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16. Abstract

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The accurate estimation of travel time data is valuable for a variety of real-time and off-line transportation applications including motor carriers. This report includes methodologies for estimating corridor travel time mean and variance from field data collection at two test sites. The test sites are two limited-access freeway corridors–one instrumented with AVI antennas and one instrumented with dual inductance loop detectors at 0.5-mile spacings. The estimates using the ITS data were compared to simultaneous instrumented test vehicle and commercial vehicle travel time data.

A procedure was outlined for using the loess nonparametric statistical technique to obtain corridor travel time mean and variance estimates from each ITS data source, commercial vehicles, and instrumented test vehicles. The estimates from each data source were then aggregated to five minutes, and the ITS data source estimates were compared to the commercial vehicle and instrumented test vehicle corridor travel time estimates. In addition, a methodology for testing the accuracy of instrumented test vehicle drivers along a corridor was developed.

The research demonstrates that commercial vehicles have statistically different travel time mean and standard deviation than AVI-equipped, vehicles which suggests it may be beneficial to provide traveler information in real-time for commercial vehicles. It was also found that AVI-equipped vehicles were not statistically different than the instrumented test vehicles and that an AVI system with an adequate number of tag reads could replace traditional data collection methods. By comparing inductance loop travel time estimates to the commercial vehicle and test vehicle data sources, the research quantifies how aggregated inductance loop detector travel time estimates do not capture the travel time variance characteristics of individual vehicles.

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EXAMINING INFORMATION NEEDS FOR EFFICIENT MOTOR CARRIER TRANSPORTATION BY INVESTIGATING TRAVEL TIME CHARACTERISTICS AND LOGISTICS

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EXECUTIVE SUMMARY

INTRODUCTION

The accurate measurement and estimation of travel time data are valuable for a variety of real-time and off-line transportation applications. Real-time applications include route guidance while off-line applications include system performance monitoring. Reliable and replicable travel time data collection techniques are necessary for accurate estimation. The recent deployment of intelligent transportation systems (ITS) in large metropolitan areas internationally and in North America facilitates the collection of data from which travel time can be estimated.

Travel time data may be estimated directly in a number of ways including instrumented test vehicles, license plate matching, probe vehicles (e.g., automatic vehicle identification, "toll tags"), or emerging technologies (e.g., inductance loop signature matching) (*1*,*2*). Alternatively, travel time data can be estimated from point speed estimates (e.g., inductance loop detectors, acoustic sensors). Because of the many technologies available and many different transportation applications, there has been no standard detection technology adopted for travel time data collection to date.

Travel time data are useful for a wide range of transportation analyses including quantifying transportation system performance, traveler information, and incident detection. A recent study has indicated that travel-time based measures satisfy the many different audiences (e.g., technical, political, public) in transportation (*3*,*4*). Ongoing research at the Texas Transportation Institute (TTI) utilizes travel-time based measures (e.g., travel rate index) in the ranking of congestion in the largest metropolitan areas throughout the United States (*5*). In addition, some metropolitan areas provide real-time travel time estimates as part of their advanced traveler information systems (ATIS).

Advances in ITS technologies and communication methods have allowed for the extensive instrumentation of roadways and for improved communication to travelers. However, the focus of ITS has generally been on providing data information to commuter traffic and the general motoring public. Motor carriers, and the consideration of freight movement and logistics for commercial vehicles are a critical element for economic prosperity, growth and trade, mobility, and safety throughout the State of Texas. There is a need to examine commercial vehicle information needs and available technologies to provide efficient motor carrier transportation logistics.

STATEMENT OF THE PROBLEM

Given the extensive use of the travel time metric for numerous transportation applications including commercial vehicle use, and the availability of ITS data suitable for travel time estimation, there is a need to investigate travel time estimation using ITS data and compare these estimates to motor carriers. Much of the work performed to date, and especially work performed prior to the implementation of ITS, largely focuses on aggregate mean travel time estimation.

While this method is important, there is a need for research that studies disaggregate temporal variation in travel time characteristics such as mean and variance.

With the implementation of ITS, there is the opportunity to perform disaggregate temporal analyses on travel time distributions due to the relatively large amount of data available, rather than relying on the previously accepted mean estimates over relatively large time intervals. The provision of variance on trip travel time is clearly of value for the variety of transportation analyses described above. ITS data sources provide the opportunity to analyze variance at a finer detail as well. There is also a need for comparison of ITS data sources that estimate travel time to a "ground truth" data source for an accuracy measurement. This comparison is especially important for link travel time information that is estimated from point detectors (e.g., inductance loop detectors). Finally, there is a need in the commercial vehicle operations (CVO) sector for information about how well ITS travel time data collected from automatic vehicle identification (AVI) and inductance loop detectors may estimate travel time mean and variance information for use in just-in-time (JIT) delivery and shipment logistics.

There are many ITS technologies in the field that can provide valuable travel time data. However, there is limited knowledge on how accurate these data are under different conditions (e.g., congestion) and how this detector accuracy affects the accuracy of the travel time estimate. There is a need for studies that investigate measures of central tendency (mean) and spread (variance) to better understand these characteristics of trip travel time data while comparing the travel time estimates to a "ground truth."

RESEARCH OBJECTIVES

This report presents the first study in which travel time mean and variance estimates over time are investigated from AVI and inductance loop data sources in concert with a "ground truth" of passenger cars along a corridor by instrumentation of chase-car test vehicles operating at less than five-minute headways along freeways. The research objectives will provide valuable information in the areas of:

1. Estimation and comparison of corridor travel time mean and variance estimates over time from AVI and test vehicle data;
2. Estimation and comparison of corridor travel time mean and variance estimates over time from dual inductance loop detector and test vehicle data;
3. Estimation and comparison of corridor travel time mean and variance estimates over time from commercial vehicle and ITS data (AVI and inductance loop); and
4. Identification of commercial vehicle information needs from a telephone survey of trucking companies and trucking professionals.

RESEARCH METHODOLOGY

Literature Review and Survey Results

A comprehensive literature review was conducted on many aspects of travel time data collection and analyses. Literature specific to travel time distribution and variability analyses from ITS data sources, corridor travel time variance from link data, and applications in system monitoring and commercial vehicle operations were researched. The purpose of this task was to ensure that no research that may contribute to this study was overlooked or unnecessarily duplicated, or to ensure that current literature is modified to meet the needs of this study. Further, the survey results of the trucking companies and trucking professionals was performed and summarized during this task.

Develop Study Design and Perform Field Data Collection

This task included the development of the field data collection study design and the selection of two corridors for data collection. Researchers collected data on two corridors–one instrumented with AVI readers at 0.5-mile spacings along US 290 in Houston, Texas and one instrumented with inductance loop detectors at 0.5-mile spacings along IH-35 in San Antonio, Texas. Data were collected from Monday through Friday on each corridor during two sequential weeks. The data collection included the instrumentation of test vehicles with a distance measuring instrument (DMI) traversing the corridor at specified headways (less than five minutes) for an estimate of "ground truth." Finally, the AVI data were obtained from the Houston Advanced Traffic Monitoring System (ATMS) and the inductance loop data were obtained from the TransGuide® system in San Antonio for the days when chase-car data were collected.

The test vehicles for this research were not operated in the traditional floating-car technique where the "driver 'floats' with the traffic by attempting to safely pass as many vehicles as pass the test vehicle" or the average-car technique when the "test vehicle travels according to the driver's judgement of the average speed of the traffic stream" (*6*). With the floating-car and average-car techniques, the test vehicle obtains data that can be used to estimate the average travel time along the corridor. However, a chase-car test-vehicle technique allows for the collection of travel time information from which the mean and variance of vehicles can be estimated. In this research effort, the researchers used the chase-car method. When a "ground truth" comparison has been utilized in past studies, it has often been with instrumented vehicles operating in the floating-car or average-car test-vehicle technique and, therefore, information to estimate the travel time mean and variance over time is not directly measured (*7-15*).

Data Reduction and Quality Control

After the collection of the travel time data, the data required consistent cleaning and quality control measures. Data reduction was performed on the DMI test vehicle data to correct for incorrect calibration of DMIs or missing checkpoints in the data files. Data reduction and analyses of the travel time data obtained with the DMI were performed with the Computer Aided

Transportation Software (CATS). Computer code was written to perform quality control of the raw Houston AVI data and match tags. Code was also written to perform quality control and analyses of the inductance loop data available from TransGuide® in San Antonio. Standard quality control methods were used for cleaning the travel time data from each data source.

Investigation of Travel Time Estimation for System Monitoring and Multi-modal Analyses Using Automatic Vehicle Identification Data

A comparison of the travel time data collected from the Houston test corridor was investigated in this task. The investigation of travel time estimation for system monitoring was performed by comparing five-minute aggregate travel time characteristics between the test vehicles and AVI data. Travel time mean estimates were obtained by using the loess nonparametric locally weighted least squares statistical technique to provide a smooth curve between the differences in the estimated means. Analysis of variance on the travel time characteristics of mean, standard deviation, and coefficient of variation (c.v.) were also performed on the test vehicle and AVI data. Paired *t*-tests were conducted to compare the test vehicle and AVI travel time estimates from the same test vehicle.

The investigation of multi-modal analyses using AVI travel time data were performed by comparing travel time characteristic estimates from commercial vehicles and the AVI data. The loess statistical technique was used for the five-minute aggregated data. Finally, analysis of variance on the travel time characteristics of mean, standard deviation, and c.v. were performed on the CVO and AVI data.

Investigation of Travel Time Estimation for System Monitoring and Multi-modal Analyses Using Inductance Loop Detector Data

A comparison of the travel time data collected from the San Antonio test corridor were investigated in this task in a similar manner to the AVI data described above. However, prior to the travel time data comparison, the spot speed data from the inductance loop detectors were converted to travel time estimates along the corridor. The investigation of travel time estimation for system monitoring was then performed by comparing five-minute aggregate travel time characteristics between the test vehicles and inductance loop data. Travel time mean estimates were compared by using the loess nonparametric smoothing technique. As in the previous section, analysis of variance on the travel time characteristics of mean, standard deviation, and c.v. were performed for the test vehicle and inductance loop data.

The investigation of multi-modal analyses using inductance loop detector travel time data were performed by comparing travel time characteristic estimates from commercial vehicles and the inductance loop travel time data. The loess statistical technique was used for the five-minute aggregated data. Once again, analysis of variance on the travel time characteristics of mean, standard deviation, and c.v. were performed for the CVO and inductance loop data.

CONCLUSIONS AND RECOMMENDATIONS

This report describes travel time characteristics from ITS data for real-time and off-line transportation applications. Though the data used in this report are from AVI and inductance loop detectors, the methodologies presented for link and corridor travel time mean and variance estimation are applicable to any detector technology. Future technologies that provide travel time data (e.g., cellular telephones) can also use these methods. These future technologies, and advances on existing methods, will likely provide increased and more reliable data. As sample sizes increase, estimates of travel time mean, and the variance around the travel time estimate, will improve. Objectives one through three of this research are summarized in references *16* through *18* while reference *19* describes more detail on link and corridor travel time variance. Some of the key findings and subsequent conclusions are provided below along with a discussion of further research recommendations.

Chapter II describes the relevant literature in the areas of travel time mean and variance estimation as well as results to a survey of trucking companies and trucking professionals to obtain insight into motor carrier information needs and how ITS can assist in providing these information needs. Unfortunately, the response to the telephone survey was very low and the responses cannot be expected to be representative of all trucking companies. However, the survey results provided some valuable insight including the indication that particular speeds are not as important as whether the traffic is moving or not. The respondent also indicated that the technologies [e.g., global positioning system (GPS), wireless data communications] would need to reduce in cost and increase in durability and coverage area before they would be beneficial. There was also an indication that the cost of stopping at scales is minimal and well within the overall delay of a trip expected from traffic or weather conditions, and that transponders would not be beneficial especially because there is a concern for proprietary information being released.

ITS Data Reduction and Quality Control

Chapter IV includes a detailed description of the application of data reduction, imputation, and quality control techniques to screen for outliers in inductance loop detector data obtained from the TransGuide® ATMS in San Antonio, Texas. Screening rules and imputation methods are essential when reducing inductance loop detector data, and the techniques described in this report that are based upon previous research appear to work well. Standard techniques were also used to screen for outliers in the AVI data; however, imputation of missing data was not performed because standard techniques for AVI data imputation are not documented. As shown in the statistical results that are discussed below, the AVI data provide a more reliable data source for travel time mean and variance estimation.

Investigation of Travel Time Estimates for System Monitoring and Multi-Modal Analyses using AVI Data

Chapter V introduces the loess nonparametric statistical technique for estimating and comparing AVI and instrumented test vehicle, and CVO data source corridor travel time estimates. The loess procedure provided an easily understood method of local least squares for providing predicted mean values of nonparametric functions with large ITS data sets.

The first objective of Chapter V was to compare the AVI and instrumented test vehicle corridor travel time data using five-minute aggregated data. The differences between the mean predicted values were within two percent for the entire corridor from each data source. Analysis of variance (ANOVA) indicated that there was no statistical difference in the travel time mean or standard deviation from each data source at the $\alpha=0.05$ level of significance. In addition, each data source was independently studied. While the ANOVA of the test vehicle and AVI data sources separately indicated that there was a statistical difference in the travel time mean by day of week and time period, the ratio of the standard deviation to the mean (c.v.) did not indicate a statistical difference. This is valuable information for situations when it may be difficult to obtain the variability on the travel time estimate (i.e., when inductance loop detectors are used) as it could be assumed constant if known for a particular day and time period.

The average c.v. difference between AVI and test vehicles was 11.8 percent, while the largest difference occurred during the congested period ($\leq$35 mph) at 37.6 percent. The difference between AVI and instrumented test vehicles travel time mean was generally within two percent. The instrumented test vehicles used in the study also carried AVI tags on board. A paired *t*-test analyses provided statistical evidence that there was measurement error introduced by different drivers. The paired *t*-test analyses can also be used to identify drivers who are not performing the test vehicle data collection correctly. Currently, there is no methodology for performing this evaluation of drivers. In conclusion, these results indicate that with the implementation of an adequate AVI infrastructure and appropriate level of tag reads, an AVI system can replace traditional data collection techniques used for system monitoring. The additional benefit is that data can be collected dynamically, all year long, rather than at selected times.

CVO and AVI data from the Houston test corridor were subsequently compared. A statistical difference was found between the CVO and AVI travel time mean and standard deviation at the $\alpha=0.05$ level of significance. The c.v. between the two data sources was not found to be statistically different. The AVI vehicles were traversing the corridor an average of 6.1 percent faster than the commercial vehicles. The coefficient of variation was 11.4 percent different between AVI and commercial vehicles. These results are intuitive, as commercial vehicles have different operating characteristics than AVI-equipped vehicles even though ATMSs generally provide traveler information to CVO and commuters based on information from AVI-equipped vehicles. For JIT delivery and fleet operations that operate under strict constraints, the differences found between AVI and commercial vehicles could become significant. It may be reasonable to provide travel time maps and information in real-time specifically for commercial vehicles.

The research found that the loess statistical procedure is useful in providing travel time estimates and confidence intervals for a nonparametric function. The procedure is simple to understand and implement, and it provides results that can be produced in a user-friendly manner with minimal programming. The loess statistical procedure could be used to automate the real-time travel time mean and confidence intervals for multi-modal and system monitoring. Loess could also be used to analyze historical archived data for off-line performance monitoring.

Investigation of Travel Time Estimates for System Monitoring and Multi-Modal Analyses Using Inductance Loop Detector Data

Two methods were presented in Chapter II and then in Chapter VI for determining travel time mean estimates from inductance loop detector spot speed estimates. The first estimation technique assumes that the spot speed is valid for half the distance to the next adjacent detector while the second method uses the average speed from the two adjacent detectors and uses that speed to estimate the travel time along the link of interest. It was found that both methods provided results that were within two percent during the time period over which the data were collected. For the remaining analyses throughout the report, the first method was used. A method using loess to obtain mean corridor travel time estimates from link travel time estimates obtained from the inductance loop detector spot speeds was also presented in Chapter VI.

Comparisons of estimated travel time characteristics from inductance loop detectors and instrumented test vehicles were then compared based upon five-minute aggregated data. The loess technique was used in the comparative analyses. The average percent difference between inductance loop and test vehicle mean corridor travel time was three percent, while during uncongested conditions ($\geq$60 mph) the difference was 5.8 percent. The c.v. difference during congested conditions was large at 617 percent while during uncongested conditions it was 46.8 percent. These results provided a statistical difference at the α=0.05 level of significance. This indicates that there is a relatively large difference in the ratio of the standard deviation to the mean in the inductance loop detector travel time estimates. With these results, this report has assisted in quantifying the high variability that is found in inductance loop detector travel time estimates, especially during congested conditions.

Five-minute aggregate estimates of travel time characteristics from the inductance loop detectors were then compared to the commercial vehicles with the San Antonio data. During congested conditions, the high variability in the inductance loop detector data was again discovered. During congested conditions, the c.v. difference between the two data sources was 233.0 percent. This result was statistically different at the α=0.05 level of significance. The largest percent difference in travel time mean between the two data sources for the week of data was 5.1 percent during congested conditions. It is clear from these results, that due to the large variability in the loop detector data, it is difficult to get an accurate estimate of the variability about the corridor mean. When providing data for real-time traveler and CVO information needs, this would result in the need for large confidence intervals around the mean travel time.

Finally, a comparison of five-minute aggregate estimates of travel time characteristics from CVO and the instrumented test vehicles was performed with the San Antonio data. The largest difference between the CVO and test vehicles was found during free-flow periods at 5.6 percent and the difference was only 1.8 percent during the most congested periods. The highest percent difference in the ratio of the standard deviation to the mean (c.v.) also occurred during free-flow conditions at 259.2 percent. These results indicate that the commercial vehicles have different operating conditions than the instrumented test vehicles, especially during free-flow conditions, which further suggests that providing real-time traveler information specific to commercial vehicles may be useful for shipping logistics.

FUTURE RESEARCH NEEDS

Though this project provided several contributions to the transportation literature in the area of link and corridor travel time mean and variance estimation, there are several areas in which future work is needed.

Though the number of responses to the trucking surveys was limited, valuable insight was provided including the indication that the trucking industry is concerned about how proprietary information may be released and used from ITS technologies applied to CVO. There is also a concern for the high costs and relatively low durability of these systems. These issues must be considered in the development of ITS applications that will provide information to truckers in order for these systems to be of use to the trucking industry.

This report used data obtained along two corridors–one in Houston instrumented with AVI detectors at 0.5-mile spacings, and one in San Antonio with detectors at 0.5-mile spacings. The corridor in Houston was two miles in length and the corridor in San Antonio was 2.5 miles in length. There is a need for similar work that studies link and corridor travel time mean and variance estimates over longer corridors with varying congestion levels.

Future similar work should also be performed along a corridor in which detectors capable of measuring spot-mean speed for conversion to travel time estimates (e.g., inductance loop detectors) and detectors capable of directly measuring space-mean travel time (e.g., AVI) are located along the same corridor. This would provide the added benefit of a direct comparison of the two sources of travel time mean and variance. Future work should also include lane-by-lane analyses of the ITS data especially from inductance loop detectors to better quantify the lane-by-lane variability in the travel time estimates.

This study was successful in instrumenting test vehicles with a distance-measuring instrument for the collection of travel time data with chase vehicles. There is a need to compare DMI test vehicles with test vehicles instrumented with the global positioning system. Both methods have their advantages and disadvantages, yet these tradeoffs have not been fully quantified.

There is a need for further characterizing CVO travel time mean and variance under varying traffic conditions both temporally and spatially. CVO transportation needs for JIT deliveries and goods movement logistics are a considerable economic factor both nationally and internationally. Additional investigation of travel time mean and variance estimates for statewide shipping is also needed. Multi-modal information needs can benefit from further work in this area.

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DISCLAIMER

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CHAPTER I

INTRODUCTION

BACKGROUND

The accurate measurement and estimation of travel time data is valuable for a variety of real-time and off-line transportation applications. Real-time applications include route guidance while off-line applications include system performance monitoring. Reliable and replicable travel time data collection techniques are necessary for accurate estimation. The recent deployment of intelligent transportation systems (ITS) in large metropolitan areas internationally and in North America facilitates the collection of data from which travel time can be estimated.

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3. Estimation and comparison of corridor travel time mean and variance estimates over time from commercial vehicle and ITS data (AVI and inductance loop); and
4. Identification of commercial vehicle information needs from a telephone survey of trucking companies and trucking professionals.

ORGANIZATION OF THE REPORT

This report has been organized into seven chapters. Chapter I includes an introduction to the research and discusses the background to the problem, problem statement, project objectives, and the organization of the report. Chapter II provides a literature review of previous work specific to travel time distribution and variability analyses from ITS data sources, applications in system monitoring and commercial vehicle operations, and also a summary of motor carrier survey results. Chapter III presents the data collection performed and the study corridors. The travel time data collection procedure from each data source including instrumented test vehicles, commercial vehicles, AVI, and inductance loop detector data are included. Chapter IV describes the data reduction and quality control that were performed on the travel time data to ensure they were adequate for subsequent analyses. Standard techniques were used for the quality control of each travel time data source.

Chapter V presents analyses of travel time estimation for system monitoring and multi-modal analyses using AVI data along the entire study corridor in Houston. Statistical comparisons are made between the AVI and instrumented test vehicles for system monitoring applications while multi-modal comparisons were also made between the AVI and CVO travel time estimates. Chapter VI describes similar analyses performed on data collected in San Antonio. Comparisons were again made between the ITS data source (inductance loops) and the instrumented test vehicles. Multi-modal analyses were performed by comparing the inductance loop detector travel time mean and variance estimates with the commercial vehicle travel time mean and variance data. Changes in temporal aggregation on these estimates are also presented. Chapter VII provides the research conclusions and recommendations. Future research needs are also included. The references are then provided and are followed by a glossary of frequently used terms. Appendix A contains the motor carrier survey used in the study, and Appendices B and C contain supplemental materials for analyses in Chapters V and VI, respectively.

CHAPTER II

LITERATURE REVIEW AND SURVEY RESULTS

INTRODUCTION

This chapter will describe the literature on link and corridor travel time mean and variance estimation and related CVO literature as well as the motor carrier survey results. First, previous work on obtaining travel time estimates indirectly from spot speeds is presented. Subsequently, the relevant literature related to obtaining travel time estimates directly from probe vehicles is presented. Literature discussing how travel time mean and variability information can be of benefit to commercial vehicle operations and logistics is then presented. Finally, survey results are presented from a survey designed to provide insight into motor carrier information needs.

EARLY FLOATING-CAR AND AVERAGE-CAR TEST VEHICLE RESEARCH FOR TRAVEL TIME ESTIMATION

The first comprehensive research on travel time estimation was performed by Berry et al. in the late 1940s and early 1950s and utilized test vehicle methods to assess travel time data on arterial streets (*7*,*8*). The first study noted that test vehicles could be used to provide travel time data on signalized urban streets (*7*). Three arterial corridors were studied in California and test vehicle drivers used the average-car driving method with observers in the car to observe travel times with stopwatches to compare to a license-plate matching travel time estimation. The test vehicle travel time estimates were -0.2 percent to 9.1 percent different than the license-plate matching with an average percent difference of 2.5 for the time periods of interest. Though the study documented the need for additional test vehicle runs during congested periods, aggregation levels of at least one hour were used to obtain summary statistics of travel time mean, variance, and range. This work also provided the foundation for travel time sample size recommendations.

Additional evaluation of the differences between the average-car and floating-car technique were performed in a follow-up study by providing sample size estimates for performing travel time studies on highways (*8*). These studies evaluated the floating-car and average-car test vehicle driving techniques with license-plate matching techniques and found that both test vehicle techniques were within seven percent of the travel time mean obtained from the license-plate matching. While the focus of the research was largely on aggregated travel time mean estimates rather than estimating the mean and variance of travel time over time, it found that “the preferred instruction for test-car drivers is to specify that each driver should maintain a speed which, in his opinion, is representative of the average speed of all traffic in the stream” (*8*). This work provided the foundation for sample size and data collection procedures for travel time studies. As with the previous study, this work investigated summary statistic measures of mean and variance over large time periods of at least one hour. A recent publication funded through the Federal Highway Administration (FHWA) provides updated sample size information and procedures for test vehicle travel time data collection techniques on both arterial and freeway corridors (*1*).

LINK TRAVEL TIME ESTIMATION FROM INDUCTANCE LOOP DETECTOR POINT SPEED ESTIMATES

As noted earlier, travel time data may be estimated in a number of ways. One indirect method of travel time estimation is from spot speeds such as those received from inductance loop detectors. Many metropolitan areas have freeways instrumented with inductance loop detectors to obtain information about traffic conditions. Numerous studies have been performed that investigate the use of single-loop-detectors for speed estimation and error algorithms for single-loop-detectors (*20-25*). In the most general form, these estimation techniques use volume and occupancy and an estimate of average vehicle length to estimate a point speed. The point speed is then used for estimating the travel time over a specified roadway segment. When dual-loop-detectors are placed a fixed distance apart, approximately twelve feet, a more accurate point speed estimate can be obtained in addition to the volume and occupancy estimate. Link travel time estimates between the loop detectors can be made based upon the known distance between adjacent loop stations. This is performed by assuming the point estimate of speed is representative of the average speed between adjacent loop detectors.

Recent work in the area of using single-loop-detectors for speed estimation by Wang and Nihan identifies a corrected method for the determination of the effective vehicle length (constant "*g*") that relates speed with occupancy and volume parameters provided by the single-loop detectors as shown in Equation 2-1 (*26*). In their study, estimates of speeds using a fixed value of "*g*" provided a coefficient of determination (R^2) value of 0.41 while the corrected "*g*" value provided an R^2 value of 0.59 for the day of data studied. This work provides a method of improved estimation of speed with a dynamic value of "*g*" that can change over every five-minute aggregation interval.

$$S_i = \frac{N_i}{T \times O_i \times g} \tag{2-1}$$

where: S_i = Space-mean-speed for each time interval i;
N_i = Vehicles per time interval i (volume);
O_i = Percentage of time loop is occupied in time interval i (lane occupancy);
T = Hours per time interval i (e.g., T = 1/12 hour or five minutes); and
g = Effective vehicle length.

Recent work by Coifman utilized a similar technique of providing for a dynamic value of "*g*" for speed estimation and his methodology is readily applicable to Model 170 controller units that have a limited processing power and are currently installed in many areas in California (*27*). These studies used dual-loop-detectors to provide a "ground truth" spot speed estimate for comparison to spot speed estimates from single-loop-detectors.

Missing or suspect data are another consideration. The extent of suspect or missing data has been recently evaluated in a report by TTI that has found that about 20 percent of an average month of loop data from the San Antonio TransGuide® inductance loop system is missing. The research also notes that up to two percent can provide a suspect combination of speed, volume, and occupancy (*28*,*29*). An example of suspect data is when no speed or volume data are reported over a given time interval, but an occupancy value is reported. Therefore, there is a need for the direct measurement of travel time for "ground truth" comparison to provide insight on the travel time estimate error.

Noting the potential error created in using single-loop detector flow and occupancy data to estimate point speed and subsequent travel time, another research study developed a model for estimating travel time data directly from volume information provided by single inductance loop detectors (*30*). The model uses a mass function f_s, that is estimated for a given time interval of volume at an upstream detector, to estimate the travel time required to travel to the downstream detector. The mass function f_s is estimated by minimizing M, the squared difference between upstream and downstream arrivals (volume) as shown in Equation 2-2.

$$M = \sum_{t=(T_B+b)/\Delta}^{(T_F+a)/\Delta-1}\left(y_t - \sum_{s=a/\Delta}^{b/\Delta-1} x_{t-s}\left(f_s\right)\right)^2 \tag{2-2}$$

where: t = Time interval where possible travel times $[a,b]$ define the fit window;
T_B = Initial begin time of time interval to which b is added;
T_F = Initial final time of time interval to which a is added;
Δ = Discrete time intervals of aggregation. It is assumed that T_B, T_F, a, and b are multiples of Δ.
y_t = Downstream arrivals at t;
x_{t-s} = Upstream arrivals at $t-s$ time arrival; and
f_s = Mass function of arrivals.

The model was tested on data from Highway I-880 in Hayward, California. The model itself was initially developed and tested on the right-most lane of the freeway. The test vehicles used to compare with the estimation technique were not restricted to travel in just the right-most lane of the freeway. Preliminary results indicated differences of up to 100 seconds between the model travel time estimates and four test vehicles that maintained seven-minute headways through the corridor. The roadway was approximately 5.5 miles in length. The speed differences were 28 mph for the test vehicles and 33 mph for the estimation technique which equates to approximately 18 percent difference. While this work is promising, the authors recommended expanding the model to all lanes, decreasing the test vehicle headway to provide additional test vehicle data, and considering travel time variance in the travel time mean estimate.

Other studies have evaluated the use of loop detectors for travel time estimation through signature-matching techniques rather than extrapolating spot speed estimates to segment travel times (*31-33*). This work has evaluated the use of vehicle signature analysis to compare space-mean travel time measures with time-mean travel time measures. The signature-matching technique attempts to match vehicles at upstream and downstream loop detectors by the unique signature a vehicle creates when passing over an inductance loop. During congested conditions, the comparison of the vehicle signature matching with a video database of travel time data from license-plate matching resulted in 3.2 percent average error and a standard deviation of 3.0 percent over a fifteen minute aggregation level. However, the estimated travel times based on the point speed measurement had an average error of 45.8 percent and a standard deviation of 31.5 percent. The congested data set consisted of approximately 1,000 vehicles observed over a time interval of approximately ten minutes. Though this research was focused on travel time mean estimation with fifteen-minute time intervals, it illustrates the suspect nature of extrapolating loop speed information for travel time estimation, particularly during congested conditions.

Work performed in Orlando, Florida, compared test vehicle estimates from vehicles instrumented with global positioning system (GPS) receivers with estimates from dual inductance loop detectors along I-4 (*9*). Speed data were aggregated to five minutes to estimate speed over a one-mile section for comparison to six test vehicle estimates. The test vehicles generally corresponded to the travel time mean estimates obtained from the loop detectors although the low sample size (six observations) was noted for the daily comparison. Test vehicle and loop detector travel time estimates were highly correlated as indicated by the correlation coefficient value of 0.83. This research showed that dual-loop-detectors could be used to obtain travel time mean estimates similar to the test vehicles, although the test vehicle sample sizes were very low and only two test vehicle runs were performed during the most congested period of four consecutive hours of speeds $\leq$30 mph along the corridor.

