your project in the assigned groups. Submit one project report per group. Place all names of the group on the report. Additional submission instructions will be provided. Submitting the report is one of several submissions you are required to complete for this term project.

Additional term project related questions will be provided. The submission instructions will follow the technical communications elements we have been emphasizing and will continue to build upon in class.

The grade you will earn on the term project is based on your performance on all the term project related submissions.

Any team member may be asked to defend aspects of the project individually. That is, although we expect different team members to take the lead on different aspects, we expect all team members to understand all components of the project.

We will also solicit specific information on how group members contributed using a peer- and self-evaluation questionnaire.

For all parts of the report, we are expecting good technical communication. You should consider the "clients" to be the instructors of this course. That is, you should assume our knowledge level and do not need to describe basic principles covered in class. However, you should be specific, but concise, on approaches used and assumptions made, and you should illustrate with example calculations if appropriate. The audience should be able to determine quickly the logic and main points. Long tables and supporting information should be placed in appendices. Summary tables and information that directly support your results and conclusions should be part of the main report. Of course, only use tables when they help summarize multiple numerical values or items.

Information in the form of tube count data, vehicle volume estimates determined form manually collected counts, and vehicle volume estimates determined from video images recorded by cameras mounted on CABS transit buses will be made available at different stages of the term project.

1. Consider only the segments for which data were collected on 25 October 2018. For these segments use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 25 October 2018, 24 October 2019, and 5 November 2020 to estimate the following:

   - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 10/25/2018
   - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 10/24/2019

- Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 11/5/2020
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 10/25/2018
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 10/24/2019
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 11/5/2020

2. Quantify the differences among 2018, 2019, and 2020 volumes for common segment-direction-hours and in 12-hour VMT.

   Compare the differences and discuss whether you believe they might reflect a systematic change in VMT among 2018, 2019, and 2020 or if the differences could be attributable to day-to-day variation in campus travel.

   Compare the estimated changes (single values) you determined from the field video-based volumes between the years 2018 and 2019 and between the years 2019 and 2020 to the corresponding (distributions of) subjective Growth Factors based on the estimates each of you submitted as part of Term Project Assignment 2. Discuss the similarities and differences between the field data-based and subjective estimates using quantitative measures to support your discussion.

3. Consider **all** segments for which either manual or road tube data were collected on 5 November 2020. For these segments, use manual-based volume estimates and road tube data to estimate the following for 11/5/2020:

   - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval
   - 12-hour (7:00 am to 7:00 pm) segment-direction-volumes
   - 12-hour VMT between 7:00 am and 7:00 pm aggregated across the set of segments specified above

4. Consider **all** segments for which either manual or road tube data were collected on 5 November 2020. For these segments, use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 5 November 2020 to estimate the following for 11/5/2020:

   - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval
   - 12-hour VMT between 7:00 am and 7:00 pm aggregated across the set of segments specified above

   Reproduce the calculation of the video-imagery volumes for each direction of the segment that has the same number as your group number from 12 pm to 1 pm. Present the logic and show your calculations.

5. Quantify the differences between the 2020 manual- and tube-based volume estimates (from your answers to question 3 above) and the 2020 video-based volume estimates (from your answers to question 4 above) for common segment-direction-hours and for 12-hour VMT. Compare the quantified differences to other quantified differences of volumes or volume-derived measures you determined throughout the semester.

6. Discuss the potential benefits of using bus-based video imagery to determine segment volumes and VMT over time, keeping in mind the analysis you conducted and presented in part 5.

   We expect your response to question 6 to be between ½ and 1 page, but to be well thought out and well presented.

Term Project Groups

Group 1	Group 2	Group 3
Alexopoulos, Steven	Beachy, Justin	Beharry, Cassidy
Androw, Cameron	Deighan, Ryne	Coppenger, Hayleigh
Coleman, Tyler	Faircloth, Jalen	Harvey, Kenneth
Dembek, Brandon	Poling, Will	Shah, Harsh
Miller, Nick		

Group 4	Group 5	Group 6
Bloch, Isaac	Breier, Mitch	Dakwar, Joshua
Gardner, Jacob	Dong, Zixuan	Dixon, Adam
Gartrell, Oliver	Jaques, Sophie	Folwarczny, Drew
Fornaro, Anthony	Maag, Sydney	Frusciante, Alejandro
Wheeler, Ryan	Wang, Jintong	Greve, Ryan

UPDATE 4

The Ohio State University **Autumn 2022**
CIVILEN 5720 Transportation Engineering Data Collection Studies
Department of Civil, Environmental and Geodetic Engineering

Date Handed Out: Thursday, 20 October 2022
Update 4 (typo correction in questions 3, 4, and 5): Monday, 5 December 2022
Date Due: Monday, 12 December 2022 at noon

Term Project (30% of course grade): Estimating Campus Segment Volumes and VMT Using Data from Multiple Sources

Work on your project in the assigned groups indicated at the end of this statement. Submit one project report per group. Place all names of the group on the report. Additional submission instructions will be provided. Submitting the report is one of several submissions you are required to complete for this term project.

Additional term project related questions will be provided. The submission instructions will follow the technical communications elements we have been emphasizing and will continue to build upon in class.