Another recent study also used instrumented test vehicles operating in the floating-car technique to compare with the inductance loop travel time estimates in San Antonio (*10*). The study investigated a seven mile corridor of IH-35 both northbound and southbound. Because this corridor also included areas with splits between upper/lower decks of the freeway, travel time runs were performed along all these segments. The vehicles were instrumented with an electronic distance-measuring instrument (DMI), and two methods of extrapolating travel times from the point measures of the dual-loop-detectors were tested in comparison to the test vehicles. The first estimation method assumes the spot speed estimate from a given loop detector is valid half the distance to the adjacent loop detector for the calculation of travel time. The second method computes speed, and subsequent travel time, as an average of the spot speed for two adjacent loops on a given link.

Figure 2-1 illustrates a sample corridor over which both travel time estimation methods will be shown algebraically. Equation 2-3 presents the travel time estimate for the first technique in which the spot speed at each station is assumed to be constant half the distance to each adjacent detector. Equation 2-4 shows the algebraic relationship for the second technique that assumes the speed of travel between adjacent detectors is equal to the average of the spot speeds at each adjacent detector location.

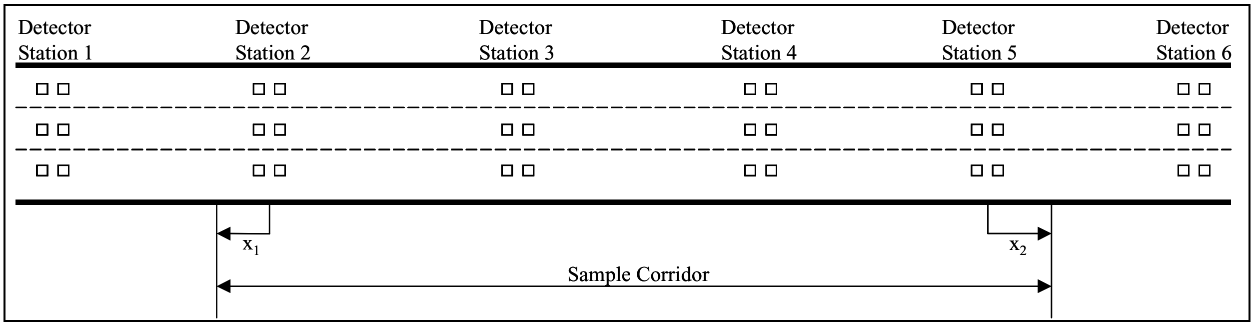

FIGURE 2-1 Sample Corridor Used to Illustrate Two Travel Time Estimation Techniques from Dual Inductance Loop Detector Spot Speed Data

$$TT_1 = A + \sum_{i=2}^{n-2}\left(\frac{l_{i,i+1}}{2S_i} + \frac{l_{i,i+1}}{2S_{i+1}}\right) + B \qquad (2\text{-}3)$$

where:

$$A = \begin{cases} \dfrac{X_1}{S_2} & if\ \ X_1 \le \dfrac{l_{1,2}}{2} \\ \dfrac{l_{1,2}}{2S_2} + \dfrac{\left(X_1 - \dfrac{l_{1,2}}{2}\right)}{S_1} & otherwise \end{cases}$$

$$B = \begin{cases} \dfrac{X_{n-1}}{S_{n-1}} & if\ \ X_2 \le \dfrac{l_{n-1,n}}{2} \\ \dfrac{l_{n-1,n}}{2S_{n-1}} + \dfrac{\left(X_2 - \dfrac{l_{n-1,n}}{2}\right)}{S_n} & otherwise \end{cases}$$

i = Detector station i;
$l_{i,i+1}$ = Distance between detector station i and $i+1$;
S_i = Spot speed at detector location i;
L = Ordered set of detectors in corridor {1,.....n}. To be in the set, the detector must be in the corridor.
n = Number of detector stations in set L;
X_1 = Distance upstream of the first detector in the set as shown in Figure 2-1;
X_2 = Distance downstream of the last detector in the set as shown in Figure 2-1; and
TT_1 = Travel time computed with technique 1.

$$TT_2 = \frac{X_1}{\left(S_1 + S_2\right)/2} + \sum_{i=2}^{n-2} \frac{l_{i,i+1}}{\left(S_i + S_{i+1}\right)/2} + \frac{X_2}{\left(S_n + S_{n+1}\right)/2} \tag{2-4}$$

The results of the study indicated that the half the distance method compared to the floating cars provided R^2 values up to 0.997 with nine observations. In comparison, the second method of travel time estimation resulted in R^2 values up to 0.957 with nine observations. Sample *t*-tests were performed, and it was found that each method did not have significantly different results than the floating test vehicles. The research had low sample sizes, especially during congested periods when only one run was performed in the northbound direction during congestion. Though this research provides insight into travel time mean estimation, like many previous studies, it focused on the mean of travel time estimates without consideration of travel time variance.

A recent study evaluated the accuracy of travel time estimates displayed on dynamic message signs (DMS) that are based upon inductance loop and sonic detector speed data (*11*). The study was performed on a fifteen-mile corridor of eastbound (inbound) I-10 in northwest San Antonio, Texas. Dual inductance loop detectors are located at 0.5-mile spacings along the corridor. DMS travel time estimates are calculated by obtaining the lowest speed of two adjacent loop detector stations and assuming that speed is constant throughout the link. Floating test vehicles instrumented with GPS equipment traversed the corridor at ten-minute headways for comparison to the DMS travel time estimates.

The study resulted in 102 travel time runs during the morning peak and 98 travel time runs during the off-peak periods collected from April 25 to May 31, 2000. The standard deviation of the travel time distribution was from 1.5 to 3.0 minutes. With the assumption of a normal distribution, the author notes that this would indicate that travel time data fluctuate around the mean from 1.5 to 3.0 minutes about 68 percent of the time. The standard deviation of the travel time distributions varied from 0.3 to 0.9 minutes for the off-peak runs in the afternoon. Again, with the assumption of a normal distribution, the author notes that travel times tend to fluctuate 0.3 to 0.9 minutes around the mean for 68 percent of the time.

The study presents a successful procedure for using GPS to evaluate the accuracy of DMS travel time estimates in San Antonio. It also provides insight that the two-minute update window used by the DMS may be exceeded more than 30 percent of the time. To build upon this work, this report studies a shorter segment to provide smaller headways between successive test vehicles, and it compares several estimation techniques for determining the variance about the estimate compared to observed data.

Research performed in The Netherlands compared travel time estimates from a license-plate survey to those obtained with the use of trap inductance loop detectors (*12*). The relationship between the two indicated that space-mean travel time data provided a 10 percent improvement during heavy congestion as compared to time-mean travel time data obtained from the inductance loop detectors. Using the time-mean speed variance to approximate the space-mean variance, the study used the relationship shown in Equation 2-5 to relate travel time measures from space-mean speeds and time-mean speeds (*12*). By substituting $\bar{v}$ for *E(v)* and $\hat{\sigma}(v)$ for $\sigma^2(v)$, and solving Equation 2-5 for an approximation of $\bar{v}_{space}$, Equation 2-6 is obtained. This approximation of space-mean speed was tested on empirical data.

$$E\left(v_{space}\right) \approx E\left(v_{time}\right) - \frac{\sigma_{time}^2}{E\left(v_{space}\right)} \tag{2-5}$$

where:

$E(v_{space})$ = Expected value of space-mean speed;
$E(v_{time})$ = Expected value of time-mean speed; and
σ^2_{time} = Time-mean speed variance.

$$\bar{v}_{space} \approx \frac{\bar{v}_{time}}{2} + \sqrt{\frac{\bar{v}_{time}^2}{4} - \hat{\sigma}^2\left(\bar{v}_{time}\right)} \tag{2-6}$$

where: $\bar{v}_{space}$ = Estimate of space-mean speed;
$\bar{v}_{time}$ = Estimate of time-mean speed; and
$\hat{\sigma}^2\left(\bar{v}_{time}\right)$ = Estimate of time-mean speed variance.

The study found that the best estimator for travel time "turned out to be a dynamic travel time estimation using a correction for space-mean speed, and basing traffic speed on the speed-flow relationship for speeds lower than twenty mph" (*12*). This study used data aggregated to five minutes and defined congestion as the ratio of the observed travel time to the free-flow travel time. The research focused on travel time mean estimation over five-minute periods and demonstrated that real-time mean travel time estimates from loop detectors had errors up to 10 percent for moderate congestion periods (*13*,*14*).

The studies discussed above have focused on travel time mean estimation along freeway corridors. Sisiopiku has recently documented the characteristics of several available models for estimating travel time from loop detector output (flows, occupancies, or both) for arterial streets (*34*). Her study indicated that error rates of the models generally range from 10 to 20 percent. The study concluded by indicating many of the shortcomings of existing models. One of these conclusions is the fact that most of the models are site specific and that transferring the models to other traffic conditions is difficult. Sisiopiku also notes that important factors such as link length, distribution of traffic between movements, traffic composition, platoon dispersion, and driver behavior are not included in the models. The need for further work that estimates travel times along the corridor rather than for specific links is also indicated.

Further work by Sisiopiku has found that during conditions of low demand there is no apparent relationship between travel time and occupancy using simulated fifteen-minute data (*35*). The study is based upon data from the Advanced Driver and Vehicle Advisory Navigation Concept (ADVANCE) project as well as simulation. An empirical study of the data found that for occupancies in the range from seventeen to 60 percent there was a linear relationship with travel time. It was concluded that occupancy percent is a better predictor than volume for link travel time. Finally, the study indicates that link travel time predictions are not possible when occupancies are over about 90 percent because of queues over the loop detectors.

Palacharla and Nelson have performed subsequent work that uses fuzzy logic and neural networks for dynamic arterial travel time estimation (*36*). The application uses fuzzy logic along with neural networks to estimate travel time from both loop detector volume and occupancy data. The fuzzy neural network method is recommended because travel time prediction accuracy is improved. In comparison to probe vehicle data, the fuzzy neural network had a 25 percent mean squared error. It was found that fuzzy expert systems alone were 87 percent less accurate than the fuzzy neural networks. The authors conclude that using fuzzy neural networks is more flexible than linear regression because the fuzzy neural networks allow for a method to consider non-linear relationships, which are present between link travel time and occupancy.

LINK TRAVEL TIME ESTIMATION FROM PROBE VEHICLE DATA SOURCES

Probe vehicles can also be used to obtain travel time information by direct measurement. Probe vehicles are vehicles that are in the traffic stream for purposes other than travel time data collection, but may be used for this purpose. One example is AVI where vehicles instrumented with "toll tags" for electronic toll collection are identified at select checkpoints along an instrumented corridor to provide travel time data. This technology allows the detectors to provide travel time data for a segment of roadway. This space-mean travel time provides a direct measurement of travel time rather than the estimate provided by inductance loop detectors described above. Due to the limited implementation of such systems, previous work is limited. Early preliminary work in the State of Washington was performed to evaluate the use of AVI for travel time system monitoring and found that the technology could improve the system performance evaluation (*37*).

The planning for the implementation of an AVI system in Houston, Texas, began in 1991 (*38*). The system now covers approximately 230 centerline miles of freeways in Houston and provides real-time roadway performance that is sent to an Internet traffic map (http://traffic.tamu.edu/traffic.html). The potential incident detection benefits of the real-time travel time information available through the AVI system in Houston have also been documented (*39*) The AVI data have since been utilized for ramp metering analysis along the Katy Freeway (I-10) (*40*) and for quantifying the travel time benefits of the high-occupancy vehicle (HOV) facilities in Houston (*41*). In addition, research has been performed on the system to determine necessary probe vehicle sample sizes (*42*) and travel time variability factors (*43*).

More recently, research has been performed with the use of AVI data for travel time estimation. Limited studies have been performed that compare an estimate of "ground truth" to probe vehicle travel time estimates. This is valuable information because AVI vehicles are a "non-random" sample which may cause differences from "ground truth." One recent study performed an assessment of travel time estimates from the AVI readers in San Antonio (*15*). The study compared aggregate travel time means from the AVI system to probe vehicle estimates obtained from GPS-instrumented probe vehicles collecting travel time information. Aggregation levels of two, five, and fifteen minutes were used. Probe vehicle drivers "sought to take the path of least resistance along with the other through-traffic by maneuvering to the rightmost lane, which was usually the least congested" (*15*). During uncongested periods, the test driver made an intentional effort to stay in the center lane of the highway. GPS probe vehicle runs were performed in the a.m. (6:30 to 9:00), midday (11:00 to 1:00), and p.m. (3:30 to 6:00) over three days on IH-35 in San Antonio. About three or four travel time runs were performed for each time period along the freeway segments in the study.

The study generally found that the GPS probe vehicle runs were very similar to the AVI travel time data obtained for the same time period. The average root mean square errors were found to be 4.1 percent, 2.9 percent, and 2.6 percent for two-minute, five-minute, and fifteen-minute aggregation, respectively. Data were limited during congested periods. Eighty-eight percent of the AVI reads collected were obtained when speeds were greater than forty-six miles per hour. It was also noted that during congestion many drivers used the right-most lanes while the AVI system is not designed to cover the right-most lanes in the system. Though the study provided valuable insight, as with many of the previous studies discussed, the focus of the study was on the estimation of the aggregate mean travel time rather than travel time variance. The study also did not provide insight into the measurement of the mean and variance of travel time over time since floating-car runs were performed and probe vehicle sample sizes were relatively low.

COMMERCIAL VEHICLE OPERATIONS

This report also investigates the travel time distribution differences between commercial vehicles and travel time estimates from ITS data sources. Commercial vehicles have fundamentally different operating characteristics and information needs than general commuter traffic. Further, the trucking freight market is significant at nearly 81 percent of the $529 billion in freight expenditures in 1998 (*44*). This is a seven percent growth in trucking freight over 1997. Advanced technologies such as GPS are increasingly showing potential for small business and commercial vehicle freight management to provide real-time travel time information (*45*). The multi-billion dollar trucking industry can clearly benefit from improved estimates of mean and reliability of travel time information.

One recent study has determined that commercial vehicle companies are placing a greater emphasis on reliability, transit time, cost, damage control, and efficiency in their operations (*46*). These elements are clearly inter-related, and the reliability of the travel time estimate has become highly critical for logistical operations and just-in-time (JIT) deliveries. The study further notes that commercial vehicle companies are more concerned with the characteristics of trip reliability, transit time, cost, damage control, and efficiency rather than what specific route or mode(s) shipments take. Therefore, companies are receptive to real-time travel time information that will assist them in avoiding highly congested areas.

Golob and Regan performed a study of nearly 1,200 motor carriers and determined that 82 percent of them indicated that traffic congestion is a serious or critically serious problem, and 85 percent of the respondents felt that congestion will only get worse (*47*). In a related study, the same authors found that nearly 27 percent of the commercial vehicle companies were late making deliveries often or very often as a result of congestion (*48*). It is clear that the commercial vehicle market could benefit from timely and accurate mean and reliability of travel time estimates from ITS technologies.

Travel time mean and variability estimates would also be beneficial for many transportation applications including real-time traffic assignment and the inclusion of freight transportation in travel demand models. With real-time traffic assignment, ITS data specific to commercial vehicles can be used to inform drivers in real-time of different routes to pickup cargo. A recent study utilized simulation to demonstrate the potential savings from simple diversion strategies for commercial vehicles. Using idealized scenarios for the simulation, the study finds reductions in travel distance from five to 10 percent (*49*).

Another benefit of improved mean and reliability estimates of commercial vehicle ITS data would be the inclusion of freight transportation in travel demand models. One recent study describes how travel demand forecasting models have historically been developed for passenger trips and not for commercial vehicle (freight) trips (*50*). The authors note that while freight transport provides a significant contribution to the economy, the industry also creates externalities (e.g., congestion, increased air pollution). However, despite these distinctly different characteristics, freight transportation has typically been modeled in a similar fashion to passenger cars. ITS data sources for commercial vehicles that include improved estimates of mean and variance on travel time could improve travel demand estimates for commercial vehicles and provide improved information for decision-makers that utilize such models for numerous transportation applications.

SURVEY RESULTS

One objective of this research effort was to examine motor carrier information needs and various technologies and data sources that may provide the most useful information source to assist motor carriers in providing efficient logistics. To assist in this objective, the research team prepared a telephone survey of questions related to motor carrier information needs and the ability of ITS to provide this information. The survey instrument is shown in Appendix A. Several trucking and shipping companies as well as trucking professionals were contacted to provide responses to the survey. Unfortunately, only two surveys were completed. One survey was completed by telephone conversation and another survey was completed by e-mail and returned to the research team. It is speculated that the trucking companies were leery of filling out the surveys and providing potentially proprietary information even though the responses to the surveys were confidential. The research team did obtain some noteworthy responses to the two completed surveys and these results are below. Due to the very limited sample size, these responses cannot be expected to be typical for all shippers and trucking companies, but they do provide some valuable insight to information needs for trucking companies. Noteworthy responses to the survey include the following:

1. In response to the type of advanced technologies trucking companies will use (question 9), one trucking professional indicated that these systems are not always consistent in one state, and that companies may be reluctant to purchase the equipment as the government or the technology itself may dictate that they should buy a different system in the future after they have installed a system. The trucking company that did respond to this question indicated that transponders are not currently used because their cost is not justified. The company indicated that two-way communications is used and that GPS is being tested on some units. They also noted that they have identified no benefit to AVI or toll cards as linehaul drivers are paid by the mile.

2. Question 12 asked what type of information is desired while on route. One trucking company indicated that very little, if any, information is needed en route, other than occasional incident and rerouting information. This information is provided for longer trips to the drivers by two-way communications. The other respondent to the survey indicated that a way to know what's ahead, along with alternate routes would be useful. They also indicated that this information would be valuable because if there was significant congestion and delays ahead, the driver would stop at a rest stop to rest and then continue the trip later. Traffic congestion, weather, and incidents were cited as causing delays on typical trips.

3. In response to whether drivers would be interested in trip travel time estimates and trip reliability, (question 16) one respondent indicated that this information would be useful, but that they are generally able to provide this information because the trips tend to be very repetitive. Another respondent indicated that particular speeds are not as important [i.e., whether traffic is flowing at 45 mph (72 kph) or 55 mph (89 kph)] as whether the traffic is simply moving or not. Incident information and alternative routes were indicated as more important than particular traffic speeds.

4. Regarding technical, institutional, or economic hurdles to identifying, collecting, and disseminating appropriate information needs for motor carrier logistics (question 19), one respondent indicated that the technical issues included ruggedness, durability, reliability, and scaleability of an information system. Institutional concerns included the fact that they do not care to share proprietary information with either the government or competitors and do not want to be coerced into doing so. They indicated that they are already subject to far more stringent standards for operating, maintenance, and safety due to their larger size than many of their competitors. The concern is that much of the technology will only make monitoring them even easier. Economic hurdles were indicated as the largest concern. The respondent notes that there is far too much hype and far to

little payback for most of the technologies, and that it is developed for an entirely different trucking or transportation operation and the vendors/developers and institutions just assume it will also apply to their business, without having any knowledge of how the trucking business really works. They indicated that reduction by two orders of magnitude in the cost of GPS and wireless data communications accompanied by two orders of magnitude improvement in ruggedness, durability, and coverage area for communications is needed.

5. Regarding the use of transponders (questions 22-27), one respondent indicated that the cost associated with stopping at scales is almost zero. They indicated that it is a marginal indirect impact of unmeasurable amount, due to slight delay in transit. However, they indicate that the delay is well within the normal noise level of transit times due to traffic and weather conditions. They indicated that there is no benefit to having transponders, and they indicated their concern of being forced to invest in unwanted technologies and then to be forced to share proprietary information with parties having little or no means of effectively securing it. Finally, they indicated that their company would not be willing to invest in pre-clearance transponders (question 27). In question 40, they indicated they have a serious privacy concern with data collected by transponders or other ITS technologies.

6. When asked how ITS could assist their company by providing information regarding congested segments of roadway (question 30) one response was that there would be little benefit adequate to offset the costs of such a system. They indicate further that if the highway is congested then the neighboring streets will also be congested, and they mention that their twin 28 foot (8.5 meter) pups are restricted to the national designated highway network anyway.

CONCLUDING REMARKS

This chapter has described several studies that have been performed on travel time mean and variance estimation from ITS data sources. It was found that travel time mean estimation has been the focus of most of the literature and very little work has been performed on estimating the travel time variance. Travel time mean estimation is traditionally obtained by producing summary statistics of mean at a selected temporal aggregation level–usually five or fifteen minutes. Occasionally travel time variance is also computed. Often these analyses do not include comparison to a "ground truth" travel time estimation method for comparative analyses. When "ground truth" methods are used, the sample sizes are often small, especially during the most congested periods. It is during these congested periods that the performance of ITS technologies for travel time estimation is of most interest for real-time and off-line transportation applications. The research presented in this report will investigate ITS data sources in comparison to a "ground truth" estimate in both practical and statistical comparisons for corridor travel time mean and variance.

The literature described in this chapter begins by describing travel time estimation from single-loop inductance loop detectors from which speed must be estimated. Assuming the speed is constant along the link of interest, travel time is then computed over the link. Dual (trap) inductance loop detectors provide for a direct measurement of spot speed, which is an improvement over single loop inductance detectors. A number of approaches were identified for translating the point speed estimates to link travel time estimates. However, all of the equations assume that the point speed is constant over some distance and this may be problematic for some traffic applications. In contrast, probe vehicle data (e.g., AVI tags) provide a direct measurement of the travel time along the link of interest and eliminate the need to extrapolate point speed estimates to link travel time data. However, errors can still be introduced due to limited tag reads obtained by the system (i.e., increased numbers of tag reads decrease the error in the travel time mean and variance estimate).

The errors introduced by travel time mean and variance estimation from inductance loop detectors and AVI detectors will be discussed in this report. The non-linear relationship of link travel times over time will be estimated with a nonparametric statistical technique with data from all data sources (e.g., test vehicle, AVI, inductance loops, CVO) and then compared.

There is also limited work on how to use ITS data for commercial vehicle operations. Specifically, there is a need for work that compares travel time estimates from AVI and inductance loop detector data with commercial vehicle travel time mean and variance estimates. There also remains a need for comparisons of travel time mean and variance estimates with a ground-truth estimate. This report will present analyses that address all these needs. The following chapter will describe the data collection and study corridors. Analyses of mean and variance travel time estimates with AVI, inductance loop detector, and CVO data are shown in detail in Chapters V and VI.

Finally, the results of a survey intended to provide insight into motor carrier information needs and various technologies and data sources that may provide the most useful information source to assist motor carriers in providing efficient logistics were presented and the results were described in this chapter. Because the number of responses to the telephone survey was very small, the responses cannot be expected to be representative of all trucking companies. However, some valuable insight was provided by the survey results including the indication that particular speeds are not as important as whether the traffic is moving or not. It was also indicated that the technologies (e.g., GPS, wireless data communications) would need to reduce in cost and increase in durability and coverage area before they would be beneficial. There were also indications that the cost of stopping at scales is minimal and well within the overall delay of a trip expected from traffic or weather conditions, and that transponders would not be beneficial especially because there is a concern for proprietary information being released.

CHAPTER III

DATA COLLECTION AND STUDY CORRIDORS

INTRODUCTION

This chapter will describe the field data collection that was performed as part of this study. Data were collected along two study corridors. One of these test corridors was US 290 on the northwest side of Houston, Texas, and the other test corridor is located on IH-35 on the southwest side of San Antonio, Texas. Several different data types were collected at each of these test corridors. At both study locations, travel time data were collected with instrumented test vehicles and commercial vehicle travel time data were collected by video. AVI data were collected in Houston, while dual (trap) inductance loop detector data were collected in San Antonio. The AVI readers and inductance loop detectors are at approximately 0.5 mile-spacings at each site. This chapter will describe what type of data were collected and how the data were collected along the corridors, and describe the two test corridors.

EXPERIMENTAL DESIGN

The careful selection of the study corridors was important to ensure that adequate samples of each data source were obtained. A study corridor in Houston was desired where the AVI detectors were spaced at the highest density. Because US 290 in Houston is the only freeway with AVI antennas spaced at a 0.5-mile distance, it was selected. The specific location of the study corridor along US 290 was selected by ensuring an adequate amount of AVI tag reads obtained from each antenna. The site also required a convenient turn-around location for the instrumented test vehicles that were traversing the corridor. Ten observations every half hour were desired with the seven instrumented test vehicles that were available. A two-mile corridor of US 290 was selected along which the instrumented test vehicles could traverse the corridor and return to the beginning of the corridor in time to ensure that three-minute headways could be maintained between test vehicles throughout the data collection period. Another necessity in the study corridor site selection was a location to set up the synchronized video cameras to obtain travel time estimates from commercial vehicles. These criteria were all satisfied on a two-mile segment along inbound US 290 in Houston from West Little York to Tidwell. The specific characteristics of the corridor are described in a later section of this chapter after the data collection methods are described.

A study corridor in San Antonio was required where the inductance loop detectors were located at 0.5-mile spacings. The San Antonio freeway network includes instrumentation of both inductance loop and acoustic detectors. To ensure that measurement error of the two different technologies was not introduced, a corridor was desired that included only dual inductance loop detectors. Many of the potential study corridors in San Antonio included freeway-to-freeway interchanges, and these areas were avoided because of the possibility of subject vehicles exiting the study corridor. A study corridor also required the presence of inductance loop detectors that were historically obtaining adequate data. Similar selection criteria as the Houston study corridor included the need for locations where the instrumented test vehicle drivers could turn around along the corridor and safely return to the beginning of the study corridor while maintaining three-minute headways. As in Houston, another consideration for the San Antonio study corridor were locations such as overpasses or pedestrian bridges that could be used as checkpoints for the instrumented test vehicle drivers. An area for locating the synchronized video cameras for the commercial vehicle travel time data was also desirable. A 2.5-mile corridor on the southwest side of San Antonio along inbound IH-35 was found that satisfied these selection criteria. This corridor is also described in a later section of this chapter after the data collection methods are described.

DATA SOURCES

Instrumented Test Vehicles

Test vehicles were instrumented with an electronic distance measuring instrument. The DMI allows for the collection of speed information at approximately 0.5-second time intervals, and the technology has been used extensively in collecting travel time for planning studies, congestion indices, and estimating acceleration characteristics in air quality and fuel consumption models (*51-54*). Figure 3-1 provides a schematic of the DMI instrumentation in a vehicle. Electronic pulses are read from the vehicle transmission into the DMI, and the subsequent output data from the DMI are collected on an onboard laptop computer. The data files are saved in ASCII text format. Figure 3-2 shows the data acquisition equipment including the DMI in one of the test vehicle vans. The commercially available Computer Aided Transportation Software (CATS) was used for the DMI data collection and reduction.

Figure 3-3 provides an abbreviated sample of data from a typical DMI test vehicle run. Each line represents a single observation, and these observations are numbered sequentially in the first column. Note that observations 14 to 369 and 385 to 797 have been removed for illustration purposes. The CATS software prompts the user for typical header information prior to each travel time run. This information includes the roadway name, roadway type, roadway direction, date, scheduled time, weather condition, light condition, pavement condition, driver name, mile start, and computer start time (initiated when program begins). This information appears at the top of the example run in Figure 3-3. The mile start is generally used to identify where along the corridor a particular run may have begun, but for this study the vehicle number and/or description was entered. The “!!!MARK!!!” indications that appear along the right side of the data file are printed to the DMI run when the driver presses the space bar on the laptop computer during the run at each checkpoint.

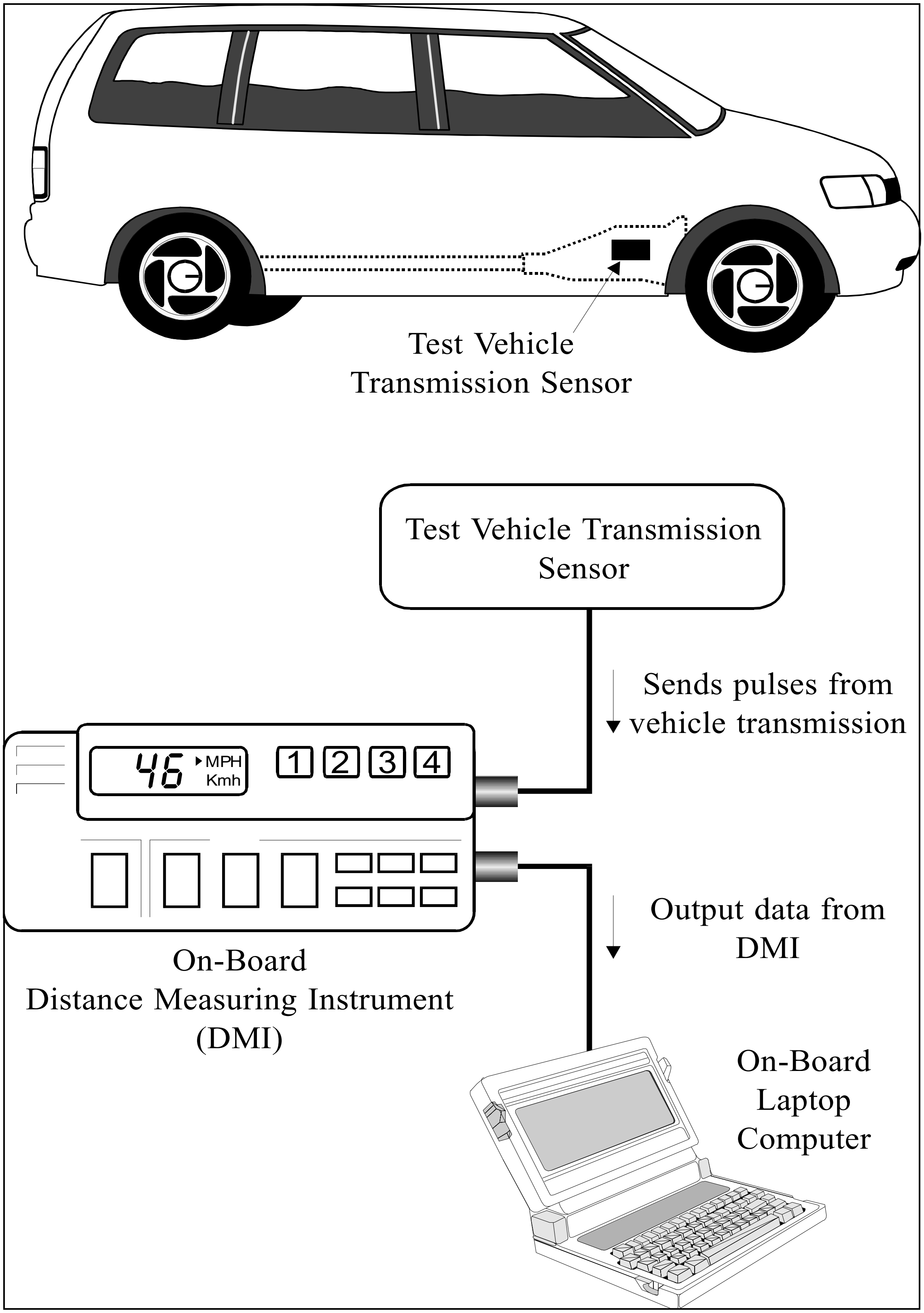

FIGURE 3-1 Schematic of DMI Instrumentation Setup (Adapted from Reference *1*)

FIGURE 3-2 DMI Instrumentation in Test Vehicle Van

These checkpoint marks are later used for quality control of the raw data files, as needed, for runs that may be too short or too long as the result of an incorrect calibration on the vehicle's DMI. This is discussed further in the following chapter on quality control and data reduction. The first "!!!MARK!!!" is printed at the start-up of the DMI data file prior to the scrolling values. From left to right, the data fields include the observation number (which is numbered consecutively for every 0.5-second observation), cumulative miles, incremental miles from the previous data line, speed, and time.

At the end of each travel time run, five questions were asked of the test vehicle driver as shown at the bottom of Figure 3-3. The CATS software allows for changing the questions as necessary for the study needs. The function keys can be changed for use as "hot keys" to indicate stalls, queues, or other items of interest that the driver can note during the run by hitting the key of interest at the appropriate location along the corridor. For example, Figure 3-3 shows a "STALL ON RIGHT SHOULDER" during observation 371 at time 8:25:15.63.

```
ROADWAY NAME       : ,US 290
ROADWAY TYPE       : ,FREEWAY
ROADWAY DIRECTION  : ,EAST BOUND
DATE TODAY         : ,10/26/1999
SCHEDULED TIME     : ,08:21
WEATHER CONDITION  : ,CLEAR
LIGHT CONDITION    : ,NORMAL DAYLIGHT
PAVEMENT CONDITION : ,DRY
DRIVER             : ,Bill Eisele
MILE START         : ,12
START TIME         : ,08:22:11.74

,!!! MARK !!!

   1.,   0.000, 0.000,   3  ,08:22:11.74
   2.,   0.001, 0.000,   3  ,08:22:12.34
   3.,   0.001, 0.000,   3  ,08:22:12.83
   4.,   0.001, 0.001,   3  ,08:22:13.33
   5.,   0.002, 0.001,   5  ,08:22:13.82
   6.,   0.003, 0.001,   5  ,08:22:14.32 , !!! MARK!!!
   7.,   0.004, 0.002,   8  ,08:22:14.81 , !!! MARK!!!
   8.,   0.006, 0.002,   8  ,08:22:15.31 , !!! MARK!!!
   9.,   0.007, 0.002,  10  ,08:22:15.80
  10.,   0.009, 0.002,  10  ,08:22:16.29
  11.,   0.011, 0.002,  13  ,08:22:16.79
  12.,   0.013, 0.003,  13  ,08:22:17.28
  13.,   0.015, 0.003,  15  ,08:22:17.78
 370.,   1.463, 0.005,  36  ,08:25:15.13
 371.,   1.468, 0.005,  36  ,08:25:15.63 ,STALL ON RIGHT SHOULDER
 372.,   1.473, 0.006,  36  ,08:25:16.12
 373.,   1.478, 0.006,  38  ,08:25:16.62
 374.,   1.483, 0.006,  38  ,08:25:17.11
 375.,   1.489, 0.006,  37  ,08:25:17.60
 376.,   1.494, 0.005,  37  ,08:25:18.10
 377.,   1.498, 0.005,  36  ,08:25:18.59
 378.,   1.503, 0.005,  36  ,08:25:19.09
 379.,   1.507, 0.005,  34  ,08:25:19.58 ,!!! MARK!!!
 380.,   1.512, 0.005,  34  ,08:25:20.08
 381.,   1.516, 0.005,  33  ,08:25:20.57
 382.,   1.521, 0.005,  33  ,08:25:21.06
 383.,   1.525, 0.005,  32  ,08:25:21.56
 384.,   1.529, 0.005,  32  ,08:25:22.05
 798.,   3.020, 0.004,  24  ,08:28:47.75 ,!!! MARK!!!
 799.,   3.023, 0.003,  24  ,08:28:48.24 ,!!! MARK!!!
 800.,   3.026, 0.003,  22  ,08:28:48.74 ,!!! MARK!!!

Q. ,Were any incidents, stalls etc. observed ?
A. ,"Yes, before Gessner."

Q. ,How was the weather during the run ?
A. ,"Clear and sunny."

Q. ,Did you observe any major queue build up during the run ?
A. ,"No."

Q. ,Did you need to take any detours ?
A. ,"No."

Q. ,Any other comments ?
A. ,"No."
```

FIGURE 3-3 Abbreviated Sample of a DMI ASCII File

Automatic Vehicle Identification Data

The Houston study corridor along US 290 included AVI readers at approximately 0.5 mile spacings. The AVI data were obtained along the study corridor for the readers located in the test section. In addition, the instrumented test vehicles had AVI tags in their vehicles. Figure 3-4 shows a sample of the raw AVI data format that was used in the analyses after being anonymized and cleaned for outliers as discussed in the next chapter. The first column is the anonymous tag number for the vehicle. The second column of data is the equipment inventory number of the reader. The third column is the AVI antenna number. The antenna number is followed by the time stamp and the date the observation was obtained.

```
162655 2045   26  7:01:59  10/26/99
346381 4022   64  7:02:01  10/26/99
249268 6012  134  7:01:17  10/26/99
094465 5085  172  7:03:06  10/26/99
453389 2064   41  7:02:53  10/26/99
078191 2045   26  7:02:01  10/26/99
416348 4018   53  7:02:03  10/26/99
196837 6012  134  7:01:18  10/26/99
211179 5085  172  7:03:10  10/26/99
097470 6014  134  7:01:19  10/26/99
401924 2064   41  7:02:54  10/26/99
153076 5085  172  7:03:12  10/26/99
244587 4022   64  7:02:08  10/26/99
146099 2045   26  7:02:06  10/26/99
131947 6009  137  7:01:21  10/26/99
076665 6083  143  7:00:11  10/26/99
194911 5087  172  7:03:18  10/26/99
275414 2064   41  7:02:56  10/26/99
065426 4019   53  7:02:10  10/26/99
```

FIGURE 3-4 Raw AVI Data Format

Inductance Loop Data

The San Antonio corridor along IH-35 included dual (trap) inductance loop stations at approximately 0.5-mile spacings. The loop data collected in San Antonio are in the format shown in Figure 3-5. Data are collected at thirty-second intervals and sent to the TransGuide® ATMS. The data have the date and time in the first and second columns, respectively. The third line shows whether the data are from an exit or entrance ramp (EX or EN) or from the mainlane by indicating the specific lane, numbered from inside to outside lane, as L1, L2, or L3. The interstate name and mile marker are also provided in column three. The speed, volume, and occupancy values are indicated in columns four, five, and six, respectively, for the thirty-second period. The loop detectors are six feet by six feet and are centered in each lane. The second loop in each lane is twelve feet away from the first, and speed calculations are made when vehicles pass the second loop (*10*). Volume and occupancy data are reported from the first loop detector the vehicle passes.

```
11/02/99 07:15:04  EX1-0410E-025.581    Speed=57  Vol=004  Occ=002
11/02/99 07:15:04  EX1-0410W-025.347    Speed=56  Vol=003  Occ=002
11/02/99 07:15:04  L1-0410E-025.407     Speed=68  Vol=011  Occ=009
11/02/99 07:15:04  L1-0410W-025.348     Speed=37  Vol=015  Occ=019
11/02/99 07:15:04  L2-0410E-025.407     Speed=57  Vol=010  Occ=008
11/02/99 07:15:04  L2-0410W-025.348     Speed=44  Vol=012  Occ=016
11/02/99 07:15:04  L3-0410E-025.407     Speed=57  Vol=008  Occ=008
11/02/99 07:15:04  L3-0410W-025.348     Speed=37  Vol=012  Occ=026
11/02/99 07:15:04  L1-0410N-012.327     Speed=50  Vol=018  Occ=016
11/02/99 07:15:04  L2-0410N-012.327     Speed=47  Vol=016  Occ=018
11/02/99 07:15:04  L3-0410N-012.327     Speed=53  Vol=011  Occ=017
11/02/99 07:15:05  L1-0410S-013.117     Speed=70  Vol=015  Occ=012
11/02/99 07:15:05  L2-0410N-013.117     Speed=28  Vol=013  Occ=009
11/02/99 07:15:05  L3-0410N-013.117     Speed=27  Vol=017  Occ=029
```

FIGURE 3-5 Raw Inductance Loop Data Format

Commercial Vehicle Travel Time Data Collection

One of the fundamental questions that this research effort will address is the difference between travel time distributions (mean and variance) of commercial vehicles and instrumented test vehicles. Therefore, travel time information based upon commercial vehicles was collected at the same time as the test vehicle and AVI or loop data. This was performed by placing a video camera at the beginning, middle, and end of each test corridor. The video had a time stamp on it that was synchronized for each of the cameras. The data reduction would later be performed by manually matching a given commercial vehicle at each station and recording the time stamp on the cameras.

To assist in the commercial vehicle tracking, the data collection form shown in Figure 3-6 was developed. This form includes the date, recorder's name, and station information. The form also included information that could be used to assist the video data reduction. These logs were collected at two of the three video stations. At the third station, a video trailer was used that did not need to be monitored. The commercial vehicle logs were also useful as the data collection personnel could record and provide anecdotal experiences of watching the commercial vehicle traffic trends during the data collection.

FIELD DATA COLLECTION

The sections above have described the different formats and types of data used in the study. This section will further describe the actual field data collection including how data were collected with the instrumented test vehicles.

COMMERCIAL VEHICLE DATA COLLECTION FORM

Date:______________ Page number (start over each day): _________________

Recorder's name: _______________

City (circle one): Houston San Antonio

Data Collection Station (1st is the first station encountered by travel direction) (circle one): 1st 2nd 3rd

What is the nearest cross-street to you and where is it relative to you?____

NOTE: Pickups and SUVs are not trucks! Record buses (not in HOV lane) and pick-ups with trailers. Identify distinguishable features to the extent possible!!

Time	Cab and/or Trailer Color	Company of Truck (Ryder, Kroger, UPS, Roadway)	No. of Axles	Type of Truck (flat-bed, gravel, garbage, dump, enclosed)	Lane No. (e.g., 1 is inside shoulder–farthest from you, etc.)	Distinguishable Features (e.g., make of truck, roof spoilers, front of truck–flat or "nose," cargo type, dents, etc.)

FIGURE 3-6 Field Data Collection Form for Commercial Vehicles

Data Collection Dates and Weather Conditions

Data were collected along US 290 in Houston, Texas, from October 25, 1999 (Monday) through October 29, 1999 (Friday). Congested conditions were of primary interest, and, therefore, the morning peak period was targeted. Data collection for the instrumented vehicles was performed from approximately 6:00 a.m. to 11:00 a.m. to ensure collection of data during the congested times of interest. Data were collected along IH-35 in San Antonio, Texas, from November 1, 1999 (Monday) to November 5, 1999 (Friday) from approximately 6:00 a.m. to 10:00 a.m.

Weather conditions were sunny and dry over the ten days of data collection. AVI data for Houston and inductance loop data for San Antonio were obtained after the data collection from archived data sources.

Test Vehicle Data Collection Driver Instructions

One element that separates this study from previous studies is the collection of travel time distribution data from which mean and variance travel time estimates will be made. To obtain the data for estimation of passenger cars in the traffic stream, the chase-car driving technique was used. By "chasing" random vehicles in the traffic stream, the driver collects data from which the mean and variance of vehicles can be estimated rather than just the mean. The travel time mean only is usually provided in test vehicle studies that utilize an average-car or floating-car technique (*6*). To provide data for travel time estimation, the test vehicle drivers were given explicit directions for selecting and chasing random vehicles in the traffic stream. One individual served as a "scheduler" to keep the vehicles on a consistent three-minute headway schedule at the staging area. This person provided the drivers with the lane number in which they would find a vehicle to chase. Figure 3-7 shows the staging area used for the IH-35 corridor in San Antonio at the south end of the study corridor on an adjacent side street.

The test vehicle instructions were as follows:

1. Obtain the lane number from the scheduler in which you will find your vehicle to chase. Note that lane one is the inside lane or "fast lane" (next to the HOV lane in Houston), lane two is the middle lane, and lane three is the lane closest to the on-ramp.
2. Start your DMI run. You should have the header information entered and be ready to go. Ensure that you are receiving data (i.e., data are scrolling up the screen).
3. Proceed to the freeway at your scheduled time and get in the lane instructed by the scheduler.
4. While maneuvering to your designated lane, be sure to hit the first checkpoint (Beltway 8 in Houston and the first pedestrian bridge in San Antonio). It is alright if you mark this point even if you are not in your designated lane yet. It is very important that this first checkpoint be marked.

FIGURE 3-7 IH-35 Staging Area in San Antonio, Texas

5. Safely maneuver to your designated lane and count two vehicles up in front of you. That is the vehicle that you will follow. Safely follow this vehicle throughout the travel time run and then exit at Tidwell in Houston and Nogalitos in San Antonio.
6. Turn around at Tidwell in Houston and Nogalitos in San Antonio to return to the start point for the next travel time run and to receive directions from the scheduler.
7. Do not exit the travel time run prior to the designated exit. If the vehicle you are following exits, continue your travel time run by following a vehicle in lane three (which you will be in because you are following the vehicle) until you reach the end of your travel time run.
8. If there is not a vehicle in your designated lane when you are ready to enter the freeway (i.e., free-flow or a large gap), follow a vehicle in the adjacent lane. This will ensure that we do not hold up the on-ramp waiting for a vehicle to be present. This will only be a significant concern when traffic conditions are light.
9. If the vehicle you are following is darting from lane to lane, remember that you do not need to stay "glued" to the back of the vehicle. Keep them within a reasonable distance of you and attempt to continue following them. Do not make unsafe maneuvers just to stay directly behind your designated vehicle.

When the traffic conditions were beginning to approach free-flow conditions, the test vehicle drivers were instructed to go back to a floating-car technique for safety reasons to ensure the posted speed limit was not exceeded. With the floating-car technique, drivers were instructed to pass as many vehicles as pass them and to stay in the middle lane. This transition generally occurred around 9:30 a.m. in Houston and 8:45 a.m. in San Antonio. The primary data of interest for this study were during congested conditions, and floating-car instructions were only used when the congested periods were over.

The data collection included the use of seven DMI-instrumented vehicles. In general, the Houston study corridor experienced more severe congestion over a longer period of time. At the Houston study site, the seven vehicles were routinely necessary to maintain three-minute headways. At the San Antonio study corridor, only six instrumented vehicles were necessary to maintain the three-minute headways. There was still a need for seven vehicles at most times during the data collection as vehicle maintenance was occasionally necessary. DMI calibration was also performed at the TTI office in Houston where a 1,000 foot course is measured off in a nearby parking lot to calibrate the instruments. A course was also made in San Antonio near the test corridor for the calibration of the DMIs as necessary. Calibration was performed at the beginning of the week of data collection at each site and then again mid-week.

Commercial Vehicle Video Data Collection

As previously indicated, three video cameras were set out along each corridor to record video of the traffic stream. This video was used to obtain truck travel time information from the time stamps on the cameras that were synchronized with the instrumented test vehicles. One video camera was set up at the beginning, middle, and end of each corridor. Figure 3-8 shows a video data collection setup at the middle of the San Antonio corridor. At the first two stations along each corridor, an individual would monitor the camera and record relevant information shown in the form in Figure 3-6. However, at the last station on each corridor, the video trailer was used. The following chapter will discuss the data reduction and quality control procedures used for the data collected in the study.

FIGURE 3-8 Video Data Collection on Site at the Middle Station of IH-35 Test Corridor

HOUSTON STUDY CORRIDOR

The first study corridor is located northwest of downtown Houston along US 290. The area of Houston where the study corridor is located is indicated in the box shown in Figure 3-9. Figure 3-10 shows more detail of the corridor. The corridor is a six-lane freeway cross section with a reversible HOV lane down the center of the freeway. Entrance and exit ramps are also shown in Figure 3-10 for the eastbound direction–the primary direction of interest for analysis. The corridor is approximately level except for three to four percent grades at overpasses for Gessner and Fairbanks. There are five AVI reader stations along the corridor as shown in Figure 3-10. The "X"s in Figure 3-10 show the locations used as checkpoints for the test vehicles along the corridor. These checkpoints were later used for quality control purposes for the instrumented test vehicle runs when calibration errors were experienced.

These techniques are discussed in Chapter IV, which describes the data reduction in further detail. The test vehicles and AVI data collection are described in more detail in a latter section of this chapter. The distances along the corridor in Houston were obtained by using standard DMI data collection practice and slowly traveling in the rightmost lane and marking the DMI at each checkpoint of interest starting at the center of the Beltway 8 overpass. Table 3-1 shows these distances in miles starting with the center of the Beltway 8 overpass.

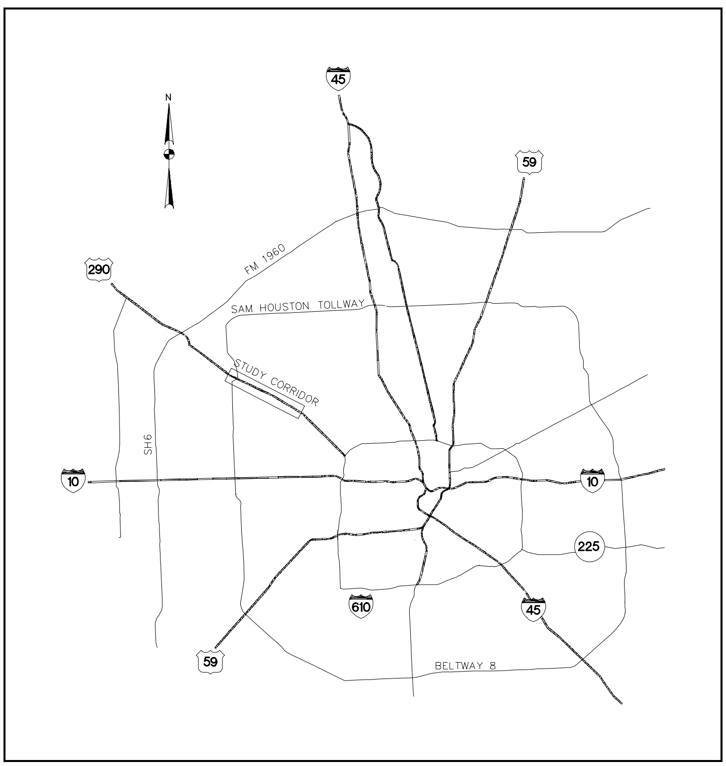

FIGURE 3-9 Regional US 290 Test Corridor Map Showing Location in Houston, Texas

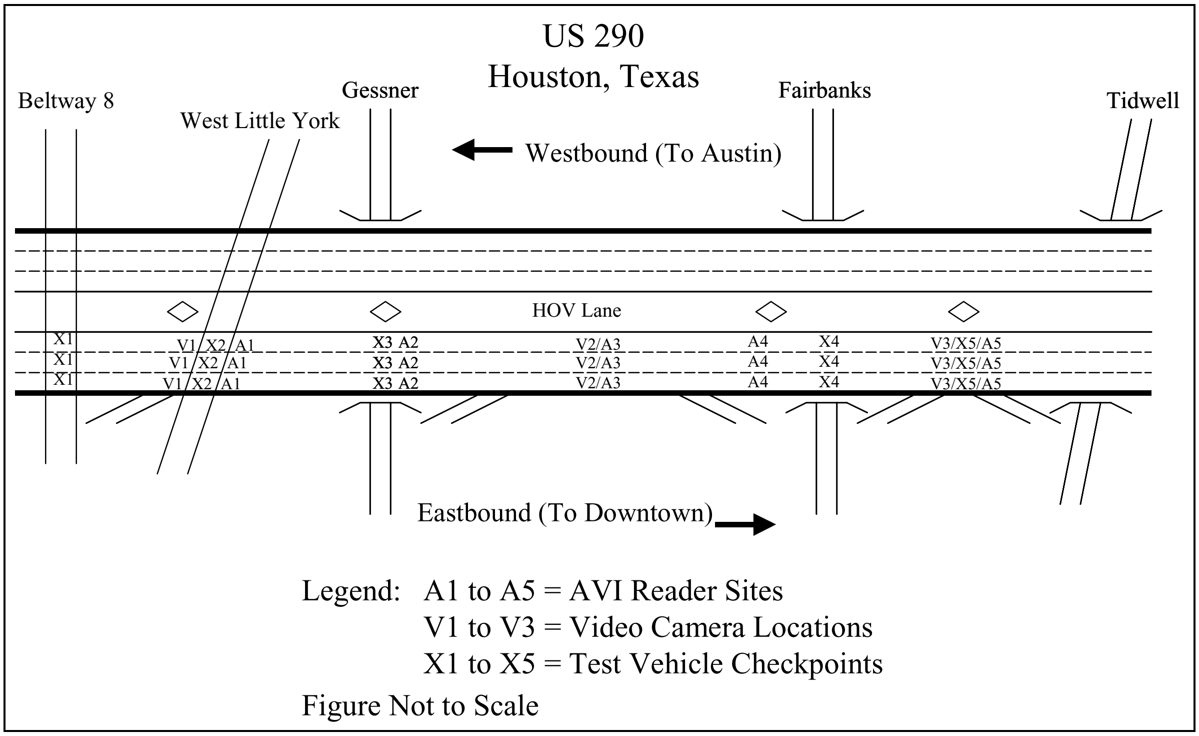

FIGURE 3-10 US 290 Test Corridor in Houston, Texas

TABLE 3-1 Observed Distances Along US 290 Corridor Used for Analysis Measured from DMI

Geographic Feature of Interest	Reference in Figure 3-10	Distance from Beginning of Corridor in Eastbound Direction (miles)
Beltway 8	X1	0.000
Video camera screenline	V1	0.467
West Little York	X2	0.507
AVI antenna #1	A1	0.513
Gessner Road	X3	1.006
AVI antenna #2	A2	1.051
Video camera screenline	V2	1.540
AVI antenna #3	A3	1.548
AVI antenna #4	A4	1.995
Fairbanks	X4	2.125
Video camera screenline	V3	2.508
AVI antenna #5	A5 / X5	2.525

Figure 3-11 through Figure 3-18 are photographs of key points of the US 290 corridor in Houston, Texas. Figure 3-11 shows a photograph of the eastbound traffic on the test corridor taken from the West Little York overpass. The nearest car in the photograph is located where the first vehicle screenline was located. Figure 3-12 illustrates the second set of AVI antennas located on a cantilever post just east of Gessner as a truck passes below. The first set of AVI antennas are located on the downstream side of West Little York (under the overpass). Figure 3-13 displays the location of the third AVI station located under the overhead sign bridge taken facing the west. The relatively level nature of the corridor can be seen from this photograph taken midway through the corridor. Figure 3-14 illustrates the overhead sign bridge taken facing the east showing the third station of AVI readers hanging below the sign. Figure 3-15 displays the fourth station of AVI readers hanging from the side of a roadside exit ahead sign. This is just before the checkpoint at Fairbanks. Figure 3-16 illustrates the fifth, and final, AVI reader station along eastbound US 290. Figure 3-16 also displays the video trailer location for the final commercial vehicle screenline. Figure 3-17 displays a close-up of this AVI reader station and the antenna configuration. Finally, Figure 3-18 shows the fifth AVI reader station taken toward the west showing oncoming traffic. Figure 3-18 also illustrates the back of the third video camera (trailer) and the level nature of the corridor east of Fairbanks.

FIGURE 3-11 Eastbound US 290 from West Little York Overpass

FIGURE 3-12 US 290 at the Second AVI Antenna Taken Looking Up from Gessner

FIGURE 3-13 US 290 at the Third AVI Reader Taken to the West

FIGURE 3-14 US 290 at the Third AVI Reader Taken to the East

FIGURE 3-15 US 290 at the Fourth AVI Reader

FIGURE 3-16 US 290 at the Fifth AVI Reader

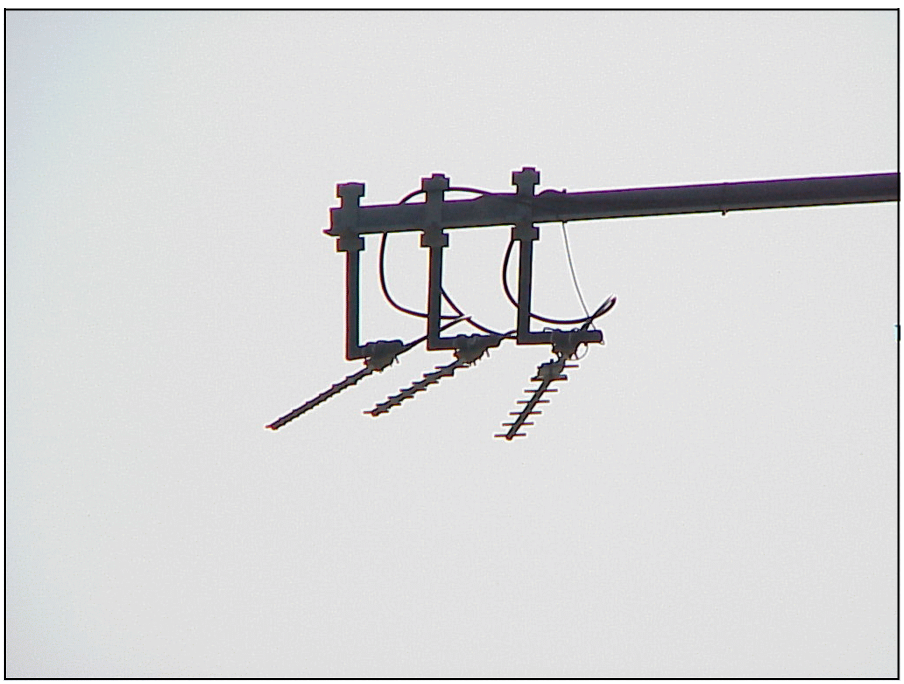

FIGURE 3-17 Close-up of AVI Antenna Configuration

FIGURE 3-18 US 290 Taken Looking West Showing the Fifth AVI Station

SAN ANTONIO STUDY CORRIDOR

The San Antonio study corridor location is shown in the box in the lower lefthand corner in Figure 3-19. The corridor is on the southwest side of downtown San Antonio. A detailed schematic of the study corridor is shown in Figure 3-20. Similar to the US 290 corridor in Houston, the IH-35 corridor is a three-lane freeway in both directions. Entrance and exit ramps are shown in Figure 3-20 for the northbound direction, which is the primary direction of interest for analysis. The corridor is relatively level with three to four percent grades on three overpasses at Southcross, Division, and Malone/Theo. There are four sets of dual (trap) inductance loop detector stations along the corridor as shown in Figure 3-20. Video cameras were placed along the corridor at the beginning, middle, and end for recording commercial vehicle travel time information. The "X"s in the figure show the checkpoints that were used for the test vehicle drivers. Table 3-2 shows the distances along IH-35 used for analysis as measured from the DMI.