The grade you will earn on the term project is based on your performance on all the term project related submissions.

Any team member may be asked to defend aspects of the project individually. That is, although we expect different team members to take the lead on different aspects, we also expect each team member to understand all components of the project.

We will also solicit specific information on how group members contributed using a peer- and self-evaluation questionnaire.

For all parts of the report, we are expecting good technical communication. You should consider the “clients” to be the instructors of this course. That is, you should assume our knowledge level and do not need to describe basic principles covered in class. However, you should be specific, but concise, on approaches used and assumptions made, and you should illustrate with example calculations if appropriate. The audience should be able to determine quickly the logic and main points. Long tables and supporting information should be placed in appendices. Summary tables and information that directly support your results and conclusions should be part of the main report. Of course, only use tables when they help summarize multiple numerical values or items.

Information in the form of tube count data, vehicle volume estimates determined form manually collected counts, and vehicle volume estimates determined from video images recorded by cameras mounted on CABS transit buses will be made available at different stages of the term project.

1. Consider **only the segments for which data were collected on 25 October 2018**. For these segments use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 25 October 2018, 24 October 2019, 5 November 2020, and 4 November 2021 to estimate the following:

    - Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 10/25/2018

- Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 10/24/2019
- Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 11/5/2020
- Volumes for each segment-direction-hour in the 7:00 am to 7:00 pm interval for Thursday, 11/4/2021
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 10/25/2018
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 10/24/2019
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 11/5/2020
- 12-hour VMT aggregated across the set of segments specified above from 7:00 am to 7:00 pm for Thursday, 11/4/2021

2. (a) Quantify the differences among 2018, 2019, 2020, 2021 volumes for common segment-direction-hours and in 12-hour VMT using measures you should be familiar with from this course. Compare the differences and discuss whether you believe they might reflect a systematic change in volumes and VMT among 2018, 2019, 2020, and 2021 or if the differences could be attributable to day-to-day variation in campus travel.

   (b) Compare the differences you found in part (a) to differences that would be expected from ODOT Annual Adjustment factors for functional classes U 5-7, urban collector and local roads. Interpret the differences. Do so while keeping in mind that ODOT factors are based on urban collector and local roads across any kind of such roads and across an entire calendar year while differences in part (a) reflect changes only to a university campus and for the specific day of collection namely a weekday in late October or early November.

3. Consider **all** segments for which either manual or road tube data were collected on 5 November 2020. For these segments, use manual-based volume estimates and road tube data to estimate the following for 11/5/2020:

   - 12-hour (7:00 am to 7:00 pm) two-way segment~~-direction~~ volumes
   - 12-hour VMT between 7:00 am and 7:00 pm aggregated across the set of segments specified above

   Notes: The road tube volumes provide control counts, whereas the manual counts provide coverage counts. Determine appropriate factors from the control counts. You need to decide and explain briefly but clearly how you decided to use the different sets of factors from the multiple control count segments to determine a set of factors for a specific coverage count segment. Different factors can be used for different coverage count segments. If a segment contains both a manual count and a road tube count for the same time interval, you may use the road tube count.

4. Consider **all** segments for which either manual or road tube data were collected on 5 November 2020. For these segments, use volumes determined from vehicle count data extracted from video imagery taken from cameras mounted on CABS buses recorded on 5 November 2020 to estimate the following for 11/5/2020:

   - 12-hour (7:00 am to 7:00 pm) two-way segment~~-direction~~ volumes

- 12-hour VMT between 7:00 am and 7:00 pm aggregated across the set of segments specified above

Notes: These values should be different than the 2020 values determined in part 1 because the networks are different in this part and in part 1. As in part 1, estimate the 12-hour volumes from the addition of hourly volumes.

5. Quantify the differences between the 2020 manual- and tube-based volume estimates (from your answers to question 3 above) and the 2020 video-based volume estimates (from your answers to question 4 above) considering the 12-hour two-way segment~~ direction~~ volumes and 12-hour VMT. Compare the quantified differences to other quantified differences of volumes or volume-derived measures you determined throughout the semester.

6. Discuss the potential benefits of using bus-based video imagery on a regular basis to determine hourly segment volumes, longer period (e.g., 12-hour in this project) segment volumes, VMT, and changes over time, considering the analyses you conducted in this project, and lessons learned throughout the course.

   We expect your response to this question to be1/2 to 1 page, but to be well thought out and well presented.

Term Project Groups

Group 1
Abdirahman, Khadijo
DeMarzo, Danielle
O'Neill, Brock
Schneider, Noah
Sosko, Megan

Group 2
Barone, Rick
Hargraves, Michael
Kim, Hyunhwa
Kopechek, Michael
Mbow, Babacar
Voss, Tyler

Group 3
Crain, Mac
Harris, Max
Kerich, Danielle
Mohammed, Massara
Ren, Lanming
Zhang, Linghao

Group 4
Emmett, Chris
Kuhlman, Reese
Kwiatt, Collin
Paselsky, Mike
Schwartz, Cameron

Group 5
Gaskey, Michael
Goldenbaum, Tyler
McDaniel, Ian
Mutlak, Dean
Tondra, Brandon
Williams, Mason