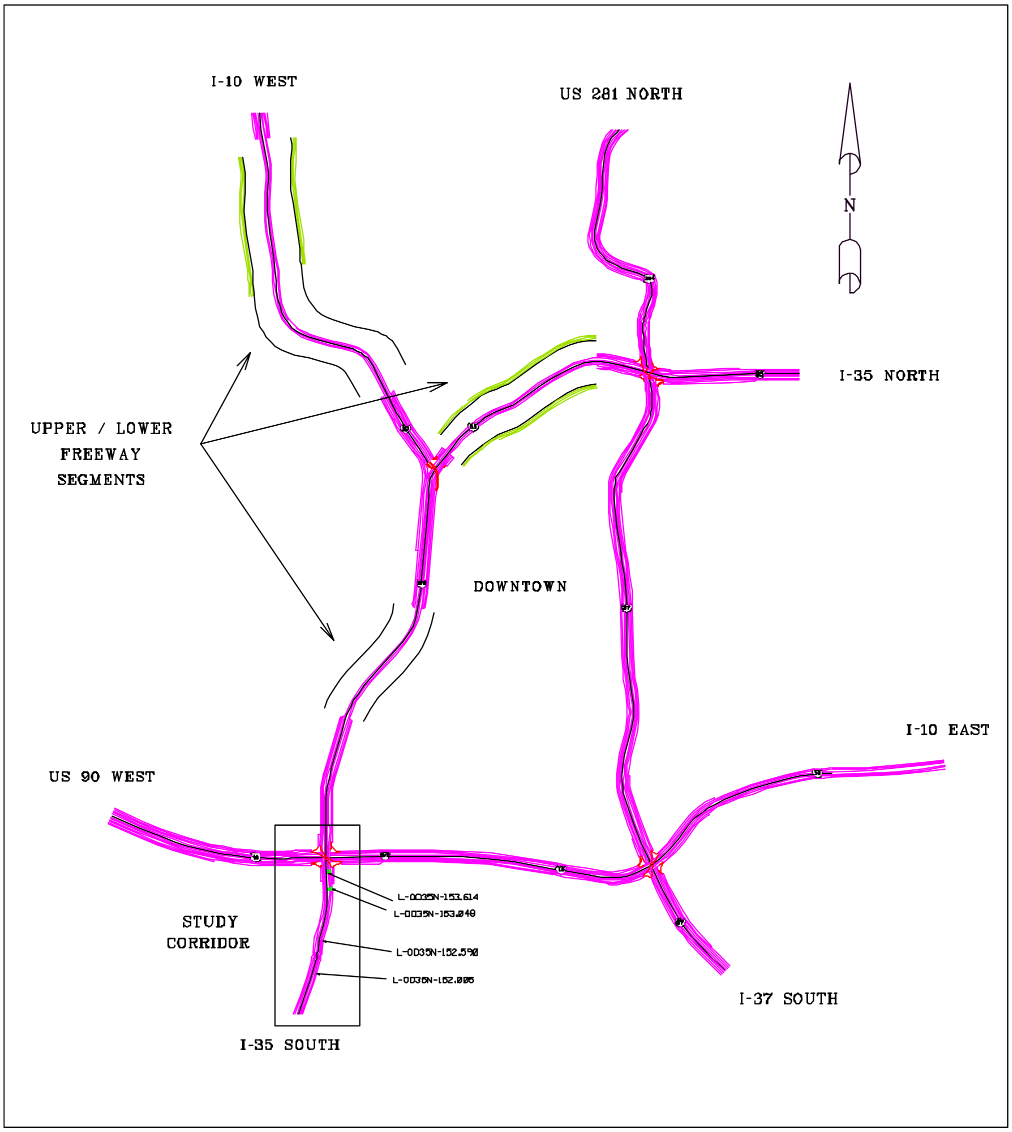

FIGURE 3-19 Regional IH-35 Test Corridor Map Showing Location in San Antonio, Texas

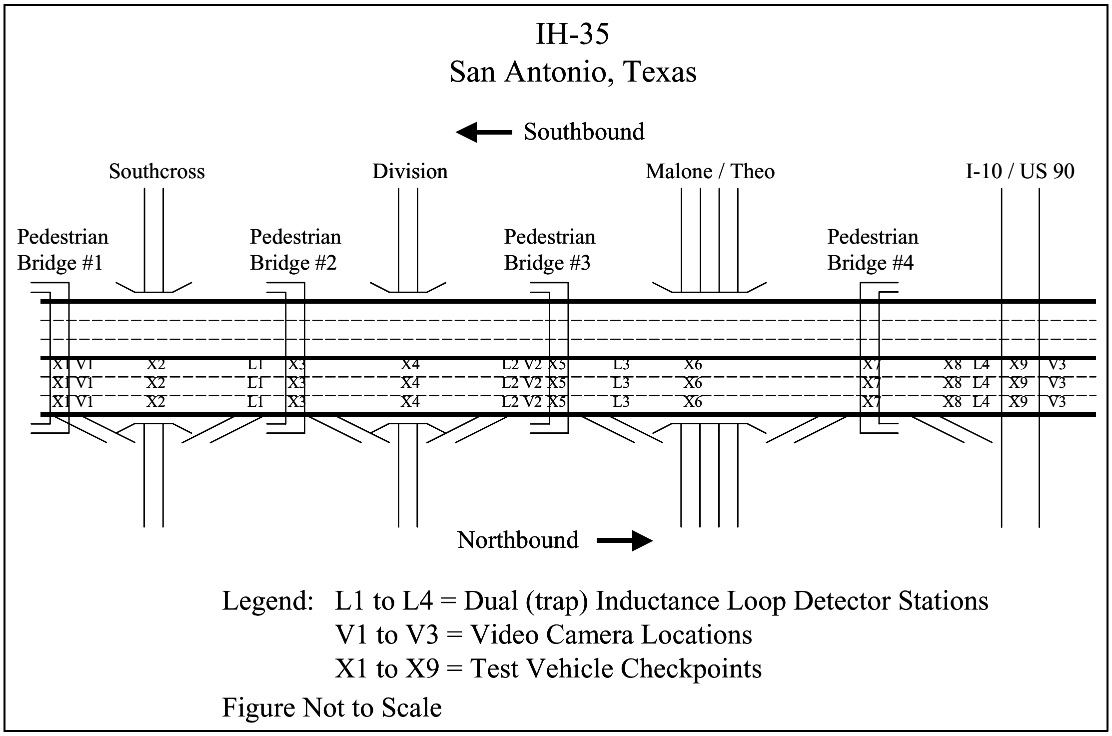

FIGURE 3-20 IH-35 Test Corridor in San Antonio, Texas

TABLE 3-2 Observed Distances Along IH-35 Corridor Used for Analysis Measured from DMI

Geographic Feature of Interest	Reference in Figure 3-20	Distance from Beginning of Corridor in Northbound Direction (miles)
Pedestrian bridge #1	X1	0.000
Video camera screenline #1	V1	0.046
Southcross	X2	0.369
Loops #1 (detector 152.005)	L1	0.689
Pedestrian bridge #2	X3	0.823
Division	X4	1.214
Loops #2 (detector 152.590)	L2	1.274
Video camera screenline #2	V2	1.505
Pedestrian bridge #3	X5	1.542
Loops #3 (detector 153.048)	L3	1.732
Malone	X6	1.760
Pedestrian bridge #4	X7	2.049
Painted Gore	X8	2.159
Loops #4 (detector 153.614)	L4	2.298
I-10 / US-90	X9	2.372
Video camera screenline #3	V3	2.453

Figure 3-21 through Figure 2-31 show more detail of the IH-35 corridor in San Antonio through photographs of the site. Figure 3-21 illustrates the test corridor just south of the first pedestrian overpass. This photograph clearly displays the northbound three-lane cross section. Figure 3-22 shows the IH-35 corridor just to the north of the first pedestrian overpass. The "Speed Limit 60" sign is the screenline for the first commercial vehicle video station. Figure 3-23 illustrates the IH-35 corridor south of the second pedestrian overpass while Figure 3-24 presents the corridor north of the second pedestrian overpass. These photographs show the continued three-lane cross section and relatively level nature of the corridor. Figure 3-25 shows the IH-35 corridor south of the third pedestrian bridge and Figure 3-26 displays the corridor to the north of the third pedestrian bridge. The sign that is shown from the back in Figure 3-25 is the second video screenline.

Figure 3-27 is also taken to the north of the third pedestrian overpass, and it is zoomed-in to provide the signage for the Malone and Theo exit. Figure 3-28 displays the test corridor south of the fourth pedestrian overpass, and Figure 3-29 illustrates the corridor north of the fourth pedestrian overpass. Figure 3-28 and Figure 3-29 demonstrate the pavement markings and signage for the exit to IH-10/US 90. Figure 3-30 also shows a zoomed-in photograph north of the fourth pedestrian overpass to include the signage for those motorists exiting onto I-10/US 90. Figure 3-31 shows the I-10/US 90 overpass. This is the final test vehicle checkpoint location. Figure 3-31 also illustrates the video trailer for the final commercial vehicle data collection along the corridor.

FIGURE 3-21 IH-35 South of the First Pedestrian Overpass

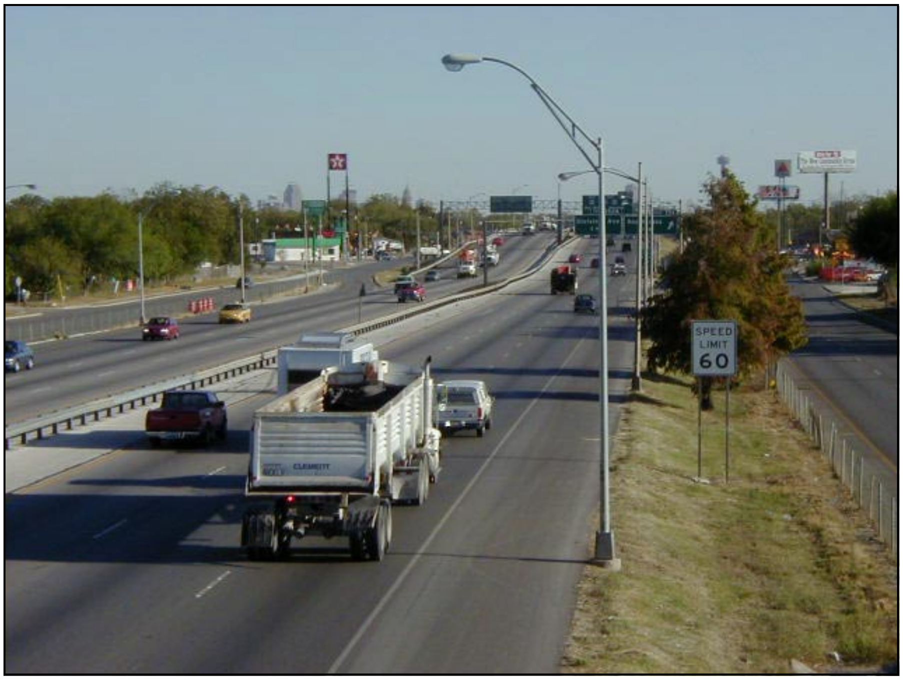

FIGURE 3-22 IH-35 North of the First Pedestrian Overpass

FIGURE 3-23 IH-35 South of the Second Pedestrian Overpass

FIGURE 3-24 IH-35 North of the Second Pedestrian Overpass

FIGURE 3-25 IH-35 South of the Third Pedestrian Overpass

FIGURE 3-26 IH-35 North of the Third Pedestrian Overpass

FIGURE 3-27 IH-35 North of the Third Pedestrian Overpass Showing the Malone Exit

FIGURE 3-28 IH-35 South of the Fourth Pedestrian Overpass

FIGURE 3-29 IH-35 North of the Fourth Pedestrian Overpass

FIGURE 3-30 IH-35 North of the Fourth Pedestrian Overpass Showing I-10/US 90 Exit

FIGURE 3-31 I-10/US 90 Overpass

CONCLUDING REMARKS

This chapter has described the data collection and study corridors used in the study. Instrumented test vehicle data were collected from Monday, October 25, 1999, to Friday, October 29, 1999, along the US 290 test bed in Houston, Texas. AVI and commercial vehicle data were collected simultaneously. In San Antonio, instrumented test vehicle data were collected from Monday, November 1, 1999, to Friday, November 5, 1999, along the IH-35 test bed in San Antonio, Texas. Simultaneous inductance loop and commercial vehicle data were collected.

The data collected will be used as input to the comparison of the mean and variance of the link travel time estimates from the instrumented test vehicles and commercial vehicles in Houston, Texas, to the AVI data source. Similar comparisons will be made in San Antonio with respect to inductance loop detector data. These analyses will be performed in Chapter V for the Houston data and Chapter VI for the San Antonio data. However, prior to these final analyses, data reduction and quality control were performed on the collected data as discussed in Chapter IV.

CHAPTER IV

DATA REDUCTION AND QUALITY CONTROL

INTRODUCTION

Chapter III discussed the study corridors and how the data along each corridor were collected. This chapter will describe the data reduction and quality control. For the instrumented vehicle runs, the data reduction and quality control included a detailed error analysis where suspect data were examined and discarded, if necessary. For the AVI and inductance loop detector data, data reduction and quality control included the removal of outliers. The methods used for the data screening and quality control are discussed in this chapter.

DISTANCE MEASURING INSTRUMENT DATA

To ensure the accuracy of the test vehicle travel time data, the DMI data were thoroughly examined for any errors through extensive quality control. The drivers of the test vehicles had the opportunity to insert any notes in the end of the DMI file to indicate any difficulties that may have been encountered in the travel time run to aid in the quality control. These questions are shown at the bottom of Figure 3-3.

As discussed in the previous chapter, the DMI is connected to the test vehicle's wiring system. Vehicles use electronic pulses to determine speed and to operate the cruise control system. The calibration number is the number of electronic pulses per unit distance, and this number varies by vehicle. After the operator installs the DMI unit, it is calibrated on a 1,000 foot course. The calibration number multiplied by the number of electronic pulses gives the distance traveled. Speed is then calculated by dividing distance by the internal clock time.

After the data were collected each day, the data files from each laptop computer were downloaded and collected on a central computer. The CATS software was used to process the data from each run and summarize it into executive summaries, gather statistics of interest, and write the speed profile graph. In reading each travel time run file, the CATS program reads each observation sequentially until reaching the first "!!!MARK!!!" as indicated in Figure 3-3. After this mark is found, the CATS program determines the location of each checkpoint from the observed distances measured in the field that are presented in Tables 3-1 and 3-2 for Houston and San Antonio, respectively. The differences in the time stamp at each of the locations provides the travel time between checkpoints.

Error analysis was performed on each travel time run. Speed profiles that plot the speed of the test vehicle at any location along the test corridor were investigated. The checkpoints were shown on the graph and so are the locations where the driver pressed the spacebar. The proximity of these marks serves to verify that the DMI worked properly. Figure 4-1 presents a sample speed profile showing the checkpoint locations along with triangles along the x-axis to indicate where the driver marked each checkpoint. Two common problems identified below may be noted and corrected from the use of these graphs.

1. The marks may seem to be shifted when compared to the yardstick marks, which indicates that the driver may have missed the first checkpoint (Beltway 8 in Houston or the first pedestrian bridge in San Antonio). This is corrected by inserting the appropriate mark in the raw data file by measuring back from the first known correct mark and reprocessing the run through CATS.

2. If the marks appear to all be present, but they are improperly spaced at an increasing distance, it is likely that the DMI in the vehicle had the incorrect calibration number. The CATS program has a utility to adjust a DMI file for this problem. Because the distances and speeds are off a linear amount, they can be corrected by multiplying them by the ratio of the old calibration number to the new calibration number as shown in Equations 4-1 and 4-2.

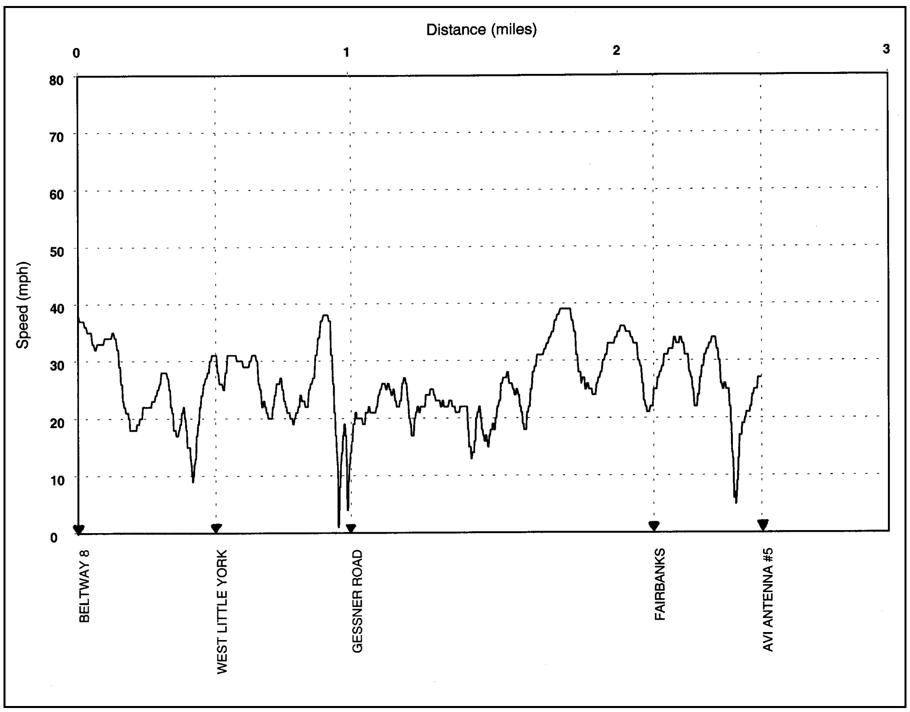

FIGURE 4-1 Sample DMI Speed Profile Showing Vertical Checkpoints and Checkpoint Marks

$$(D_M)_i = (D_O)_i \times \frac{(C_O)_i}{(C_N)_i}, \; i = 1 \text{ to } N \tag{4-1}$$

where:
- i = Observations in file to be adjusted;
- N = Total number of observations;
- $(D_M)_i$ = Modified distance for ith observation;
- $(D_O)_i$ = Original (measured) distance for ith observation; and
- $(C_N)_i$ = New calibration number used for correction;

$$(S_M)_i = (S_O)_i \times \frac{(C_O)_i}{(C_N)_i},\ i = 1 \text{ to } N \tag{4-2}$$

$(C_O)_i$ = Old calibration number used in the field;
$(S_M)_i$ = Modified speed for *i*th observation; and
$(S_O)_i$ = Original (measured) speed for *i*th observation.

Table 4-1 and Table 4-2 summarize the results of the quality control for the DMI data from Houston and San Antonio, respectively. Table 4-1 displays the total number of files by category of interest for each day of data collection in Houston along with the times during which the data were collected. The same information is provided in Table 4-2 for the San Antonio data. The total number of files is shown in the first row. The second row indicates the number of files that were calibrated while the third row indicates the number of files in which the first checkpoint was missed. Row four includes the number of files in which the time or date was adjusted. This occasionally occurred when the time or date stamp was improperly set on a laptop. The number of equipment or operator errors also included. Equipment errors most commonly included computer and/or DMI connections loosening while operator error commonly included missing too many checkpoints. Unfortunately, data were lost for one driver on both the Thursday and Friday data collection in Houston and these are included in the equipment and operator error row. Finally, Table 4-1 and Table 4-2 include the number of files that were used for analysis calculated as the difference between the total number in row one and the number with equipment or operator errors. Overall, approximately 93.0 percent of the travel time runs at each study location were used in the analysis while the remaining 7.0 percent had equipment or operator errors. Therefore, only a small number of files required any changes.

The goal of this research was to sustain three-minute headways between each test vehicle. This headway was not always possible because of equipment and/or vehicle difficulties. The number of missed three-minute headways are also listed. Throughout the week of data collection in Houston, 53 three-minute headways were missed while only twenty headways were missed in San Antonio. Missed three-minute headways resulted in headways of six minutes because the next vehicle was released at the subsequent three-minute headway time period. The lower number in San Antonio is attributed to the experience gained in the data collection methods and the fact that congestion was not as extensive in San Antonio, as will be described in detail in the following chapters. There were also no corrections made in San Antonio due to calibration errors or missing the first checkpoint while in Houston 17 travel time runs were calibrated and five missed the first checkpoint.

TABLE 4-1 Quality Control Summary for Houston DMI Files

Category	Date					Totals	Percent[2]
	Monday 10/25/1999 6:15 to 11:00	Tuesday 10/26/1999 6:08 to 10:58	Wednesday 10/27/1999 6:01 to 10:42	Thursday 10/28/1999 6:01 to 10:16	Friday 10/29/1999 6:05 to 10:19		
Total Number of Field Travel Time Runs	88	93	91	83	85	440	N.A.
Number Calibrated	10	2	0	0	5	17	4.2
Number that Missed First Checkpoint	0	0	2	3	0	5	1.2
Number with Time or Date Adjustment	1	1	0	0	0	2	0.5
Number with Equip. or Operator Error	7	3	2	10	11	33	7.5
Number of Missed Three-Minute Headways	14	8	6	13	12	53	N.A.
Total Number of Files for Analysis[1]	81	90	89	73	74	407	92.5

[1]The number of files for analysis equals the total number of field travel time runs minus the number of files with an equipment or operator error which could not be used.

[2]Percent values are relative to the total number of files for analysis (final row) except for equipment and operator errors (data row 5) which are relative to the total number of field travel time runs (data row 1). The percentage for the total number of files for analysis (final row) is relative to the total number of field travel time runs (data row 1).

TABLE 4-2 Quality Control Summary for San Antonio DMI Files

Category	Date					Totals	Percent[2]
	Monday 11/1/1999 6:21 to 10:03	Tuesday 11/2/1999 6:05 to 10:06	Wednesday 11/3/1999 6:24 to 10:03	Thursday 11/4/1999 6:33 to 10:04	Friday 11/5/1999 6:34 to 9:49		
Total Number of Field Travel Time Runs	78	82	75	71	67	373	N.A.
Number Calibrated	0	0	0	0	0	0	0
Number that Missed First Checkpoint	0	0	0	0	0	0	0
Number with Time or Date Adjustment	12	0	0	0	0	12	3.4
Number with Equip. or Operator Error	11	12	1	0	1	25	6.7
Number of Missed Three-Minute Headways	7	11	1	0	1	20	N.A.
Total Number of Files for Analysis[1]	67	70	74	71	66	348	93.3

[1]The number of files for analysis equals the total number of field travel time runs minus the number of files with an equipment or operator error which could not be used.

[2]Percent values are relative to the total number of files for analysis (final row) except for equipment and operator errors (data row 5) which are relative to the total number of field travel time runs (data row 1). The percentage for the total number of files for analysis (final row) is relative to the total number of field travel time runs (data row 1).

After these summaries were generated and the field corrections noted, it was further imperative that all travel time runs be reduced consistently. This was necessary to reduce errors between observed distances and the location where the test vehicle driver hit the checkpoint. Drivers were instructed to hit the first and last checkpoint three times and each subsequent checkpoint one time. The metric shown in Equation 4-3 was used to determine the percent error in each travel time run. The metric was used to correct the starting mark of each travel time test vehicle run to reduce the error between where the drivers hit the checkpoints and the true location of the checkpoints.

$$\text{Weighted Average Corridor Percent Error} = \sum_{i=1}^{N} (LPE_i)\left(\frac{L_i}{L_T}\right) \tag{4-3}$$

where: LPE_i = Link percent error = $D_i / L_i \times 100$;
L_i = Observed link length calculated from $(D_O)_i$ values;
L_T = Observed corridor link length calculated as sum of L_i values;
D_i = $(D_M)_i - (D_O)_i$. When this value is positive, the driver hit the checkpoint after the true location of the checkpoint;
$(D_M)_i$ = ith distance in miles measured from the first checkpoint in the field where the test vehicle driver hit the spacebar to indicate the location of the checkpoint;
$(D_O)_i$ = Observed distance in miles measured from the first checkpoint to the ith checkpoint measured in the field and presented in Table 3-1 (Houston) and Table 3-2 (San Antonio); and
N = Number of observations ($D_i s$).

Computer code was written in SAS to minimize the quantity "E" shown in Equation 4-4. Minimizing "E" provides a subsequent minimization of the weighted average corridor percent error in Equation 4-3. This was performed by first calculating "E" and checking whether the value was positive or negative. Complete enumeration was then performed at 0.001 mile steps.

$$E = \sum_{i=1}^{N} D_i \tag{4-4}$$

If "E" was overall positive, then the code was used to minimize the function by "sliding" the D_i in steps of -0.001 mile–the significance of the distance information provided by the DMI. If "E" was overall negative, the program would "step" +0.001 mile. When "E" was minimized, the program would stop this iterative procedure. All 407 files from the Houston test corridor and 348 files from the San Antonio test corridor were manually corrected the amount necessary to minimize Equation 4-4 by moving the first "!!!MARK!!!" in the data file forward or backward appropriately.

After the function was minimized, the weighted average corridor percent error was computed as shown in Equation 4-3. Figure 4-2 and Figure 4-3 show the frequency distributions of the weighted average corridor percent error for the Houston DMI data before and after the correction, respectively. Figure 4-4 and Figure 4-5 show the frequency distributions of the weighted average corridor percent error for the San Antonio data before and after the correction, respectively. The Houston data were corrected from a percent error of 1.24 to 0.18, and the data from San Antonio were corrected from 0.11 percent to 0.06 percent. The Houston errors are likely higher than San Antonio due to more congestion in Houston which will be shown in future chapters and the fact that the test vehicle drivers had gained more experience when they were in San Antonio.

Equation 4-3 and Equation 4-4 provided a method to quantify the amount that the driver marks at checkpoints were off for a given file. However, the metric is based upon all the checkpoints in the file when, in reality, the driver instructions emphasized that the drivers must hit the first checkpoint accurately. Therefore, more weight must be given to the first checkpoint. To ensure this, each DMI run was ultimately reinvestigated manually, and the time stamp at each checkpoint of interest was manually found in the file and put into a Microsoft Excel file to be read directly into the SAS statistical software for travel time calculation for the links of interest. Though time consuming, this ensured each time stamp and subsequent travel time was read correctly from the raw DMI data files. While the previous method using Equation 4-3 was overruled, the results of Equation 4-3 for each run provided an estimate of which travel time runs would likely require the most scrutiny in the subsequent quality control analyses.

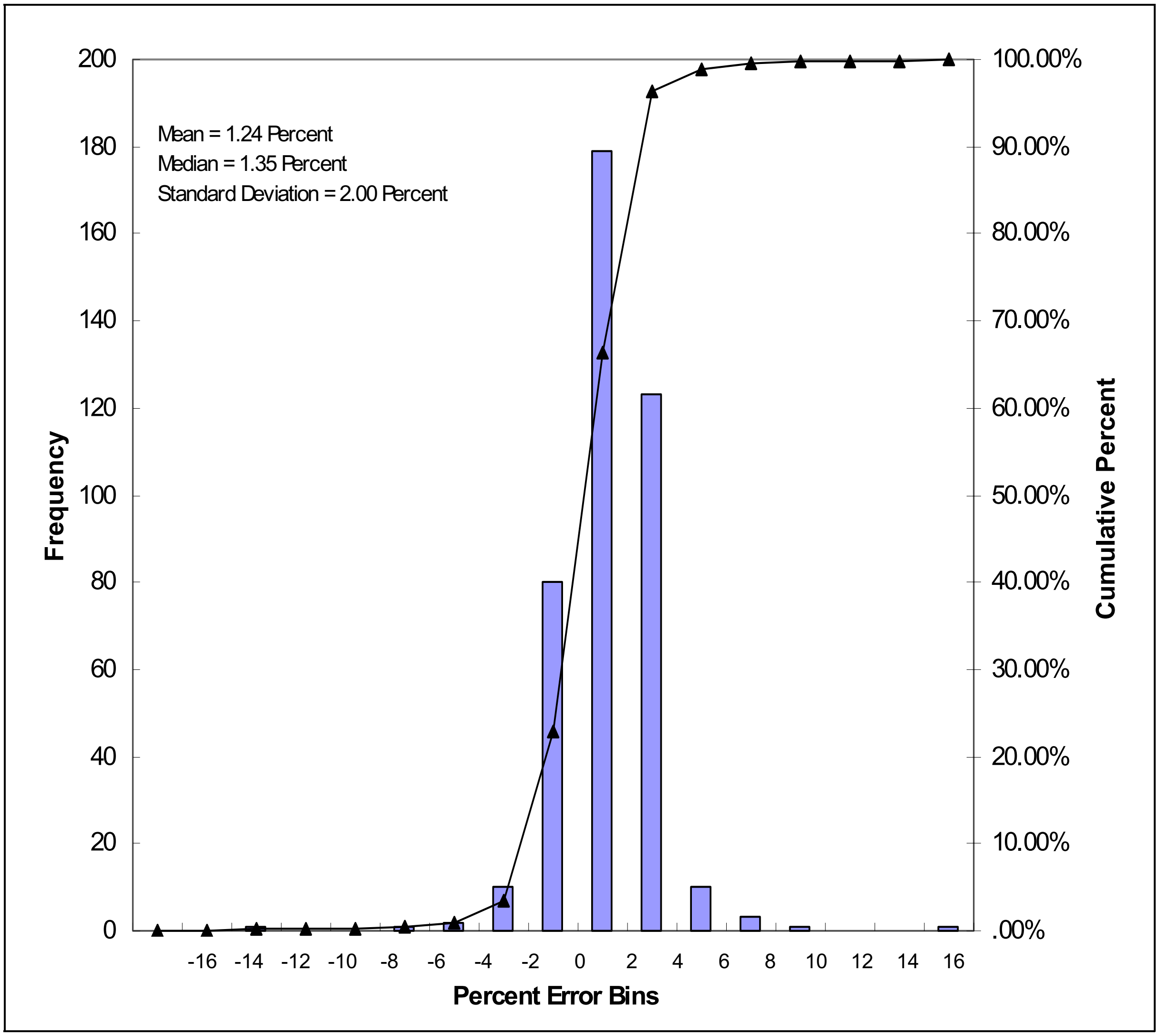

FIGURE 4-2 Frequency Distribution of Errors in DMI Files for Houston Data Before Correction

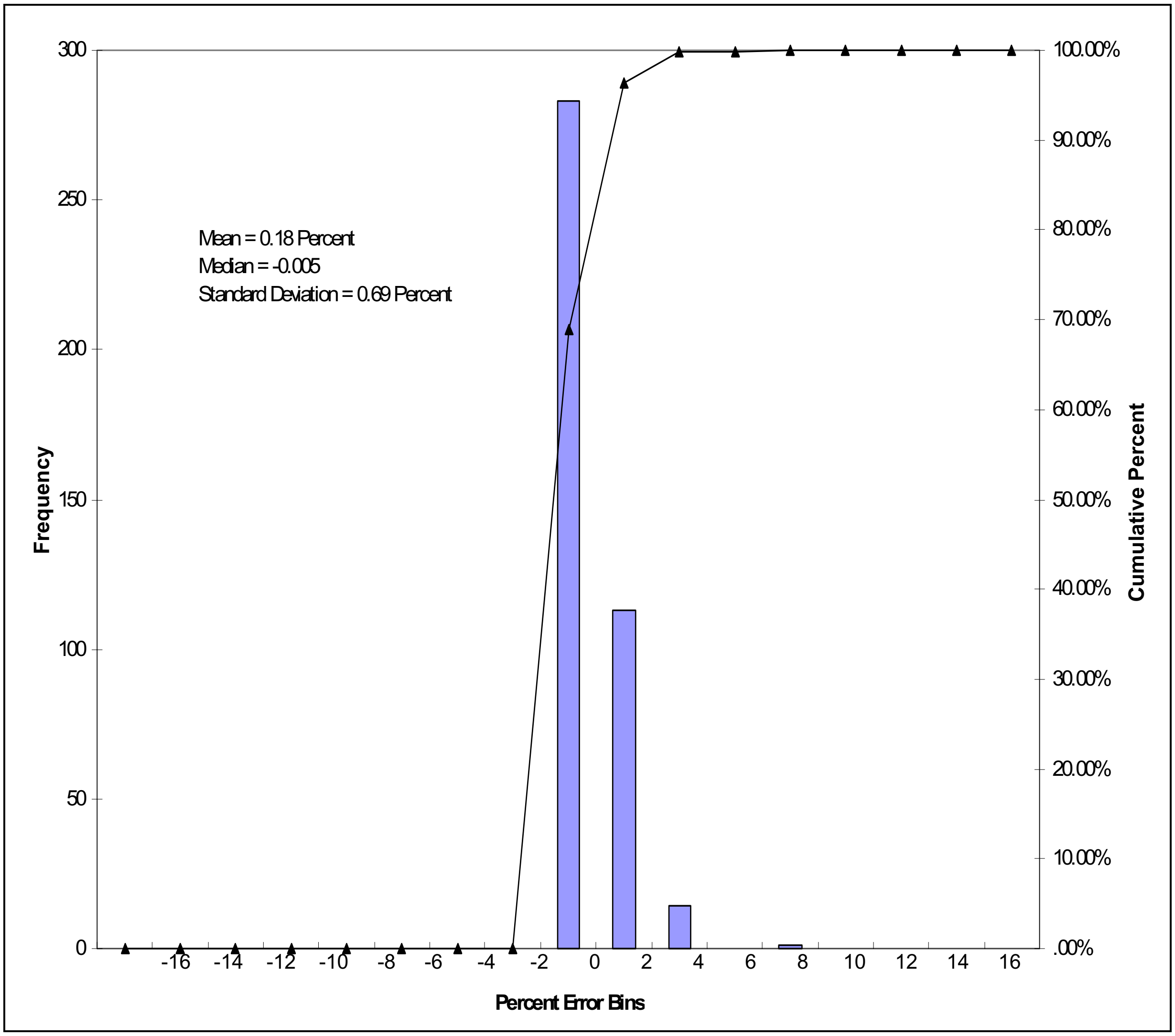

FIGURE 4-3 Frequency Distribution of Errors in DMI Files for Houston Data After Correction

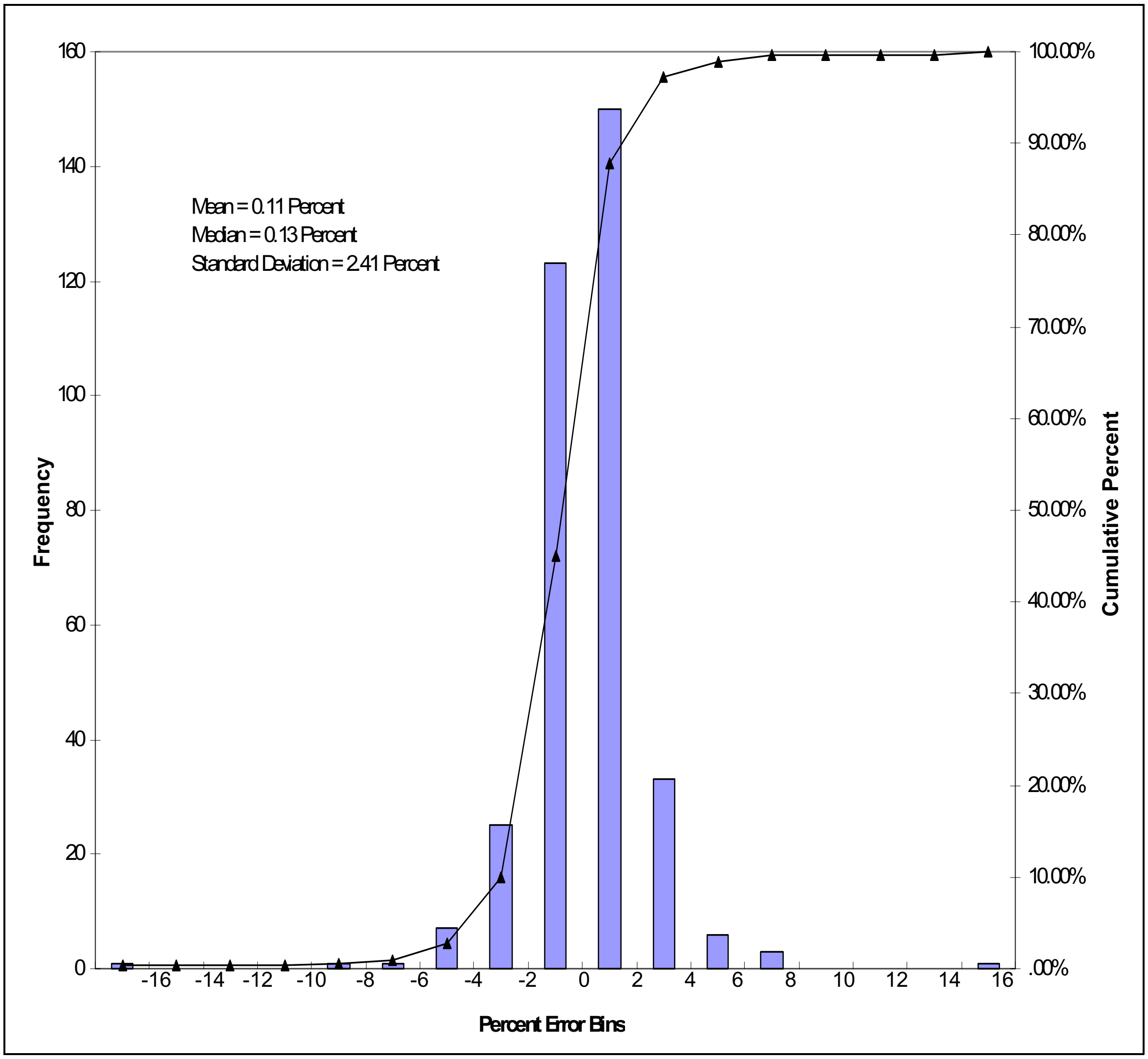

FIGURE 4-4 Frequency Distribution of Errors in DMI Files for San Antonio Data Before Correction

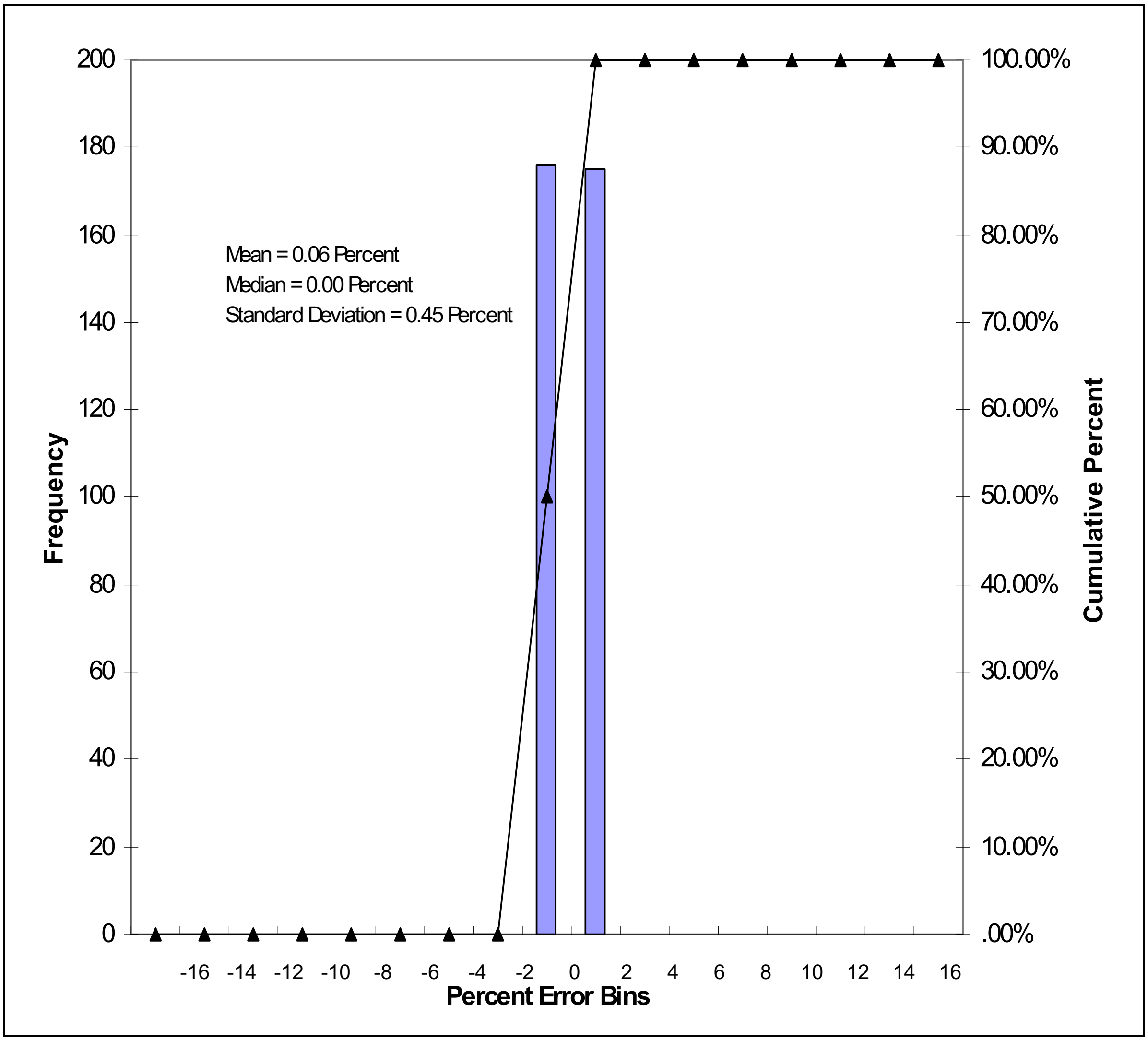

FIGURE 4-5 Frequency Distribution of Errors in DMI Files for San Antonio Data After Correction

AUTOMATIC VEHICLE IDENTIFICATION DATA

AVI data were also collected for the AVI detectors located on the US 290 test bed for the test vehicle data collection time periods. Matched travel time data from the AVI system were cleaned to screen for outliers. The primary source of these outliers are motorists that are read at one of the early stations along the corridor, exit the freeway, and then re-enter the freeway. This provides large outlier readings of travel time.

Dixon and Rilett developed a method to address these outliers in the Houston AVI data set (*55,56*). This method results in AVI data of the format shown in Figure 4-4. Mean link travel time and standard deviation were then calculated from these raw tag reads at each station along the US 290 corridor. A computer program developed by Dixon was then used to process all the AVI reads into raw link travel times. Two threshold values were used. The first threshold value was based upon a rolling mean, standard deviation, and median of the previous ten observations. This threshold assumed that the travel times of vehicles were normally distributed and a 95.0 percentile of the travel time beyond which the probe vehicles had likely exited US 290. The first threshold was calculated by summing the rolling travel time mean with the product of the z-score and the rolling travel time standard deviation.

Dixon and Rilett developed a second threshold as the nature of the sampling of the AVI tag data can result in rather large changes from one AVI observation to the next under some traffic conditions. Without another threshold, it is possible that the link travel times could jump to a value higher than the primary threshold value. If these are the true traffic conditions, these data should be kept, and using the primary threshold only would cause these data to be rejected. The second threshold value is based on the more robust measure of the median. To test for situations when too many data points could have been improperly rejected, the second threshold was programmed to be applied when ten consecutive data points were rejected according to the primary threshold. The median was based upon the ten consecutive data points. The value of ten is used since there would not likely be more than five sequential exits. The threshold used was defined by multiplying the median by 1.8. Dixon notes that the value of this multiplier itself is not as important as long as it is large enough to accept true link travel times that had previously been rejected with the primary threshold and small enough to reject travel times of vehicles that have exited the roadway and then returned. After observations were kept based upon the secondary threshold value, the primary threshold was updated with the data that were kept based upon the secondary threshold. The use of a primary and secondary threshold provided a robust technique for following varying traffic conditions.

Table 4-3 presents the number and percent of observations that were removed for each AVI antenna combination as a function of time of day. The average percent of data removed for adjacent antennas was 2.1 percent, while from antennas #1 to #3 and #3 to #5 the average percent of data removed was 3.0 percent. The average was 3.2 percent for the entire corridor.

TABLE 4-3 Number and Percent of Observations by Day Removed Due to Outlier Thresholds

Date	AVI Antenna						
	#1 to #2	#2 to #3	#3 to #4	#4 to #5	#1 to #3	#3 to #5	#1 to #5
Monday 10/25/99	21 0.8%	24 3.7%	4 0.6%	32 1.8%	22 3.1%	33 5.7%	57 3.6%
Tuesday 10/26/99	72 2.7%	26 3.9%	32 4.9%	57 2.5%	30 2.9%	20 2.5%	74 3.6%
Wednesday 10/27/99	57 2.2%	24 4.2%	21 2.9%	40 2.1%	31 4.4%	13 2.7%	61 3.2%
Thursday 10/28/99	62 2.1%	50 5.5%	21 2.4%	20 0.9%	16 2.5%	12 2.2%	57 2.7%
Friday 10/29/99	74 2.6%	13 1.7%	18 2.6%	27 1.3%	12 1.8%	14 2.6%	53 2.8%
Percent Averages =	2.1%	3.8%	2.7%	1.7%	2.9%	3.1%	3.2%

Figure 4-6 shows a sample plot of link travel time data connected by linear interpolation for US 290 for Monday from AVI antenna #1 to #5. Each data point represents one vehicle and the appearance of vertical slices of missing data occur at intervals along the travel time profile. This occurs because not all of the tag reads along a link are reported due to the large amount of data coming into the system from several antennas. When these data are matched, the missing data shown in Figure 4-6 occur. Further, AVI antenna #3 generally had only 29 percent of the raw tag reads of the other AVI antennas along the corridor. Along links two and three of the corridor, this resulted in matching approximately 20 percent of the matches in links one and four. The difficulty of obtaining a continuous stream of travel time information was another reason to do the data quality control described in this section.

INDUCTANCE LOOP DATA

Extensive quality control and data reduction were also performed on the inductance loop detector data. The data were cleaned by investigating suspect combinations of speed, volume, and occupancy, as well as studying the elapsed time between subsequent observations at a particular station. The polling cycle of the San Antonio data during the data collection effort was thirty seconds, but the cycle occasionally skips to sixty or ninety seconds. This can occur when the entire system is being polled and the capacity of the local controller units in the field is met. This section will describe the quality control on these data for these situations.

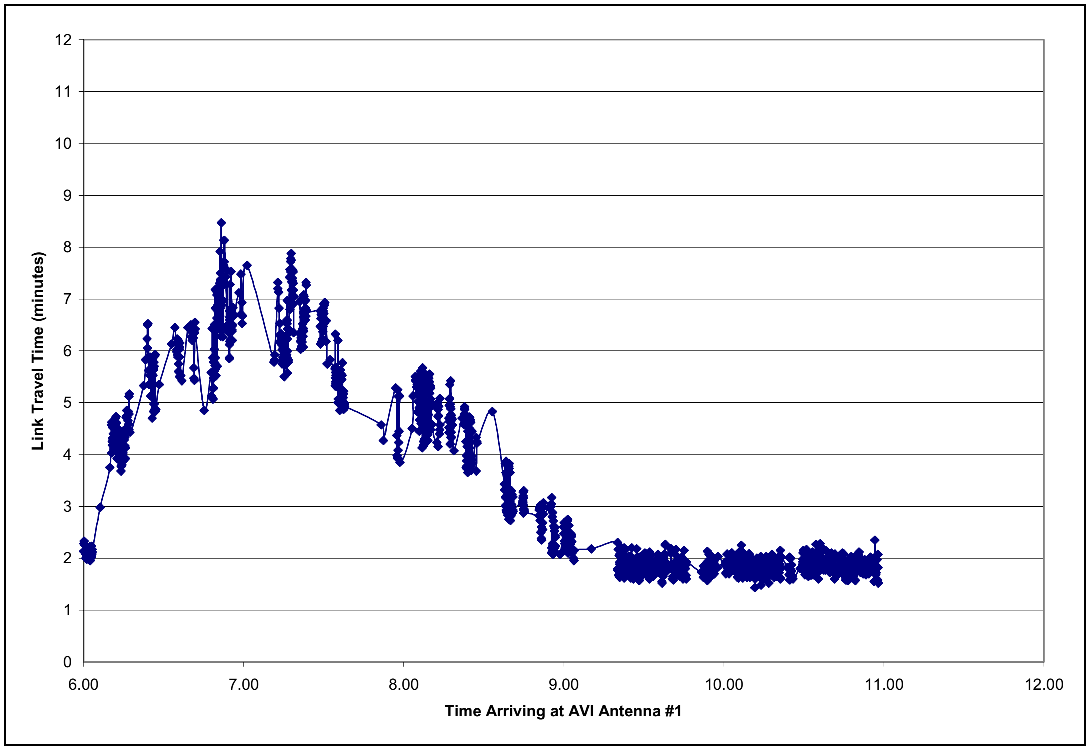

FIGURE 4-6 Link Travel Time Data for US 290 for Monday from AVI Antenna #1 to #5

Data for all five days were investigated during the 6:00 a.m. to 10:00 a.m. time period. Table 4-4 displays the screening rule combinations of speed, volume, and occupancy that were used to identify suspicious data for each day of loop detector data. These rules were established in previous work for the TransGuide® loop detector data (*28*,*29*,*57*,*58*). Table 4-4 shows the number of occurrences of each screening rule by day of the week. Rule one represents when all traffic parameters are zero. This occurs when vehicles are either stopped over the loop detectors or if there are no vehicles present. Investigation of the cases when this occurred in the data showed that these observations resulted due to vehicles not being present because adjacent lane loop detectors had traffic at free-flow speeds. These data were removed from the data set so that speeds would not be improperly adjusted prior to travel time calculations. Suspicious data rule two, when speed and volume are zero and occupancy is greater than or equal to ninety-five, did not occur.

Rule three identifies observations when the speed, volume, and occupancy are in the acceptable and expected ranges for a thirty-second polling cycle. Rules four through six are used to identify suspicious combinations of speed, volume, and occupancy, and their cause is unknown. There were only nine observations in these categories for the entire week, and they were removed from the data set. Suspicious data rule seven, when speed is greater than zero and volume and occupancy are zero, did not occur.

TABLE 4-4 Summary of Quality Control for Inductance Loop Data

Screening Rule Number and Definition	11/1/99 Monday	11/2/99 Tuesday	11/3/99 Wednesday	11/4/99 Thursday	11/5/99 Friday
1) Spd=0, Vol=0, Occup=0	10	5	6	8	4
2) Spd=0, Vol=0, Occup≥95	0	0	0	0	0
3) Spd≥0, 1≤Vol≤27, Occup>0	5,199	5,211	4,131	3,020	4,763
4) Spd=0, Vol=0, 1≤Occup≤95	0	1	0	0	0
5) Spd=0, Vol>0, Occup=0	1	0	1	0	0
6) Spd=0, Vol>0, Occup>0	1	1	0	2	2
7) Spd>0, Vol=0, Occup=0	0	0	0	0	0
8) Spd>0, Vol>0, Occup=0	7	2	10	2	1
9) Spd>0, Vol=0, Occup>0	0	0	0	0	0
10) Spd>0, Vol>27, Occup>0	6	4	11	5	0
Raw totals =	5,224	5,224	4,159	3,037	4,770
[1]Rule 1, total =	10	5	6	8	4
[2]Rules 4 to 6, total =	2	2	1	2	2
[3]Rule 10, total =	6	4	10	5	0
[4]Total after impution below and removing suspicious data	5,237	5,242	5,118	4,209	4,774
[5]*Percentages imputed, deleted, and missing*					
Percent and number imputed (elapsed time sixty seconds)	0.6 % 31	0.6 % 29	19.0 % 970	28.4 % 1,194	0.2 % 10
Percent and number imputed (elapsed time ninety seconds)	0	0	0.4 % 22	0	0
Percent deleted (elapsed time >two minutes)	0	0	0.3 % 16	0.2 % 7	0
[6]Percent missing	9.1 %	9.0 %	11.1 %	26.9 %	17.1 %

[1]These data occur when no vehicles are present. They are removed from the data set to avoid miscalculation of speeds.
[2]These data are suspicious and the cause is unknown. Their number is negligible, and they are removed from the data set.
[3]Volumes are beyond range defined for a thirty-second polling cycle. Unless the elapsed time between observations is greater than thirty seconds (one case on Wednesday) these data are removed.
[4]These are the totals after imputing data from sixty- and ninety-second polling shown at the bottom of the table.
[5]The percentages are calculated based upon the totals after imputing (previous row).
[6]These percentages are relative to 5,760 observations calculated by multiplying four hours of data collection, times four loop detector stations, times one station per lane, times two observations per minute, times sixty observations per hour (see Equation 4-5).

Screening rule eight data result when speed and volume are greater than zero and occupancy equals zero. This occurs because the occupancy decimal places are truncated. These observations likely have an occupancy percentage between zero and one so these data are still reliable for speed and volume use. Screening rule nine with speed and occupancy greater than zero and volume equal to zero did not occur.

Previous research has found that when the polling cycle is less than approximately two minutes, the current observation contains the sum of the traffic characteristics between the previous and current observation (*59*). Therefore, the volume indicated in the current observation is the sum of the volume since the previous observation, and the speed is the average speed since the previous observation. Therefore, the current speed is used for the speed of the previous observation, and half of the volume of the current observation is placed into the previous observation. Table 4-4 also shows the percentage of data imputed when the polling cycle was sixty or ninety seconds. It may be seen that this situation occurred mostly on Wednesday and Thursday. When the time difference between the current and previous observation was greater than two minutes, the data were removed from the data set due to the findings of previous research indicating that it is not certain how these observations reflect the traffic conditions of the previous time period (*59*). This situation occurred for only 22 observations during the week as shown in Table 4-4.

Finally, Table 4-4 presents the percent of missing data by day. The average amount of missing data is 14.7 percent. These results are similar to missing data percentages found in previous research done on the San Antonio TransGuide® system (*28*,*29*). The percentage of missing observations is calculated relative to the total number of possible observations, which is calculated as shown in Equation 4-5 for the entire data collection time period for a given day.

$$\begin{aligned}\begin{matrix}\text{Theoretical Number of}\\ \text{Observations per Day}\end{matrix} &= \begin{pmatrix}\text{4 hours}\\ \text{of data}\end{pmatrix} \times \left(\frac{\text{60 minutes}}{\text{hour}}\right) \times \left(\frac{\text{2 observations}}{\text{minute}}\right)\\ &\times (\text{3 lanes}) \times (\text{4 stations}) = \begin{matrix}\text{5,760}\\ \text{observations}\end{matrix}\end{aligned} \tag{4-5}$$

The missing data in the data set were investigated further to better understand when and where data were missing along the corridor. Table 4-5 presents the primary locations and time periods for missing data along the corridor during the week of data collection. Milepost 153.048 in lane three was the primary source of the missing data throughout the week. The missing data in lane three at detector 153.048 was investigated further to ensure the fact that the lane was missing would not provide statistically different spot speed estimates when averaged across lanes for the analyses in later chapters. A *t*-test was performed by comparing five-minute estimates of the average, variance, and coefficient of variation (c.v.) of the spot speed detector estimates with and without lane three included. The analysis was performed at the α=0.05 level of significance on the upstream and downstream detector. None of the estimates were found to be statistically different. Based on this analysis, it was concluded that the missing data in lane three would not adversely effect the statistical analyses performed later.

Milepost 152.590 was also inoperable from 6:00 a.m. to 8:00 a.m. across all lanes on Thursday. Corridor travel time analyses performed in Chapter VI with the inductance loop detector data do not include Thursday data because the 152.590 detector station was completely missing.

TABLE 4-5 Summary of Missing Inductance Loop Data

Date	Milepost	Lane Number	Time Period
11/1/99, Monday	153.048	3	6:00 a.m. to 10:00 a.m.
11/2/99, Tuesday	153.048	3	6:00 a.m. to 10:00 a.m.
11/3/99, Wednesday	153.048	3	6:00 a.m. to 10:00 a.m.
11/4/99, Thursday	152.590	1	6:00 a.m. to 8:00 a.m.
	152.590	2	6:00 a.m. to 8:00 a.m.
	152.590	3	6:00 a.m. to 8:00 a.m.
	153.048	1	8:00 a.m. to 10:00 a.m.
	153.048	3	6:00 a.m. to 10:00 a.m.
11/5/99, Friday	153.048	1	6:00 a.m. to 10:00 a.m.
	153.048	3	6:00 a.m. to 10:00 a.m.

The final quality control of the inductance loop data included the investigation of outlier data. Figure 4-7 presents a speed profile of the thirty-second aggregated data for Tuesday at detector number 152.005. The time period over which congestion occurs is approximately 7:00 a.m. to 8:00 a.m. Outlier data are clearly present. For example, outliers can be seen at 6:15 a.m. and 9:30 a.m. when speeds are shown at just over twenty mph during free-flow conditions.

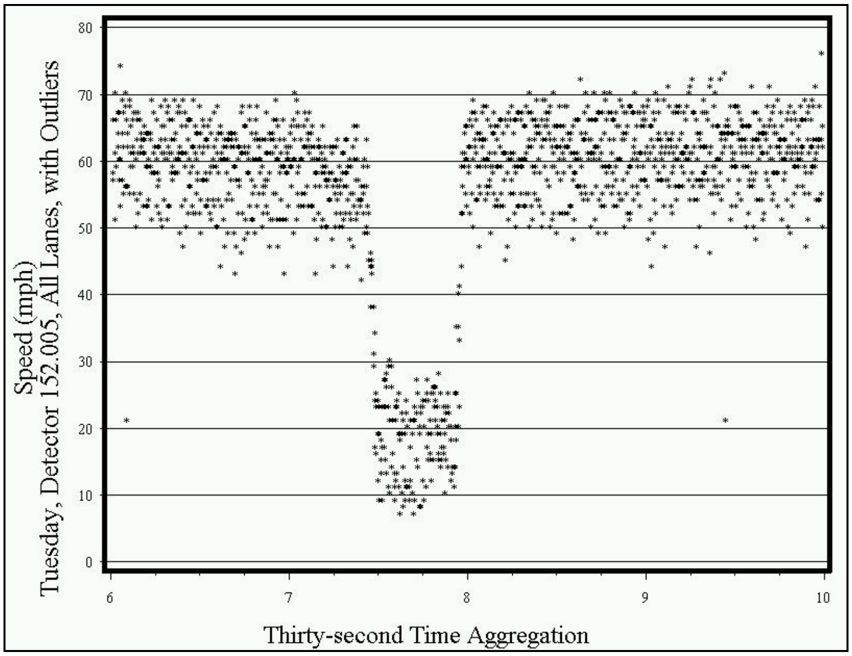

FIGURE 4-7 Speed Profile of Tuesday Detector 152.005 Data Showing Outlier Data

Standard statistical procedures were used to remove the outlier data. Statistics for determining outlier data were calculated for each fifteen-minute aggregation period during free-flow conditions. The upper quartile (75th percentile), lower quartile (25th percentile), and interquartile range (difference between upper and lower quartile) were computed. Upper and lower boundaries defining outliers for each fifteen-minute period were then calculated as shown in Equation 4-6 and Equation 4-7 using standard techniques for outlier identification (*60*).

where: $Q_{0.75}$ = Upper quartile;

$$\textit{Upper Outlier Boundary} = Q_{0.75} + (1.5 \times IQR) \tag{4-6}$$

$$\textit{Lower Outlier Boundary} = Q_{0.25} - (1.5 \times IQR) \tag{4-7}$$

$Q_{0.25}$ = Lower quartile; and
IQR = Interquartile range.

Figure 4-8 shows the Tuesday data for detector number 152.005 after the outlier data have been removed using Equation 4-6 and Equation 4-7. Table 4-6 presents the number and percent of outliers by detector and day. The total number of final observations available for analysis is also presented in Table 4-6. It was also found that lane three accounted for 70 percent of the outlier data. Clearly, there were malfunctions on the lane three detectors as they were occasionally missing entirely as shown previously in Table 4-5. With these standard quality control methods applied, the inductance loop data were acceptable for subsequent analysis.

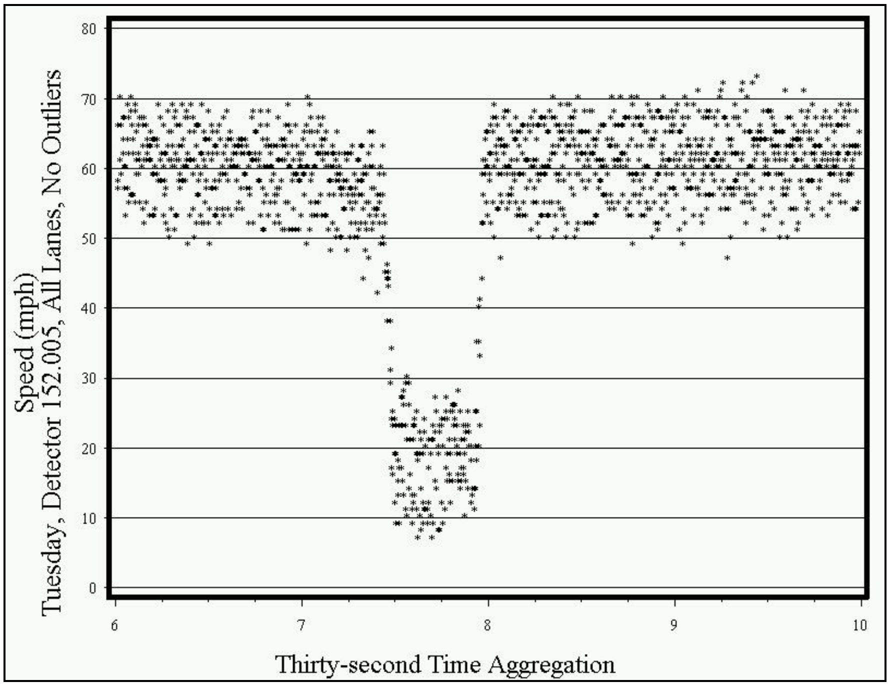

FIGURE 4-8 Speed Profile of Tuesday Detector 152.005 Data Showing Outlier Data Removed

COMMERCIAL VEHICLE DATA

Commercial vehicle data were collected by placing a video camera at the beginning, middle, and end of the test corridor. The video had a time stamp on it that was synchronized for each of the cameras with the test vehicles and the AVI system. At the first two stations along the corridor, an individual would monitor the camera and record relevant information including truck type, lane number, and distinguishable features for later use as necessary. At the last station, a video trailer was used to videotape commercial vehicles. Travel time information was obtained between stations by taking the difference in the synchronized times shown on the video at each station. In this study, commercial vehicles were defined as those trucks with more than three axles or larger than passenger pickup trucks (i.e., panel trucks or larger).

TABLE 4-6 Number and Percentage of Outlier Data by Detector and Day

Detector	Data	Total Number of Outliers and Percent	Total Number of Final Observations
152.005	Monday	33 2.3%	1394
	Tuesday	51 3.6%	1380
	Wednesday	53 3.8%	1335
	Thursday	38 2.7%	1369
	Friday	45 3.1%	1387
152.590	Monday	19 1.3%	1408
	Tuesday	6 0.4%	1424
	Wednesday	16 1.1%	1394
	Thursday	23 3.3%	667
	Friday	8 0.6%	1424
153.048	Monday	27 2.8%	927
	Tuesday	13 1.4%	939
	Wednesday	9 1.0%	919
	Thursday	7 1.0%	689
	Friday	16 3.3%	462
153.614	Monday	4 0.3%	1425
	Tuesday	2 0.1%	1427
	Wednesday	4 0.3%	1388
	Thursday	2 0.1%	1414
	Friday	3 0.2%	1429

SYNCHRONIZATION OF TIME STAMPS

It was imperative that the time stamps on each data set corresponded on each day to make travel time estimation characteristic comparisons. Time synchronization was performed in the field when possible; however, some time adjustments were made to the data after data collection. For the US 290 data in Houston, the test vehicle drivers required adjustment to the AVI system. This was performed by adjusting the laptop computers on the instrumented test vehicles to the AVI time in the field. Occasionally these time stamps would be set incorrectly on a particular laptop and the time stamp was adjusted after the data were collected. The fourth AVI antenna was used to synchronize time stamps between the test vehicles and the AVI system because it was a location where the test vehicle drivers marked as they traversed the corridor, and each driver had an AVI tag in the vehicle. This provided the difference between the AVI and test vehicles. Test vehicle time stamps were then adjusted by the median time difference for each driver. This did not alter the travel time data itself. This procedure only provided an accurate time stamp on the data for the test vehicles. This was performed for all drivers on Monday and for two drivers on Friday. For all other days of data collection, the time stamps were synchronized in the field. The commercial vehicles along the US 290 corridor in Houston were also adjusted the known time amount for each day to be synchronized with the AVI and test vehicles.

Along the IH-35 corridor in San Antonio, Texas, the data from each data source were adjusted to the GPS time. The difference between GPS and the time at which data were collected for the commercial vehicles and test vehicles was known. The time stamp on the inductance loop detectors was found to have a time difference of approximately one second per day from the United States atomic clock time from a known reference date (*11*). Further, the time difference between GPS and the United States atomic clock time was known. The inductance loop data from TransGuide® in San Antonio was adjusted to GPS time with this known information so all data sets were synchronized.

CONCLUDING REMARKS

This chapter has described the steps taken to ensure the quality of the data analyzed in the following chapters. The techniques utilized to perform quality control on the AVI and inductance loop detectors were based upon proven methods used for cleaning similar data sets in previous research. Approximately three percent of the AVI travel time data were removed as outliers, and approximately 1.6 percent of the inductance loop detector data were removed. Therefore, a large majority of the ITS data (at least 97.0 percent) used in this report were acceptable for analysis. One loop detector station (152.590) in the Thursday San Antonio data set was missing so this day of data was not used for subsequent corridor travel time data analysis. The loop detectors also necessitated imputation of data when the system did not properly poll and download the data at thirty-second increments.

The CVO and DMI data were reduced with more labor-intensive manual methods; however, these techniques were necessary to ensure the quality of the data. The commercial vehicle travel time data were manually matched from link-to-link. Ninety-three percent of the

DMI data were acceptable for analysis and did not require calibration or contain operator or equipment error. With the data screened with these quality control and data collection methods, the following chapters will present the analyses of the data.

CHAPTER V

INVESTIGATION OF TRAVEL TIME ESTIMATION FOR SYSTEM MONITORING AND MULTI-MODAL ANALYSES USING AUTOMATIC VEHICLE IDENTIFICATION DATA

This chapter discusses the analyses performed on the data collected along the US 290 corridor in Houston, Texas. The emphasis is on the estimation of mean travel time from the three data sources. Specifically, the following objectives are addressed:

1. Investigate whether deployed ITS detector technologies such as AVI can be used to provide travel time mean and variance estimates for system planning and performance monitoring. More specifically, the accuracy of the travel time estimate from the AVI data source will be investigated, as well as the trade-offs in accuracy and cost relative to current data collection techniques. AVI and test vehicle travel time characteristic estimates will be compared to satisfy this objective.
2. Investigate how well AVI systems that directly sample link travel times replicate travel conditions for commercial vehicle operations. Advanced traveler information systems (ATIS) typically monitor and provide information to commuter drivers based on data primarily from passenger cars. Intuitively, there will be a difference between travel time estimates based upon passenger cars and that actually experienced by CVO. To date this difference has not been statistically analyzed with ITS data.
3. Investigate the use of the loess statistical procedure for locally weighted nonparametric computation of travel time estimates for AVI, test vehicle, and CVO data sources. The use of the loess technique to obtain estimates of the differences between commercial vehicles and test vehicles compared to AVI is also investigated.

ANALYSIS METHODOLOGY AND LOESS STATISTICAL PROCEDURE

After the completion of the quality control and data reduction discussed in the previous chapter, the corridor travel time for each vehicle as a function of the time entering the corridor was available for each data source. The loess statistical procedure was chosen to estimate the travel time distribution properties as a function of time of day (*61-65*). This statistical technique was used because it is nonparametric and can provide estimates of both the mean and variance. A nonparametric approach is desirable as it provides a fit of the travel time distribution properties with less bias than a linear or quadratic parametric fit. Upper and lower confidence bounds can also be obtained around the mean estimate to provide an indication of the reliability of the travel time estimate over time for each data source. The SAS statistical package was used to perform the nonparametric analysis.

The key assumptions to loess are: 1) that the estimate is a linear combination of each dependent observation y_i, 2) the estimate has little or no bias, and 3) the random errors are normally distributed. Therefore, the assumptions and theoretical basis of the loess procedure are contingent upon the fact that the random errors are normal. In empirical applications, however, the lack of normally distributed data is common. This phenomena was found in all the data sets used in this report using the Kolmogorov-Smirnov test of normality at the α=0.05 level of significance. The lack of normally distributed data occurs for many reasons including round-off error and outliers in the data. In the event that the errors are not normally distributed, the Central Limit Theorem (CLT) is applicable if there are no outliers. The CLT can be applied to the estimates from loess as being approximately normal as the sample size gets sufficiently large (*66*). Outliers typically make the confidence intervals too wide but maintain coverage. Thus, the confidence limits determined are reasonable.

The goal of loess is to calculate an estimate of the dependent value $\hat{y}_i$ for each observed independent variable x_i. In estimating y_i, an interval around each x_i is obtained. The interval is created by separating the x-axis of independent variable data in half at the median of the observed data. This leads to two groups, which are both similarly divided, resulting in four intervals. This process is continued until each cell contains no more than $n\gamma/5$ observations (*64*). The set of points $x_{i-\frac{\gamma n}{2}} \ldots\ldots x_i \ldots\ldots x_{i+\frac{\gamma n}{2}}$ is used to compute the estimate $\hat{y}_i$ and is referred to as the local neighborhood. To estimate $\hat{y}_i$, the generalized cross-validated mean square error (GCV MSE) is minimized by fitting a locally weighted linear or quadratic function through the local neighborhood of points (*64*). Equation 5-1 shows the weighted regression used for $\hat{y}_i$ (*64*). Equation 5-2 describes y. Further, Equation 5-3 presents the weighting of the x_i values in the local neighborhood. After each $\hat{y}_i$ is computed, a linear interpolation between each estimate is performed to obtain the linear smoothing combination of y_i.

$$\hat{y}_i = (1, x_i, x_i^2)\,\hat{\boldsymbol{\beta}}_i \qquad (5\text{-}1)$$

$$y = \beta_o + \beta_1 X + \beta_2 X^2 + \epsilon \qquad (5\text{-}2)$$

where: x_i = Predictor variables;

$\hat{\beta}_i = (X^t W X)^{-1} X^t W y$;

$$X = \begin{bmatrix} 1 & x_{i-\frac{\gamma n}{2}} & x^2_{i-\frac{\gamma n}{2}} \\ . & . & . \\ . & . & . \\ 1 & x_{i+\frac{\gamma n}{2}} & x^2_{i+\frac{\gamma n}{2}} \end{bmatrix};$$

$$y = \begin{bmatrix} y_{i-\frac{\gamma n}{2}} \\ . \\ . \\ y_{i+\frac{\gamma n}{2}} \end{bmatrix}; \text{ and}$$

$$W = \begin{bmatrix} w_{i-\frac{\gamma n}{2}} & & & 0 \\ & . & & \\ & & . & \\ 0 & & & w_{i+\frac{\gamma n}{2}} \end{bmatrix}$$

$$w_j = \frac{32}{5}\left(1 - \left(\frac{d_i}{d_q}\right)^3\right)^3 \qquad (5\text{-}3)$$

where: w_j = Weights for the *i*th measurement;
q = γn = Number of points in the local neighborhood;
d_i = Increasing distances of the q points nearest to x_i; and
d_q = Largest distance of the q points nearest to x_i.

From reference *63*, a more simplified way to present Equation 5-1 is the vector equation $\hat{\boldsymbol{y}} = \boldsymbol{Ly}$. Because the error is defined as the difference between $\boldsymbol{y}$ and $\mathbf{y}$ the expanded matrix notation follows as $\hat{\boldsymbol{\varepsilon}} = (\boldsymbol{I} - \boldsymbol{L})\boldsymbol{y}$ where $\boldsymbol{I}$ is the *nxn* identity matrix. Letting $\boldsymbol{\delta_k} = \boldsymbol{tr}\,[(\boldsymbol{I} - \boldsymbol{L})(\boldsymbol{I} - \boldsymbol{L})']^k$ for $k=1,2$ the $E\left[\sum_{i=1}^{N} \hat{\varepsilon}_i^2\right] = \sigma^2\delta_1$, and thus the variance can be estimated by Equation 5-4. It is known that $\left(\frac{\delta_1^2}{\delta_2}\hat{\sigma}^2 / \sigma^2\right)$ is approximated by a χ^2 distribution with δ_1/δ_2 degrees of freedom. From this fact, a reliable approximation of $\hat{\sigma}^2$ is obtained. With this estimate, the statistic shown in Equation 5-5 is used to approximate the confidence interval for *y* with δ_1/δ_2 degrees of freedom and a *t*-distribution.

$$\hat{\sigma}^2 = \sum_{i=1}^{N} \hat{\varepsilon}_i^2 / \delta_1 \tag{5-4}$$

$$\frac{\hat{y}(x) - y(x)}{\hat{\sigma}(x)} \tag{5-5}$$

This section has introduced the loess statistical procedure for nonparametric analysis that will be revisited later in this chapter. First, analysis of variance between AVI and test vehicle data are presented.

AUTOMATIC VEHICLE IDENTIFICATION COMPARISON TO INSTRUMENTED TEST VEHICLES

Analysis of Variance

An analysis of variance (ANOVA) was performed for the AVI and test vehicle data using the fixed effects models as shown in Equations 5-6 and 5-7. The travel time estimates including the mean, standard deviation, and coefficient of variation (c.v.) were aggregated to five-minute periods. The c.v. is defined as the ratio of the standard deviation to the mean. Though ANOVA is not the ideal test for testing the significance of the standard deviation and c.v., there simply is not another more applicable standard test for two-way analysis. To obtain ANOVA results over time on the travel time characteristics, the five-minute travel time estimates were studied over half-hour periods. All statistical tests were performed at the α=0.05 level of significance. The fixed effects model shown in Equation 5-6 was used to produce the results discussed in Table 5-1, while the fixed effects model shown in Equation 5-7 was used to produce the results discussed in Table 5-2. Equation 5-6 tests the significance of each day of the week and each time period within each day. Because these effects are not mutually exclusive (i.e., the time variable is a component of the day variable), there is no interaction term. Equation 5-7 includes the added effect of the data source along with the related interaction effects of data source with day of the week and time period.

$$y_{ij} = \mu + \beta_i + \tau_{j(i)} + \varepsilon_{ij} \quad (5\text{-}6)$$

where: y_{ij} = Value of jth observation at i;
μ = Population mean;
β_i = Effect due to day of week (i = 1 to 5);
$\tau_{j(i)}$ = Effect due to time period (j = 1 to 10 within i); and
ε_{ij} = Random error term.

$$y_{ijk} = \mu + \theta_i + \beta_j + \tau_{k(j)} + (\theta\beta)_{ij} + (\theta\tau)_{ik(j)} + \varepsilon_{ijk} \quad (5\text{-}7)$$

where: y_{ijk} = Value of kth observation at jth location in i;
μ = Population mean;
θ_i = Effect due to data source (i = 1 to 2);
β_j = Effect due to day of week (j = 1 to 5);
$\tau_{k(j)}$ = Effect due to time period (k = 1 to 10 within j);
$\theta\beta_{ij}$ = Interaction effect of θ_i and β_j;
$\theta\tau_{ik(j)}$ = Interaction effect of θ_i and $\tau_{k(j)}$; and
ε_{ijk} = Random error term.

TABLE 5-1 ANOVA Results on Travel Time Characteristics from AVI and Test Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Value (Degrees of Freedom)	
		Day of Week	Time Period
AVI	Average	**<0.0001 (4)**	**<0.0001 (45)**
	Standard Deviation	**0.0005 (4)**	**<0.0001 (45)**
	Coefficient of Variation	0.2947 (4)	0.0442 (45)
Test Vehicle	Average	**0.0033 (4)**	**<0.0001 (43)**
	Standard Deviation	0.3077 (4)	**0.0004 (42)**
	Coefficient of Variation	0.2301 (4)	0.4559 (42)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

TABLE 5-2 ANOVA Results on Travel Time Characteristics Comparing AVI and Test Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Value (Degrees of Freedom)				
		Data Source	Day of Week	Time Period	Interaction of Data Source and Day of Week	Interaction of Data Source and Time Period
Test Vehicle and AVI	Average	0.5563 (1)	**<0.0001 (4)**	**<0.0001 (45)**	0.8674 (4)	0.9999 (43)
	Standard Deviation	0.4521 (1)	**0.0111 (4)**	**<0.0001 (45)**	0.1367 (4)	0.1786 (42)
	Coefficient of Variation	–	–	–	**0.0209 (4)**	0.0793 (42)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Table 5-1 shows the results of the ANOVA for day of week and time period. Day of week was statistically significant for the mean of both the AVI ($p<0.0001$) and test vehicle ($p=0.0033$) data. Time period was also significant for each data source. The coefficient of variation was not statistically different by day of week or time period for either data source. This indicates that while the mean of each data source may differ statistically by day of week and time period, the ratio of standard deviation to the mean (c.v.) does not have a statistical difference. This is valuable information in situations when it may be difficult to obtain the variance of the travel time estimate (i.e., inductance loop detectors), as an estimate of the variance can be obtained if the c.v. is known.

Table 5-2 shows ANOVA results for the travel time characteristics of interest by comparing the AVI and test vehicle data sources as shown in Equation 5-7. The null hypothesis (H_o) is that the AVI and test vehicle travel time characteristic value is the same. The data source was not found to be significant ($p=0.5563$) when comparing the AVI and test vehicle mean and standard deviation data. The travel time mean and standard deviation were found to be statistically different by day of week and time period. Interaction effects between the data source and date were found for the c.v. ANOVA ($p=0.0209$). After plotting the interaction effects, it was found that the average c.v. ranged from 0.08 to 0.09 for the AVI data and 0.07 to 0.10 for the DMI data. This translates to a 200 percent larger range in variability (c.v.) within the DMI data source as compared to the AVI data. This larger range results in the significant interaction effects. These results indicate that the average travel time estimate from the test vehicles and AVI are not statistically different as may be expected.

Paired *t*-test Analysis

The drivers of the instrumented test vehicles also had AVI tags on the windshields of their vehicles. This provided the opportunity to directly compare the significance of the travel time mean estimates from the two different sources through the study corridor. Thirty-three percent (136 observations) of the travel time runs along the entire corridor from AVI reader #1 to AVI reader #5 were collected from the AVI system for comparison to the test vehicles.

Table 5-3 presents the mean travel time difference, percent difference, and statistical significance for the paired *t*-test comparing the AVI and test vehicles between the AVI antennas indicated along the corridor. The difference between AVI and test vehicles was at most 1.2 seconds which equates to a maximum 2.4 percent difference. A significant difference at the α=0.05 level was found for each link comparison except between the third and fifth AVI antennas #3 and #5 (p=0.3984). Though a statistical difference was found for most links, the average difference between the two data sources with regard to link travel time is 0.2 seconds. Therefore, while statistically there are differences, for the application of system monitoring discussed here, the difference would not likely make a practical difference.

TABLE 5-3 P-Values for Each Link for Paired *t*-test Comparing AVI and Test Vehicle Data

Link Defined by AVI Antennas	Number of Observations	Mean Difference (AVI-DMI) (seconds)	Percent Difference	P-Value
1 to 2	173	-0.5	-0.9	**<0.0008**
2 to 3	48	1.2	2.4	**<0.0001**
3 to 4	39	-0.5	-1.9	**0.0050**
4 to 5	126	0.6	0.8	**0.0006**
1 to 3	46	0.8	1.0	**0.0042**
3 to 5	39	0.1	0.0	0.3984
1 to 5	136	0.8	0.3	**<0.0001**

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Table 5-4 presents the results for the entire corridor from AVI antenna #1 to #5 (entire corridor length) by day of the week. The largest percent difference is 0.5 on Tuesday, and this equates to a 1.0 second difference between AVI and test vehicles. Given the other errors in the process, these differences are small and the added cost probably would not justify using the test-vehicle data collection method for system monitoring. This decision would ultimately be up to the agency/individual performing the data collection. Only Tuesday was statistically different at the α=0.05 level of significance. It is interesting to note that when all the days of the week in Table 5-4 are combined, a statistically significant result was found as shown in Table 5-3. Upon further investigation, it was found that the larger percent differences of 0.4 and 0.5 percent occur on Monday and Tuesday, respectively. When these days are removed, the results for the remaining days indicate there is no statistical difference (p=0.0278). The larger percent differences on Monday and Tuesday are likely attributed to the fact that the drivers were in a learning mode during the early part of the week. Table B-1 in Appendix B presents p-values and percent differences for all the links by day. Statistical differences were not found in 70 percent of the thirty tests performed across days and links.

TABLE 5-4 P-Values for Entire Corridor by Day Comparing AVI and Test Vehicle Data

Day	Number of Observations	Mean Difference (AVI-DMI) (seconds)	Percent Difference	P-Value
Monday	26	1.4	0.4	0.0284
Tuesday	28	1.0	0.5	**0.0012**
Wednesday	35	0.8	0.2	0.0265
Thursday	27	0.2	0.1	0.5750
Friday	20	1.8	0.1	0.4924

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Further analyses were performed to investigate the differences between the AVI and test vehicle mean travel time estimates by driver. Figure 5-1 presents the difference in seconds between the AVI and test vehicle (DMI) corridor travel time estimates plotted against the time of arrival to the corridor. Each number on the figure represents the driver numbers in Table 5-5. This figure visually displays that drivers two and four are often on the outer edges of the data. The average differences in travel time for drivers two and four are occasionally greater than five seconds while the average differences for the other drivers are below five seconds.

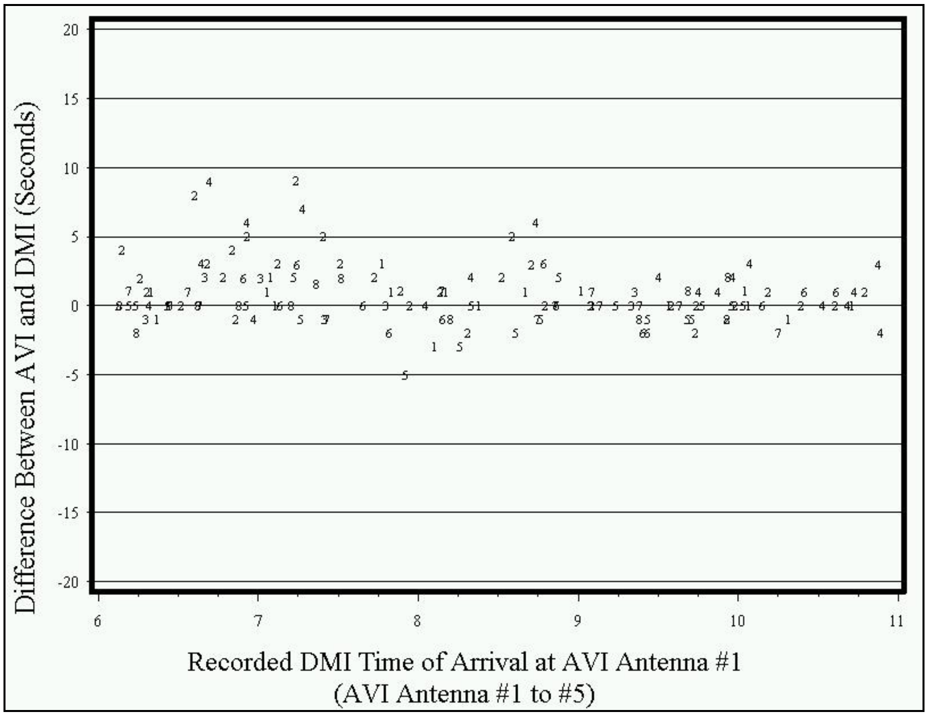

FIGURE 5-1 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver for Entire Corridor

TABLE 5-5 P-Values and Degrees of Freedom for Each Driver for Paired *t*-test Comparing AVI and Test Vehicle Data

Link Defined by AVI Antennas	Instrumented Test Vehicle Driver							
	#1	#2	#3	#4	#5	#6	#7	#8
1 to 2	0.1232 (29)	0.5497 (29)	0.1682 (8)	0.1176 (29)	0.0370 (18)	**0.0018 (22)**	**0.0012 (21)**	0.0266 (10)
2 to 3	0.1089 (8)	**0.0021 (7)**	–	**0.0103 (10)**	0.0304 (6)	0.4759 (2)	0.0797 (8)	–
3 to 4	0.6759 (6)	0.0645 (6)	–	0.4612 (9)	0.2172 (2)	0.0888 (3)	0.4831 (4)	0.4875 (1)
4 to 5	0.0588 (16)	**0.0003 (23)**	0.5312 (5)	**0.0103 (23)**	0.3592 (18)	0.3130 (15)	0.3147 (9)	0.7715 (9)
1 to 3	0.4293 (8)	0.1541 (6)	–	0.0910 (6)	0.2853 (6)	0.2491 (5)	0.98 99 (6)	1.0000 (2)
3 to 5	0.9873 (3)	0.2120 (5)	–	0.3491 (6)	0.2966 (5)	0.4021 (3)	0.0437 (6)	0.3850 (4)
1 to 5	0.2159 (16)	**0.0004 (32)**	0.3916 (8)	**0.0032 (18)**	0.1286 (19)	0.6445 (13)	0.9953 (11)	0.7354 (11)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.
Cells with no data present are indicated with "–."

Figure 5-2 shows the percent difference of the travel time estimates between AVI and test vehicles (DMI) by arrival time to the corridor. Again, drivers two and four are along the outside of the data plot. The maximum percent difference is two percent and is often the result of a driver two or four travel time run. The average percent difference is 0.3 percent. It is also interesting to note that the percent difference remains within two percent through congested and uncongested conditions. Figure B-1 to Figure B-12 in Appendix B present similar figures for each link of the corridor. Average percent differences remain below three percent for all links. While these percent differences are small, they do indicate that if DMI is being used, it is important to train the drivers, as even trained drivers will make errors.

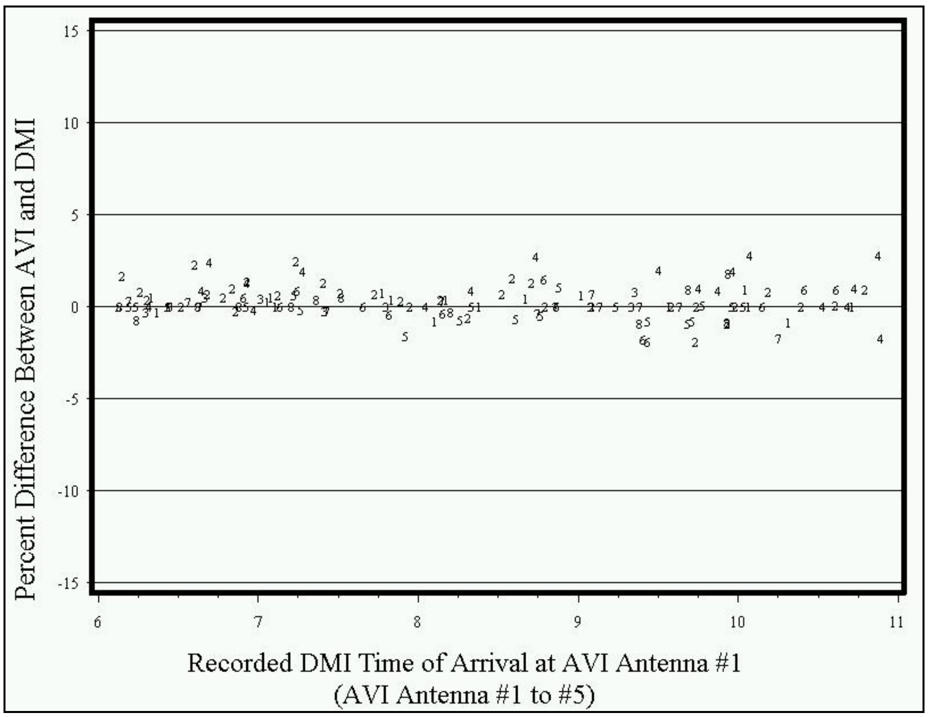

FIGURE 5-2 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver for Entire Corridor

Statistical differences were also investigated by driver with the paired *t*-test to further investigate the variability by driver (α=0.05 level of significance). Table 5-5 presents the p-values and degrees of freedom for each link for each driver. Drivers two and four have statistically different results for links two to three, four to five, and one to five. Drivers six and seven have statistically different results for link one to two. These results statistically validate the visual differences shown for drivers two and four in Figure 5-1 and Figure 5-2. Though the test vehicle drivers for this study were trained and they used the DMI prior to the data collection, these results indicate human error in measurement can still occur. It is imperative that test vehicle drivers be trained well in the use of the DMI before performing travel time data collection with the DMI. As shown here, even good instruction can result in errors, although the errors here will not likely make a practical difference. More importantly, the paired *t*-test analysis used here could be used to check the quality of data obtained from different drivers (i.e., which drivers need more training).

These results indicate small differences between the AVI and test vehicle (DMI) travel time estimates along the Houston study corridor. These differences average about two percent and are attributable to several factors that could not be controlled in this study. The first factor is the drivers themselves. Table 5-5 indicates that there are statistical differences between drivers. Though the drivers were trained on the method of test vehicle data collection for this study, human error in the marking of the checkpoints is still present. The second factor is the time when the AVI system receives a tag read. During congested conditions (i.e., speeds below 30 mph), it was observed that at times the AVI system will read a tag when the vehicle is upstream of the actual AVI antenna location, whereas, the drivers were instructed to hit the checkpoints below the AVI antennas. In addition, the "sensitivity" on a particular AVI antenna can be adjusted. If an AVI antenna's sensitivity is turned up, the antenna will read tags earlier than it would with low sensitivity settings. Finally, the physical directional setting of the AVI antenna can affect when a particular antenna reads a tag. Overall, the results are acceptable and the error range has been identified. It is anticipated that for most applications these results would be acceptable given the relative expense of performing a DMI run. Further, if market penetration is high, AVI can provide increased temporal and spatial travel time estimates with a higher reliability.

LOESS STATISTICAL FITTING TO ALL DATA SETS

The loess statistical procedure was used to provide corridor travel time estimates by time of day for all data sets for the US 290 corridor in Houston, Texas, to address the objectives noted at the beginning of this chapter. Loess is also used to provide travel time estimates of the differences between data sources. Two techniques were used as follows:

Technique 1: This technique demonstrates how loess can be used to obtain travel time estimates and confidence intervals over time for each individual data source (AVI, CVO, and test vehicle). From the travel time estimates provided by loess, the data are aggregated to five-minute averages for each individual data source. The five-minute differences between data sources of interest were then fit with loess. This technique results in the need to use loess twice. Though the loess procedure provides low-bias estimates, an estimate of the bias itself was considered and added to the estimated confidence intervals. This technique resulted in the need to estimate the fit bias twice because loess was used twice. Equation 5-8 shows how the fit bias was estimated.

Technique 2: This technique provides an estimate of the corridor travel time differences from two data sources of interest. This is estimated by taking the difference in the five-minute aggregated data from each data source first, and then performing loess on the resulting differences. The fit bias again was estimated in Equation 5-8 and added to the upper and lower confidence bounds. This technique does not include a loess travel time estimate on each individual data source as performed with technique one.

$$B_i = \left| I_i - F_i \right| \tag{5-8}$$

where: B_i = Absolute value of fit bias estimate at x_i;
I_i = Initial predicted value by loess procedure at x_i; and
F_i = Predicted value from loess procedure applied to I_i values.

Loess Statistical Smoothing

The sections that follow will describe the procedure and results of the Thursday data collection effort. Thursday was selected because it provided typical results of the week. Figures containing analyses from other days are contained in Appendix B.

The optimal smoothing value, γ, was identified by examining both linear and quadratic estimates for each data source and minimizing the GCV MSE in loess. Table 5-6 presents the smoother value, γ, number of data points, GCV MSE, and fit type for each day of data for test vehicles and AVI for technique one. Sample sizes for the test vehicles were relatively lower than AVI vehicles and ranged from seventy-three to ninety observations. The GCV MSE were 120 percent larger for the test vehicles than the AVI vehicles. There is also less variation in the smoother value for AVI data than the test vehicles. For AVI data, there is a 60 percent difference between the highest and lowest smoother value. For the DMI data, the difference is over 230 percent. This indicates that in developing loess estimators on individual AVI data, it may be possible to simply select a smoother value that is applicable for all days.

TABLE 5-6 Statistical Properties of AVI and Test Vehicle Data Source for Each Day of Data Using Technique One

Data Source	Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Test Vehicles	Monday	81	0.3865	0.1582	Quadratic
	Tuesday	90	0.1166	0.2816	Quadratic
	Wednesday	89	0.1188	0.4443	Linear
	Thursday	73	0.1713	0.4194	Linear
	Friday	74	0.1681	0.2744	Linear
AVI	Monday	1,523	0.0252	0.0811	Linear
	Tuesday	1,985	0.0204	0.1397	Linear
	Wednesday	1,853	0.0262	0.2286	Linear
	Thursday	2,023	0.0216	0.1589	Linear
	Friday	1,853	0.0327	0.1073	Linear

Figure 5-3 shows the corridor travel time by time of day for Thursday that was fitted with technique one for test vehicles. Asterisks mark the original data points and the loess linear interpolation is shown through the data along with the 95 percent confidence limits around the estimates. The confidence limits have been expanded by the addition of the bias estimate as calculated in Equation 5-8. Figure 5-4 shows a plot of the bias estimate for Thursday. The maximum value of the bias estimate is 0.03 minute (1.8 seconds) and similar results were found across all days. Figure B-13 to Figure B-20 of Appendix B provide the plots and bias estimates of the test vehicle data over time for the remaining days. The average bias across all days is approximately zero, and the maximum bias for the week occurs on Tuesday at 0.15 minute (nine seconds). Figure 5-3 and Figure 5-4 demonstrate how loess may be successfully used to provide a nonparametric locally weighted procedure to travel time data with small bias.

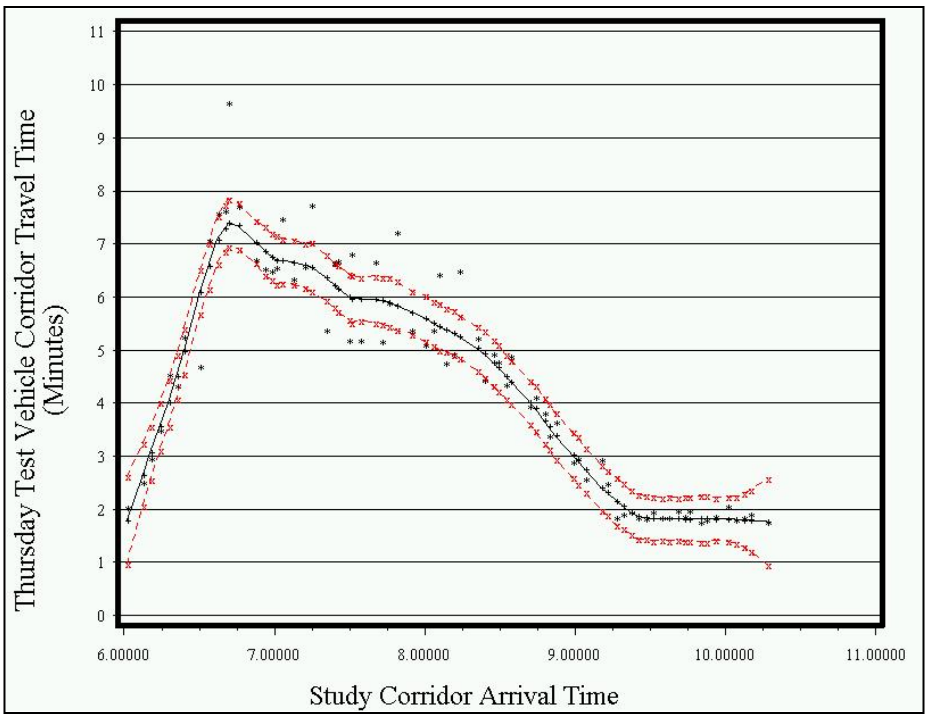

FIGURE 5-3 Thursday Corridor Travel Time by Time of Arrival for Test Vehicle Data Showing Loess Estimation and Confidence Interval

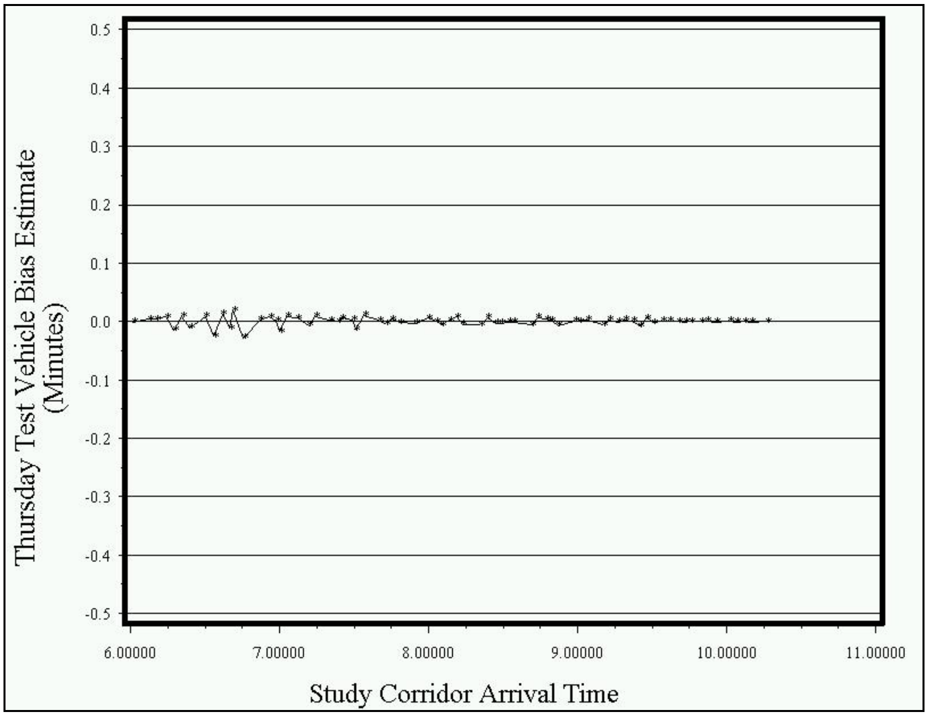

FIGURE 5-4 Thursday Bias Estimate by Time of Arrival for Test Vehicle (DMI) Data

Figure 5-5 presents the corridor travel time by time of arrival for the AVI vehicles on Thursday as fitted with the statistical properties shown in Table 5-6 for technique one. Figure 5-6 presents the bias estimate for this fitting as calculated with Equation 5-8 The maximum value of the bias estimate is 0.24 minutes (fourteen seconds), and the average bias across days for the AVI data is approximately zero. Figure B-21 to Figure B-28 present the plots of travel time estimates along with the confidence intervals that include the bias estimate, and graphs of the bias estimates over time for the remaining days of the AVI data.

After the initial fitting with the loess smoothing estimate as shown in Figure 5-3 and Figure 5-5, the predicted travel estimates were aggregated to five-minute periods for further study of the travel time characteristics and comparisons between AVI and test vehicles. Figure 5-7, Figure 5-8, and Figure 5-9, present the difference between the five-minute aggregation of AVI and test vehicle data for c.v., the bias estimate of the difference, and the final plot showing the confidence intervals with the bias added, respectively, for technique one with the Thursday data. From Figure 5-7, the maximum coefficient of variation difference between AVI and test vehicles is 0.05. The bias estimates as calculated with Equation 5-6 are shown in Figure 5-8, and the maximum is 0.10 minutes (six seconds). These values are then added to the confidence intervals presented in Figure 5-9, which shows the final difference between the AVI and test vehicles with technique one. The confidence bounds are approximately 0.5 minute (thirty seconds) across the data profile indicating the consistency across congested and uncongested periods in the estimation of the mean travel time difference.

Investigation of Figure 5-7 reveals the similarity in c.v. between AVI and test vehicles as the difference is near zero. The lack of statistical difference in c.v. was shown previously for each data source by time period (Table 5-1). Again, loess is used successfully to show the nonparametric relationship of the differences over time in Figure 5-9.

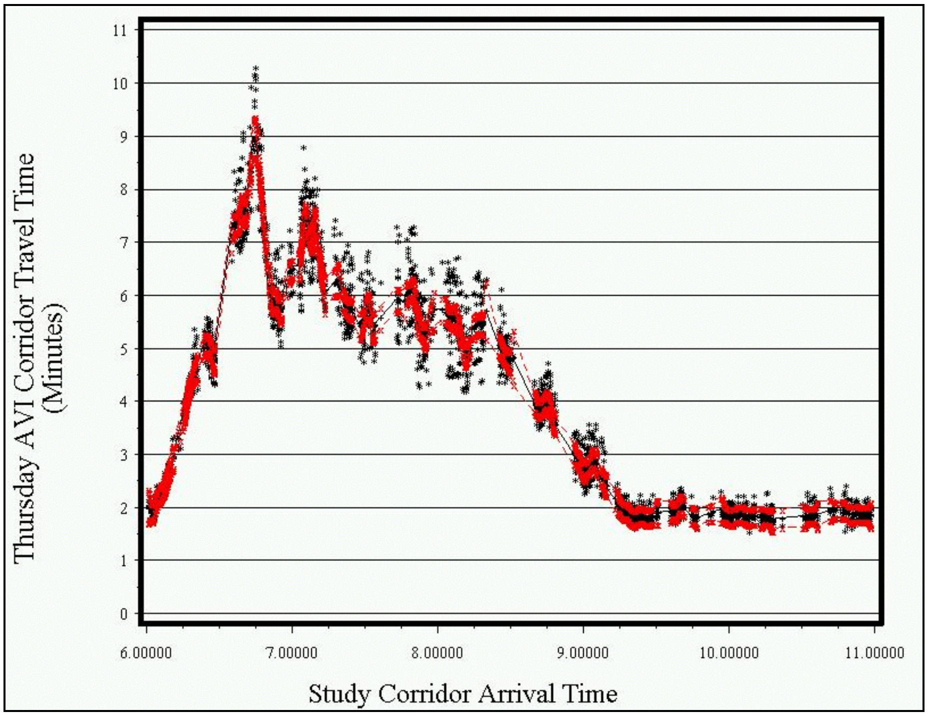

FIGURE 5-5 Thursday Corridor Travel Time by Time of Arrival for AVI Data Showing Loess Estimation and Confidence Interval

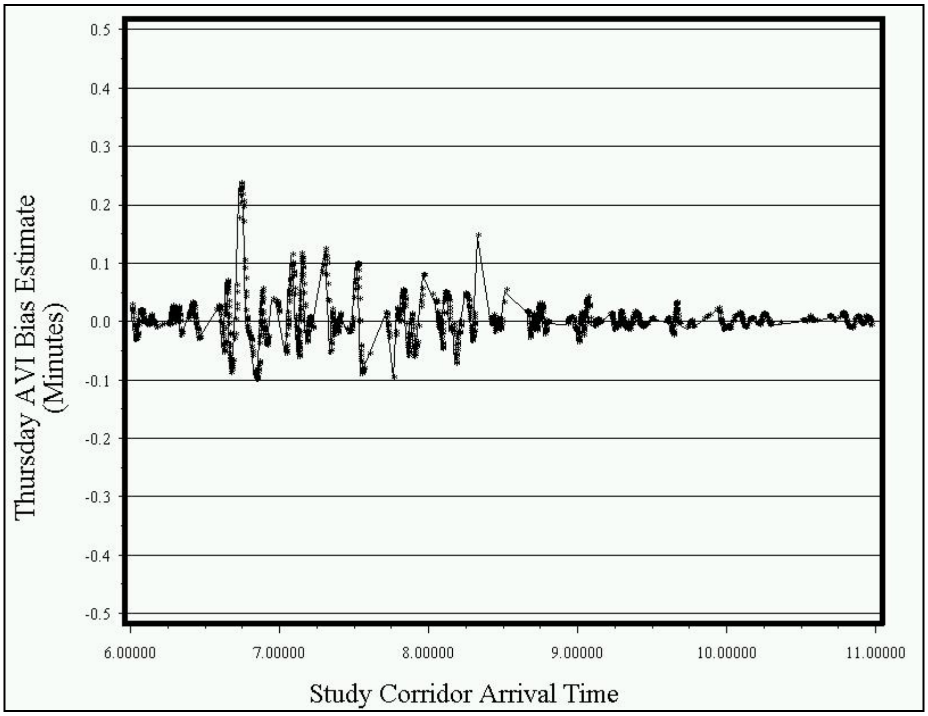

FIGURE 5-6 Thursday Bias Estimate by Time of Arrival for AVI Data

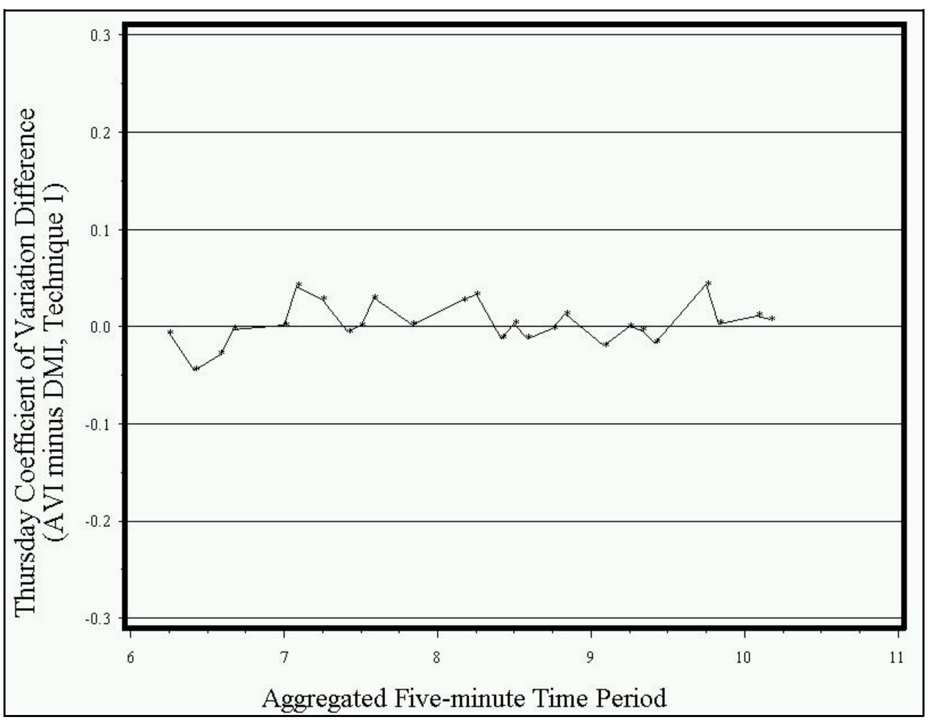

FIGURE 5-7 Thursday Coefficient of Variation Difference Between AVI and Test Vehicles with Technique One

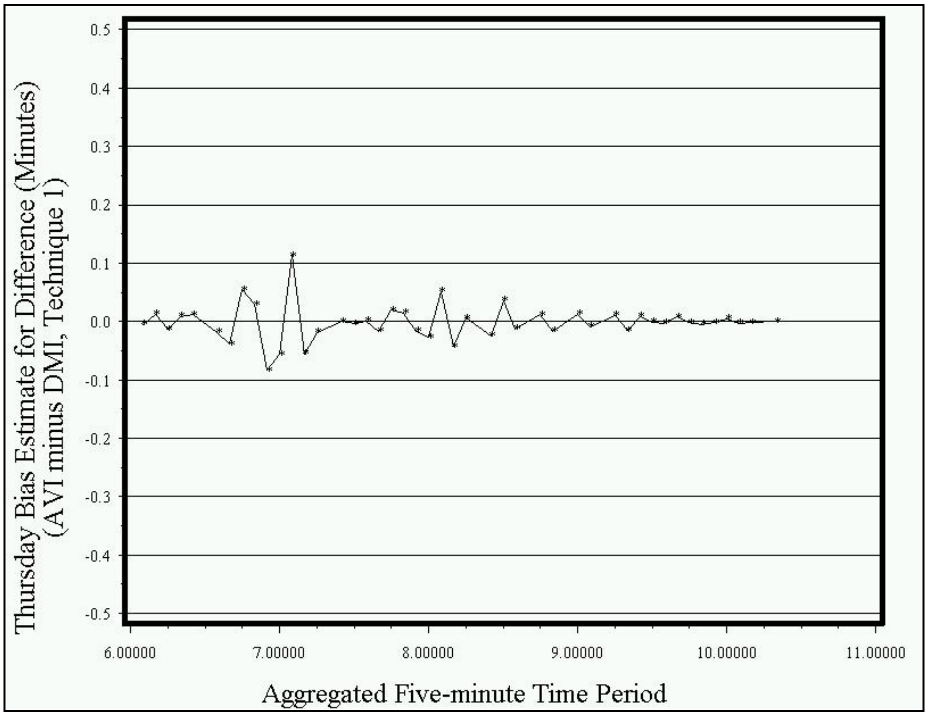

FIGURE 5-8 Thursday Bias Estimate for Differences Between AVI and Test Vehicles with Technique One

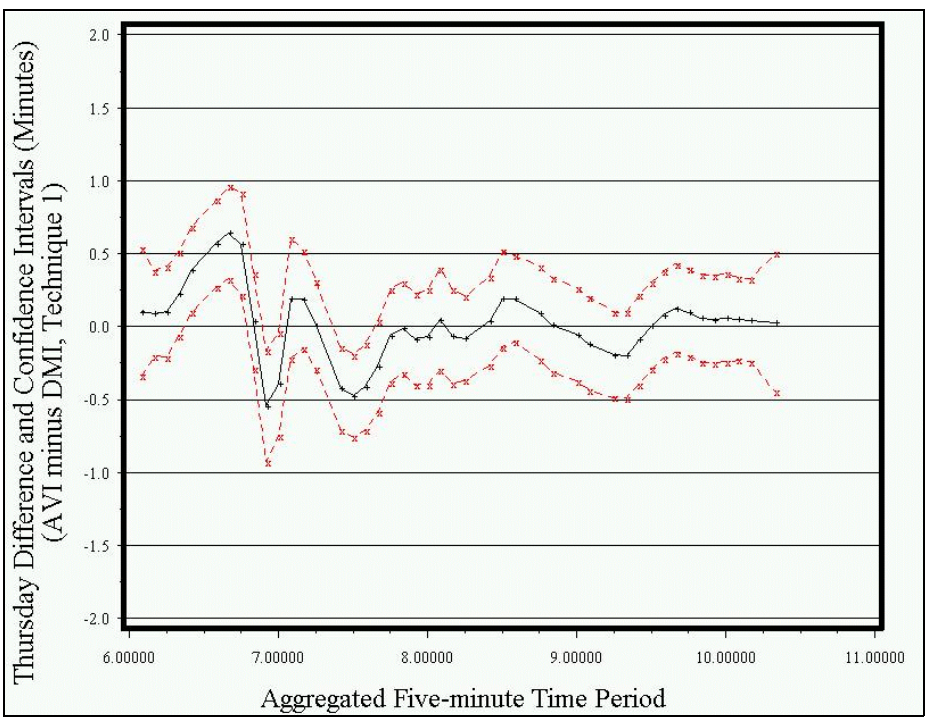

FIGURE 5-9 Thursday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

Table 5-7 shows the statistical properties of the smoothing that was performed on the five-minute aggregate differences for technique one. This is the second smoothing that was performed with this technique as shown in Figure 5-9. Sample sizes range from forty-five on Thursday to fifty-seven on Wednesday. The largest GCV MSE is 0.0917 on Thursday, the day which is shown in Figure 5-9. Figure B-29 to Figure B-55 in Appendix B present figures of the AVI variance, test vehicle variance, variance difference, c.v. difference, bias difference estimate, and final plots of differences with confidence intervals that include the added bias estimate for each day of data. The results of these additional days are similar to the Thursday data presented here, as the bias is low and always approximately zero. The loess procedure works successfully across days in providing the travel time difference estimate between AVI and test vehicles over time.

TABLE 5-7 Statistical Properties for Each Day of Data for Estimated Bias of Differences Between AVI and Test Vehicles for Technique One

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	49	0.1956	0.0579	Quadratic
Tuesday	53	0.9147	0.0568	Quadratic
Wednesday	57	0.1001	0.0855	Linear
Thursday	45	0.1234	0.0917	Linear
Friday	46	0.0976	0.0768	Linear

Table 5-8 presents the summary statistics of the second nonparametric fit bias for each day. The average bias is approximately zero, and the largest absolute value of the estimated bias occurs on Friday at 0.15 minutes (nine seconds). Investigation of Table 5-8 reveals that the nonparametric fit bias is approximately zero. Therefore, while fit bias can be estimated with this technique, its affect on the results presented in this report are effectively zero. This will be shown in subsequent sections also. Table 5-9 presents percent differences between the five-minute aggregations of the AVI and test vehicle data for Thursday. The table presents the travel time estimates of mean, variance, and coefficient of variation for different congestion levels. Across all congestion levels, the percent difference of the mean travel time was less than 0.5 percent. Variance and coefficient of variation data resulted in larger percent differences. For variance, the largest percent difference of -346.32 percent occurs when speeds are less than, or equal to, thirty miles per hour. The percent difference values can become very large (e.g., greater than 1,000 percent) due to division by such small numbers in the percent change calculations. Tables B-2 through B-5 in Appendix B present similar tables for the other days of data collection.

TABLE 5-8 Summary Statistics for Bias Estimate for Technique One Across Days

Day	Bias Estimate Statistics				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	49	0.00	0.01	-0.03	0.02
Tuesday	53	0.00	0.00	0.00	0.00
Wednesday	57	0.00	0.03	-0.07	0.05
Thursday	45	0.00	0.03	-0.08	0.11
Friday	46	-0.01	0.05	-0.15	0.10

TABLE 5-9 Percent Differences Between AVI and Test Vehicles for Thursday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Thursday	Mean	All data	45	0.21	6.82	-19.99	11.85
		≥65 mph	6	0.41	2.4	-3.95	2.51
		31 to 64 mph	14	0.49	7.48	-14.65	11.85
		≤30 mph	25	0.01	7.33	-19.99	11.69
	Variance	All data	26	-212.66	680.35	–	100.00
		≥65 mph	4	-41.5	267.76	-443.13	95.74
		31 to 64 mph	7	-24.04	98.01	-205.04	99.89
		≤30 mph	15	-346.32	872.8	–	100.00
	Coefficient of Variation	All data	26	-22.03	137.34	-459.17	99.63
		≥65 mph	4	23.21	98.38	-124.2	78.84
		31 to 64 mph	7	3.56	52.46	-73.96	96.39
		≤30 mph	15	-46.04	170	-459.17	99.63

Note: Cells with differences greater than one thousand are indicated with a "–."

Table 5-10 presents the average percent differences between AVI and test vehicles for the week. The largest percent difference (1.14 percent) was found during congested conditions (≤30 mph), and the largest percent difference in the ratio of the standard deviation to the mean (c.v.) is experienced when speeds are ≥65 mph (-326.94). The largest percent difference in variance (less than negative 1,000 percent) is also found during free-flow conditions. These numbers indicate that during congested periods there are generally larger differences between the AVI and test vehicles. This is hypothesized to be due to the differences when the driver marks the checkpoints and when the AVI tag is read. Further, the largest difference in c.v. was found during uncongested periods, which is possibly due to the instrumented vehicle drivers switching to a floating-car method for safety reasons (rather than a chase-car method) as speeds exceeded the posted speed limit of 65 mph. This switch could also contribute to the relatively large variance percent differences. Another cause for the large percent differences on the variance is the division by numbers less than one in the percent difference calculation.

TABLE 5-10 Average Percent Differences Between AVI and Test Vehicles for the Week of Data for Technique One

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	0.65	–	-138.83
≥65 mph	-0.49	–	-326.94
31 to 64 mph	0.01	–	-69.16
≤30 mph	1.14	-350.09	-52.77

Note: Cells with differences greater than one thousand are indicated with a "–."

Technique one demonstrated success in providing a nonparametric estimate of travel time for individual data sources for DMI (Figure 5-3) and AVI (Figure 5-5). It was also demonstrated that the technique can be used to provide nonparametric relationships of the differences in estimated travel time along the corridor with the 95 percent confidence intervals. The percent differences on the variance and c.v. were quite large, however, and it will be shown in the next section that technique two reduces these errors.

Loess Statistical Smoothing with Technique Two

The loess statistical smoothing technique was used to compare the AVI and test vehicle data with the second technique. Recall that technique two included aggregating the observed data to five-minute intervals and then performing the loess smoothing to obtain the travel time characteristic estimates. With this technique, only one statistical smoothing was performed; and, therefore, only one estimated fit bias was computed. Table 5-11 includes the smoother values, γ, number of data points, GCV MSE, and fit type for each day of data for each data source with technique two. The GCV MSE ranges from 0.1147 to 0.1809 with the largest GCV MSE occurring when the most amount of data were available (n=57) on Wednesday. It is interesting to note that the loess smoother is 1.0 for all days except Tuesday. This indicates that all the data were used in the local smoothing of the locally weighted estimate. In contrast, for technique one, about 30 percent of the data were used in the local predicted estimate.

TABLE 5-11 Statistical Properties of Each Data Source for Each Day of Data for Estimated Bias of Differences Between AVI and Test Vehicles for Technique Two

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	49	1.0000	0.1809	Linear
Tuesday	53	0.9507	0.1287	Quadratic
Wednesday	57	1.0000	0.1492	Linear
Thursday	45	1.0000	0.1679	Linear
Friday	46	1.0000	0.1147	Linear

Figure 5-10 illustrates the coefficient of variation difference between AVI and test vehicles performed with technique two. The maximum c.v. difference is -0.25. Figure 5-11 presents the fit bias estimate for the smoothing over time. The average estimated bias is approximately zero. Figure 5-12 presents the difference between AVI and test vehicles, along with the confidence intervals including the estimated bias, for technique two. It can be seen that the plot is much smoother than the plot obtained with technique one (Figure 5-9). In addition, the percent difference between AVI and test vehicles is within 0.55 percent across the data collection time period. Figure B-56 to Figure B-82 present similar plots for each day for the AVI variance, test vehicle variance, variance difference, c.v. difference, bias estimate, and confidence intervals including the bias estimate around the smoothed loess predictions.

Table 5-12 presents the summary statistics for the bias estimates for technique two across days. Again, the average bias estimate was approximately zero. Calculations were carried out with all digits and then rounded. The numbers in Table 5-12 shown in parentheses are rounded to the appropriate number of significant digits. Similar results were found for technique one. Table 5-13 presents the percent differences between AVI and test vehicles for Thursday by congestion level that resulted from technique two. Table B-6 through Table B-9 in Appendix B contain similar tables for the remaining days of data collection for comparison. The largest percent difference of the mean (2.3 percent) occurs during free-flow conditions while the largest percent difference of c.v. occurs during the most congested period (≤30 mph) at -79.8 percent. The larger difference during free-flow conditions may be attributed to the different data collection method being used (floating-car test vehicles rather than chase-car).

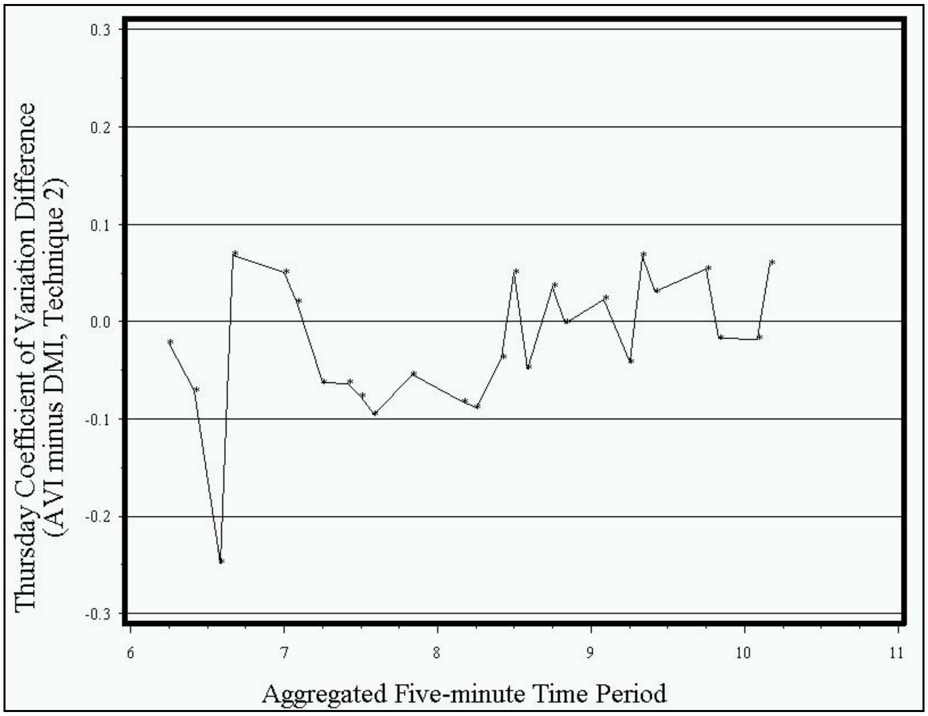

FIGURE 5-10 Thursday Coefficient of Variation Difference Between AVI and Test Vehicles with Technique Two

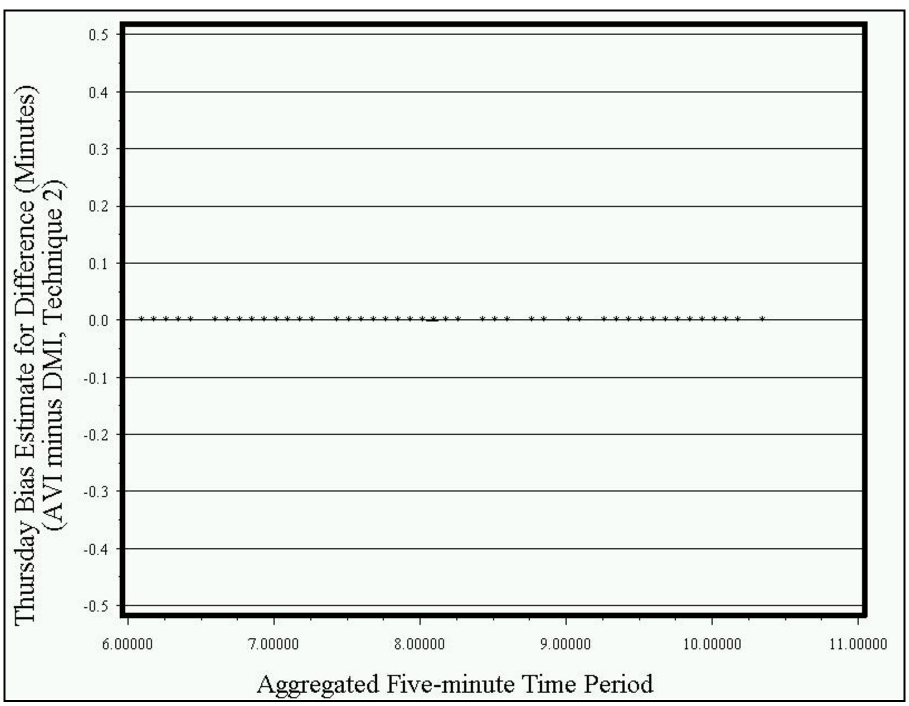

FIGURE 5-11 Thursday Bias Estimate for Difference Between AVI and Test Vehicles with Technique Two

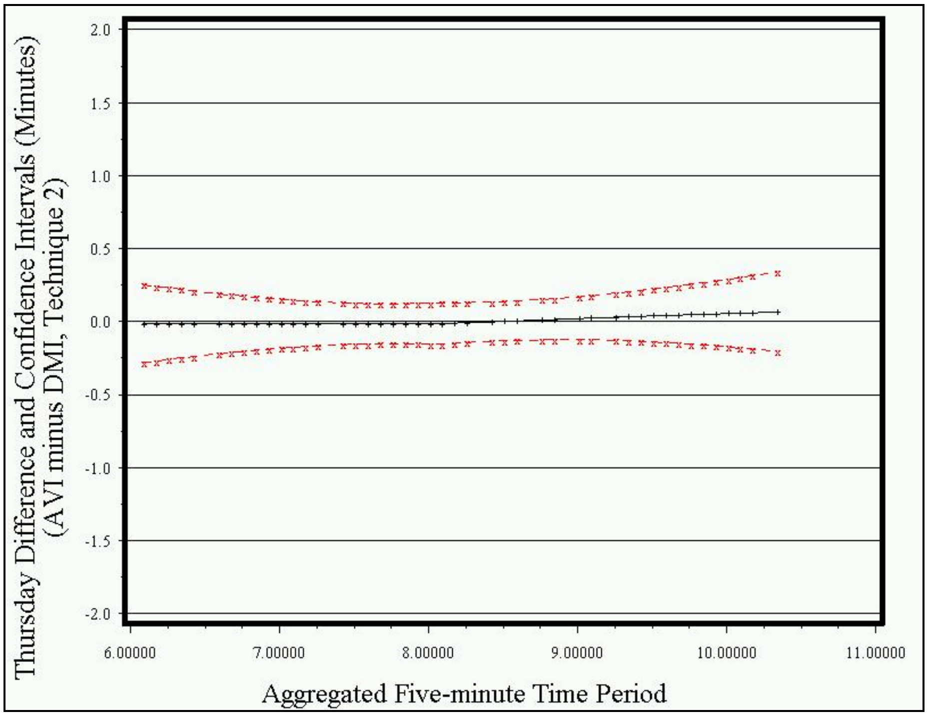

FIGURE 5-12 Thursday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

TABLE 5-12 Summary Statistics for Bias Estimate for Technique Two Across Days

Day	Bias Estimate Statistics Calculated Value (Rounded)				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	49	9.796×10^{-8} (0.00)	0.0000296 (0.00)	-0.0001 (0.00)	0.0001 (0.00)
Tuesday	53	-0.000075 (0.00)	0.00102 (0.00)	-0.00282 (0.00)	0.00336 (0.00)
Wednesday	57	-5.54×10^{-16} (0.00)	8.12×10^{-15} (0.00)	-5.70×10^{-14} (0.00)	1.77×10^{-14} (0.00)
Thursday	45	1.28×10^{-6} (0.00)	0.000101 (0.00)	-0.0005 (0.00)	0.000393 (0.00)
Friday	46	-2.14×10^{-6} (0.00)	0.000103 (0.00)	-0.000336 (0.00)	0.000405 (0.00)

TABLE 5-13 Percent Differences Between AVI and Test Vehicles for Thursday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Thursday	Mean	All data	45	0.55	7.91	-28.76	14.59
		≥65 mph	5	2.28	2.28	-0.31	5.37
		31 to 64 mph	15	1.51	8.93	-28.76	10.22
		≤30 mph	25	-0.37	8.08	-13.86	14.59
	Variance	All data	26	-225.53	681.43	–	99.81
		≥65 mph	3	32.38	82.38	-61.09	94.14
		31 to 64 mph	8	-9.00	126.71	-292.58	95.44
		≤30 mph	15	-392.60	865.59	–	99.81
	Coefficient of Variation	All data	26	-38.68	133.91	-597.61	95.65
		≥65 mph	3	29.10	52.84	-28.43	75.46
		31 to 64 mph	8	13.04	46.55	-53.88	77.66
		≤30 mph	15	-79.81	161.90	-597.61	95.65

Note: Cells with differences greater than one thousand are indicated with a "–."

Table 5-14 presents the average percent differences between AVI and test vehicles for the week using technique two. The largest percent difference of the mean of AVI and test vehicles is 2.01 percent, and it occurs on "the shoulders" of congested periods (31 to 64 mph). It is hypothesized that these differences are attributable to the difference in when the instrumented test vehicle driver marks the checkpoints and when the AVI system reads the tags. The largest variance percent difference (-202.73) and the largest c.v. percent difference (-37.63) occur during the most congested period (≤30 mph).

Table 5-15 presents the percent difference between the two techniques for estimating the mean, variance, and coefficient of variation differences over aggregated five-minute periods. The results indicate that the difference between the two techniques can be up to 100 percent in mean and over 1,000 percent in variance and c.v. These relatively large differences seem to occur because of the two smoothing steps that are performed in the first technique. Initially smoothing the data prior to taking five-minute differences and then smoothing the differences themselves results in these large percent differences. Because the standard deviation is often less than one minute, squaring these values results in even larger values and, subsequently, larger percent differences.

TABLE 5-14 Average Percent Differences Between AVI and Test Vehicles for the Week of Data for Technique Two

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	0.81	-106.51	-11.85
≥65 mph	-0.91	-21.93	8.61
31 to 64 mph	2.01	24.72	18.29
≤30 mph	0.83	-202.73	-37.63

TABLE 5-15 Percent Differences Between Techniques One and Two Comparing AVI and Test Vehicle Data

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	-19.90	–	–
≥65 mph	-46.39	–	–
31 to 64 mph	-99.50	–	278.15
≤30 mph	36.09	72.69	40.23

Note: Cells with differences greater than one thousand are indicated with a "–."

The application of loess to provide differences between the AVI and test vehicle data sources was more successful with technique two because the two data sources are within two percent. Technique two also provides smoother relationships as shown in Figure 4-12. These graphs are easier to read and are more intuitive than those found with technique one (Figure 5-9). Technique one is valuable when nonparametric relationships are desired for individual data sources. This demonstrates that loess can be used for travel time estimation from AVI data. The travel time mean and variance information from loess could be provided in real-time via Internet traffic maps to inform drivers of traffic conditions.

COMMERCIAL VEHICLE DATA COMPARISON TO AUTOMATIC VEHICLE IDENTIFICATION DATA

Analysis of Variance

ANOVA on the fixed effects shown in Equation 5-6 and Equation 5-7 was performed for comparing the CVO and AVI data after travel time characteristic data were aggregated to five-minute periods. The travel time estimates included the mean, standard deviation, and c.v. To obtain ANOVA results over time on the travel time characteristics, the five-minute travel time estimates were studied over half-hour periods. All statistical tests were performed at the $\alpha=0.05$ level of significance. The fixed effects model shown in Equation 5-6 was used to produce the results provided in Table 5-16, while the fixed effects model shown in Equation 5-7 was used to produce the results provided Table 5-17.

Table 5-16 shows the results of the ANOVA for day of week and time period. The day of week and time period were found to be statistically significant for the CVO data and the AVI data ($p<0.0001$ for all). The c.v. was not statistically significant across dates for either data source. This indicates that while CVO data and AVI data are different by day of the week, the ratio of the standard deviation relative to the mean (c.v.) does not vary from day-to-day by data source. The c.v. was statistically different across time periods ($p=0.0042$) for the CVO data, and the c.v. was not statistically significant for the AVI data ($p=0.0442$). As indicated in the previous ANOVA section, these results for the AVI data demonstrate that the variability about the mean (c.v.) appears to stay relatively constant across days and time periods. It is intuitive that commercial vehicles would vary across time periods as the larger vehicles would be more affected in terms of acceleration characteristics during congested and non-congested conditions.

TABLE 5-16 ANOVA Results on Travel Time Characteristics from CVO and AVI Data Sources

Data Source	Travel Time Variable Tested	P-Value (Degrees of Freedom)	
		Day of Week	Time Period
CVO	Average	**<0.0001 (4)**	**<0.0001 (37)**
	Standard Deviation	**0.0062 (4)**	**<0.0001 (37)**
	Coefficient of Variation	0.8833 (4)	**0.0042 (37)**
AVI	Average	**<0.0001 (4)**	**0.0001 (45)**
	Standard Deviation	**0.0005 (4)**	**<0.0001 (45)**
	Coefficient of Variation	0.2947 (4)	0.0442 (45)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

TABLE 5-17 ANOVA Results on Travel Time Characteristics Comparing CVO and AVI Data Sources

Data Source	Travel Time Variable Tested	P-Value (Degrees of Freedom)				
		Data Source	Day of Week	Time Period	Interaction of Data Source and Day of Week	Interaction of Data Source and Time Period
CVO and AVI	Average	**<0.0001 (1)**	**<0.0001 (4)**	**<0.0001 (45)**	0.7655 (4)	0.7061 (37)
	Standard Deviation	**0.0119 (1)**	**<0.0001 (4)**	**<0.0001 (45)**	0.8666 (4)	0.3339 (37)
	Coefficient of Variation	0.9736 (1)	0.4810 (4)	**<0.0001 (45)**	0.8064 (4)	0.3424 (37)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Table 5-17 presents the p-values and degrees of freedom for additional ANOVA for travel time characteristics comparing the CVO and AVI data sources as shown in the model in Equation 5-7. The null hypothesis (H_o) is that the CVO and AVI value is the same. The interaction effects were not found to be significant for any of the analyses performed. The results indicate that the CVO and AVI travel time means are statistically different ($p<0.0001$). The c.v. of the CVO and AVI data sources were not found to be significantly different ($p=0.9736$). This indicates that while the mean of each data source is significantly different between commercial and AVI vehicles, the ratio of the standard deviation and the mean does not vary by day. A similar result was found across days. While the travel time mean between CVO and AVI vehicles are statistically different by day of week, the c.v. of the two different data sources is not statistically different. The time period was found statistically significant for the mean, standard deviation, and c.v. These results indicate that between the two data sources, the standard deviation relative to the mean varies by time period along with the mean and standard deviation. This is expected for the different operating characteristics of commercial vehicles and passenger cars during varying traffic conditions such as congested and non-congested conditions.

Loess Statistical Smoothing

The loess statistical smoothing of the CVO and AVI data are discussed in this section. The smoothing of the AVI data along with the bias estimate for the Thursday day of data were previously presented in Figure 5-5 and Figure 5-6. Figure 5-13 shows the corridor travel time by time of arrival for the CVO data showing the loess estimation and confidence intervals that include the bias estimate. The value of the bias estimate over time is shown in Figure 5-14. It can be seen that the maximum value of the bias estimate is 0.25 minute (15 seconds). The average bias estimate for all days was approximately zero. Figure B-83 through Figure B-90 present the graphs of estimated travel time with the confidence intervals that include the bias estimate along with graphs of the bias estimate for each day of CVO data. Table 5-18 summarizes the statistical properties of the CVO and AVI data sources for each day of data for smoothing technique one. The GCV MSE ranges from 0.1234 for the Friday data to 0.2424 with the Wednesday data. The AVI data source includes about three times the number of observations as the CVO data for a given day, and the minimized GCV MSE values range from 0.0811 to 0.2286.

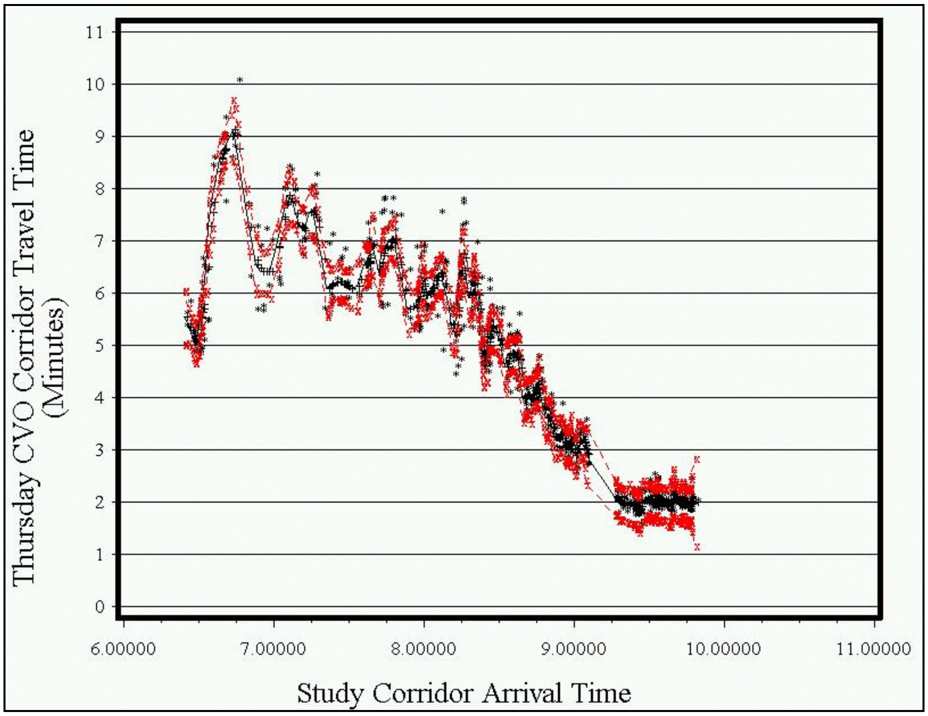

FIGURE 5-13 Thursday Corridor Travel Time by Time of Arrival for CVO Data Showing Loess Estimation and Confidence Interval

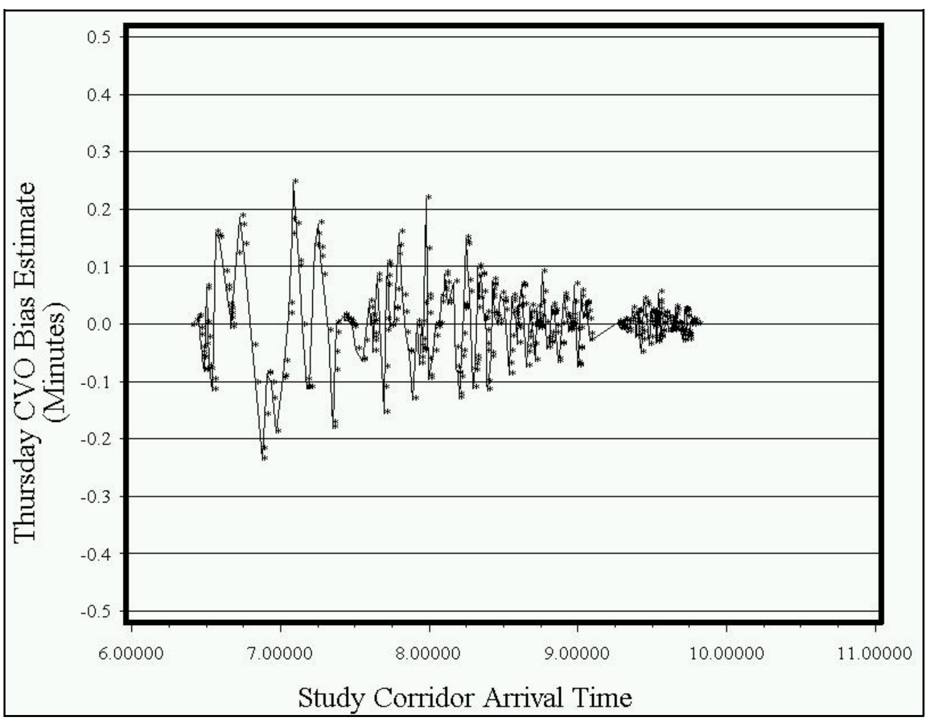

FIGURE 5-14 Thursday Bias Estimate by Time of Arrival for CVO Data

TABLE 5-18 Statistical Properties of CVO and AVI Data Source for Each Day of Data Using Technique One

Data Source	Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
CVO	Monday	654	0.1002	0.1407	Quadratic
	Tuesday	684	0.0286	0.1785	Quadratic
	Wednesday	688	0.0387	0.2424	Quadratic
	Thursday	506	0.0266	0.2218	Linear
	Friday	828	0.0210	0.1234	Linear
AVI	Monday	1,523	0.0252	0.0811	Linear
	Tuesday	1,985	0.0204	0.1397	Linear
	Wednesday	1,853	0.0262	0.2286	Linear
	Thursday	2,023	0.0216	0.1589	Linear
	Friday	1,853	0.0327	0.1073	Linear

The results of the loess travel time estimation are similar to the Thursday data presented here, as the bias is always approximately zero. The loess technique was successfully used to provide travel time estimates for the CVO data source over time, including 95 percent confidence limits. This demonstrates that loess could be used to provide commercial vehicle travel time information in real-time when such information is available.

After the loess smoothing was performed for the entire corridor for both the AVI and CVO data, the data were aggregated to five-minute intervals. Figure 5-15 presents the difference between the AVI and CVO c.v. It may be seen in Figure 5-15 that the largest c.v. difference between AVI and CVO data is 0.11. Figure 5-16 presents the bias estimate for the loess smoothing, and Figure 5-17 presents the graph of the smoothed predicted values with the confidence intervals that include the bias estimate for the Thursday data. It can be seen in Figure 5-17 that CVO vehicles require more time [up to 0.7 minute (forty-two seconds)] during congestion than the AVI-equipped vehicles and this difference nears zero at 10:00 a.m. during free-flow conditions. The bias estimates were calculated as shown in Equation 5-6, and the maximum for Thursday was calculated as 0.0047 minute (rounded to 0.00 with appropriate level of significant digits). It can also be seen in Figure 5-16 that the estimated fit bias is very small.

Table 5-19 shows the statistical properties of the smoothing across days that was performed on the five-minute aggregate differences for technique one. Recall that this is the second loess smoothing performed with this technique. Sample sizes vary from 39 to 49, and the largest GCV MSE is 0.1154 on Thursday. Figures B-91 to B-112 present figures of the CVO variance, variance difference between CVO and AVI, c.v. difference, bias difference estimate, and final graphs of the differences including the confidence intervals with the added bias estimate for each day.

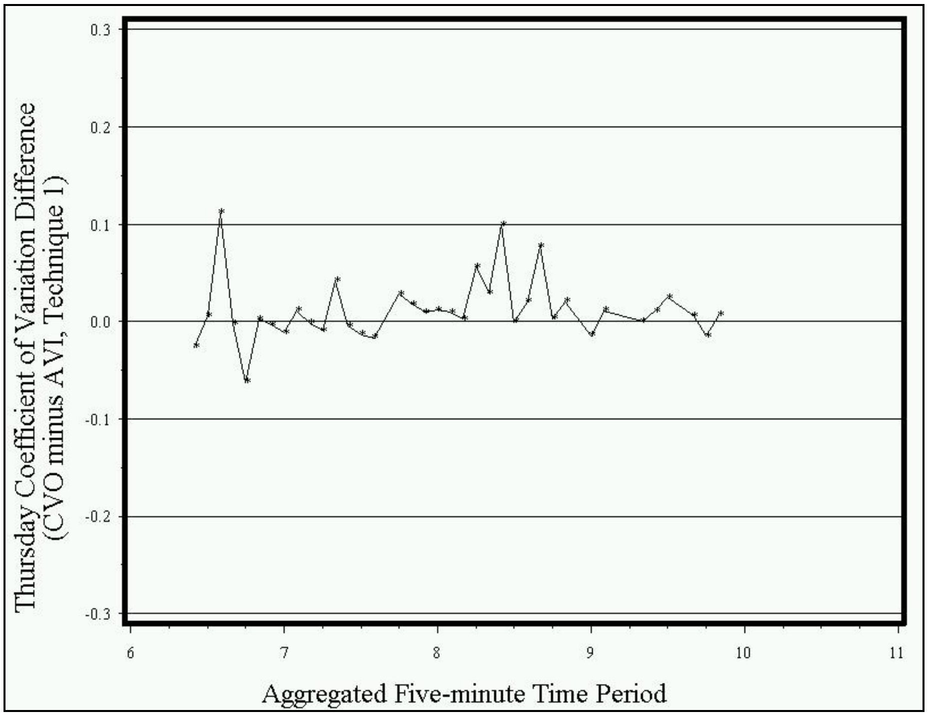

FIGURE 5-15 Thursday Coefficient of Variation Difference Between AVI and CVO Vehicles with Technique One

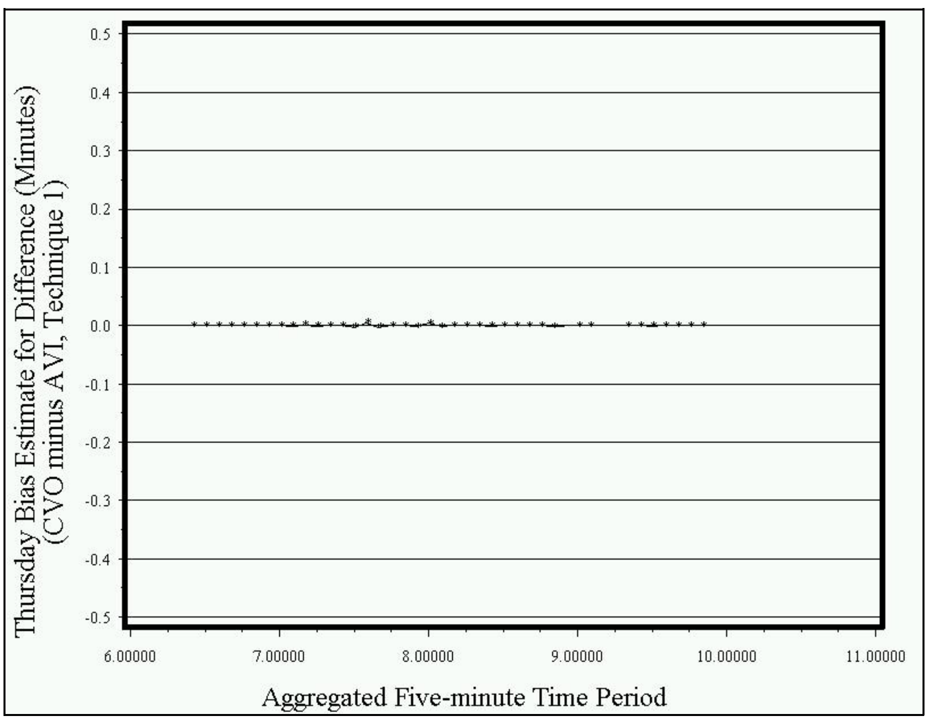

FIGURE 5-16 Thursday Bias Estimate for Differences Between AVI and CVO with Technique One

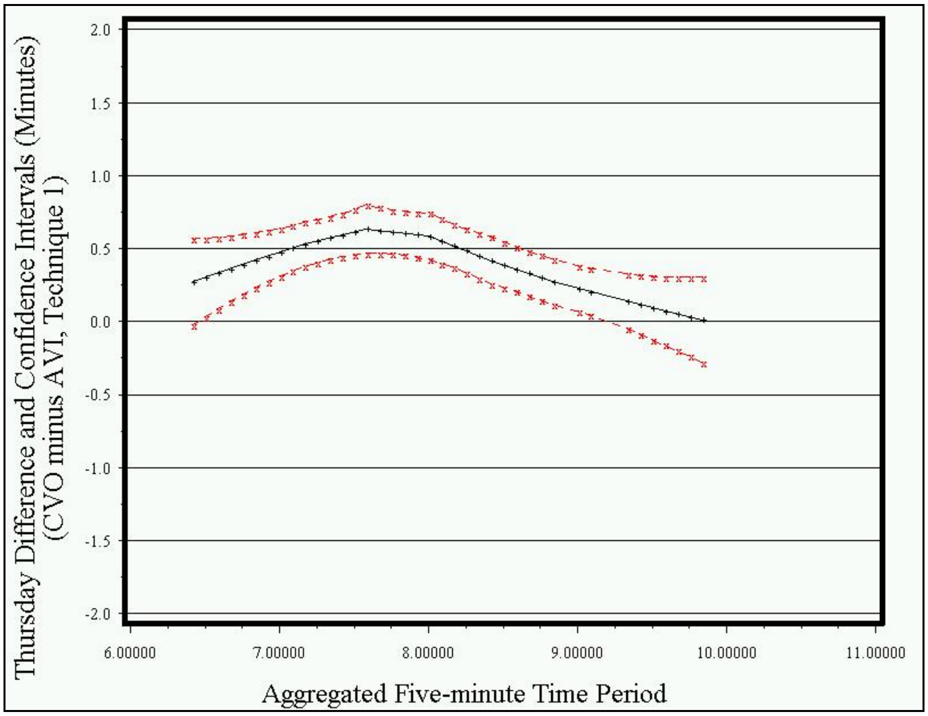

FIGURE 5-17 Thursday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

TABLE 5-19 Statistical Properties for Each Day of Data for Estimated Bias of Differences Between CVO and AVI for Technique One

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	40	0.9881	0.0503	Quadratic
Tuesday	41	1.0000	0.1036	Linear
Wednesday	49	0.1108	0.0984	Linear
Thursday	39	0.6468	0.1154	Linear
Friday	45	0.3195	0.0408	Linear

Table 5-20 shows the summary statistics for the estimated bias for each day. The average bias is approximately zero minutes, and the largest absolute value of the estimated bias occurs on Wednesday at 0.07 minute (4 seconds). These values are significant to the 0.01 decimal place, as shown in parentheses. Calculations were carried out to sixteen decimal values and then rounded appropriately in the last step. Table 5-21 presents the percent differences between the five-minute aggregations of the AVI and CVO data for Thursday. The travel time estimates of mean, variance, and coefficient of variation by different congestion levels are presented. The largest percent difference of the mean travel time was 8.8 percent during congested conditions (≤30 mph). The variance and c.v. resulted in much larger percent differences—greater than 1,000 percent difference during congested periods for the variance. Division by such small numbers in the calculation of the variances likely causes these large values.

TABLE 5-20 Summary Statistics for Bias Estimate for Technique One Across Days

Day	Bias Estimate Statistics Calculated Value (Rounded)				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	40	0.000057 (0.00)	0.000858 (0.00)	-0.0023 (0.00)	0.0028 (0.00)
Tuesday	41	0.00000178 (0.00)	0.000197 (0.00)	-0.00047 (0.00)	0.00094 (0.00)
Wednesday	49	0.00016 (0.00)	0.026 (0.03)	-0.069 (0.07)	0.053 (0.05)
Thursday	39	0.0000077 (0.00)	0.0012 (0.00)	-0.0024 (0.00)	0.0047 (0.00)
Friday	45	0.00093 (0.00)	0.0020 (0.00)	-0.0039 (0.00)	0.0042 (0.00)

TABLE 5-21 Percent Differences Between AVI and CVO for Thursday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Thursday	Mean	All data	39	7.80	5.88	-11.14	19.06
		≥65 mph	3	6.17	2.17	3.66	7.48
		31 to 64 mph	9	5.39	4.20	0.13	13.48
		≤30 mph	27	8.78	6.43	-11.14	19.06
	Variance	All data	37	–	–	-99.91	–
		≥65 mph	3	427.18	191.04	249.31	629.10
		31 to 64 mph	8	–	–	-54.18	–
		≤30 mph	26	–	–	-99.91	–
	Coefficient of Variation	All data	37	299.30	910.57	-97.34	–
		≥65 mph	3	113.47	35.69	80.29	151.23
		31 to 64 mph	8	118.47	309.54	-34.10	880.31
		≤30 mph	26	376.38	–	-97.34	–

Note: Cells with differences greater than one thousand are indicated with a "–."

Table 5-22 presents the average percent differences between AVI and CVO data for the week. The largest percent difference (6.63 percent) was experienced when speeds were ≤30 mph. The largest c.v. difference (greater than 1,000 percent) was experienced during free-flow conditions. The large variance differences are due to the division of the relatively smaller variances on the AVI data in the calculation of the percent differences. The large differences in the c.v. during free-flow conditions indicate the variability of commercial vehicles operating differently than AVI-equipped vehicles during those traffic conditions.

TABLE 5-22 Average Percent Differences Between AVI and CVO for the Week of Data for Technique One

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	6.14	–	–
≥65 mph	6.48	–	–
31 to 64 mph	4.73	–	117.4
≤30 mph	6.63	–	137.35

Note: Cells with differences greater than one thousand are indicated with a "–."

Similar to the AVI and test vehicle comparison earlier in this chapter, it was found that technique one was adequate for providing a nonparametric travel time estimate for the individual data sources of AVI and CVO. It was also shown that technique one can be used to provide nonparametric relationships of the differences in estimated travel time along the corridor with 95 percent confidence intervals. The percent differences on the variance and coefficient of variation were quite large. This is possibly due in part to the two loess procedures performed in this technique. It will be shown in the next section that technique two reduces these relatively large percent errors.

Loess Statistical Smoothing with Technique Two

The loess statistical smoothing technique was then used with the second technique. Recall that in this technique the raw travel time data were aggregated to five-minute periods and then the differences between the AVI and CVO data were calculated. Loess was then used to provide a nonparametric estimate on the differences. Table 5-23 presents the smoother value, number of observations, GCV MSE, and the fit type for each day of data. The GCV MSE values range from 0.0546 to 0.1293. About 58 percent of the observations were used for each local fit with loess.

TABLE 5-23 Statistical Properties of Each Data Source for Each Day of Data for Estimated Bias of Differences Between AVI and CVO for Technique Two

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	40	0.6854	0.0879	Linear
Tuesday	41	1.0000	0.1293	Linear
Wednesday	49	0.2331	0.1085	Quadratic
Thursday	39	0.6468	0.0867	Linear
Friday	45	0.3427	0.0546	Linear

Figure 5-18 presents the coefficient of variation difference between AVI and CVO with technique two. The maximum c.v. difference of 0.17 can be seen in Figure 5-18. Figure 5-19 shows the estimate of the fit bias for technique two. The average fit bias is approximately zero. Figure 5-20 presents the difference between AVI and CVO data along with the 95 percent confidence intervals that include the estimated bias for technique two. The plot is similar to that shown in Figure 5-17 for technique one. In general, the plots for technique two provided a much smoother model of the travel time over time than those produced with technique one. This suggests that the technique two models may be more appropriate for estimating differences between the two data sources. Two loess smoothing operations in technique one may introduce more variability into the estimates. Figure B-113 to Figure B-134 of Appendix B include plots for each day of the CVO variance, the variance difference between CVO and AVI, bias estimates, and the confidence intervals including the bias estimate around the smoothed loess predictions for each day.

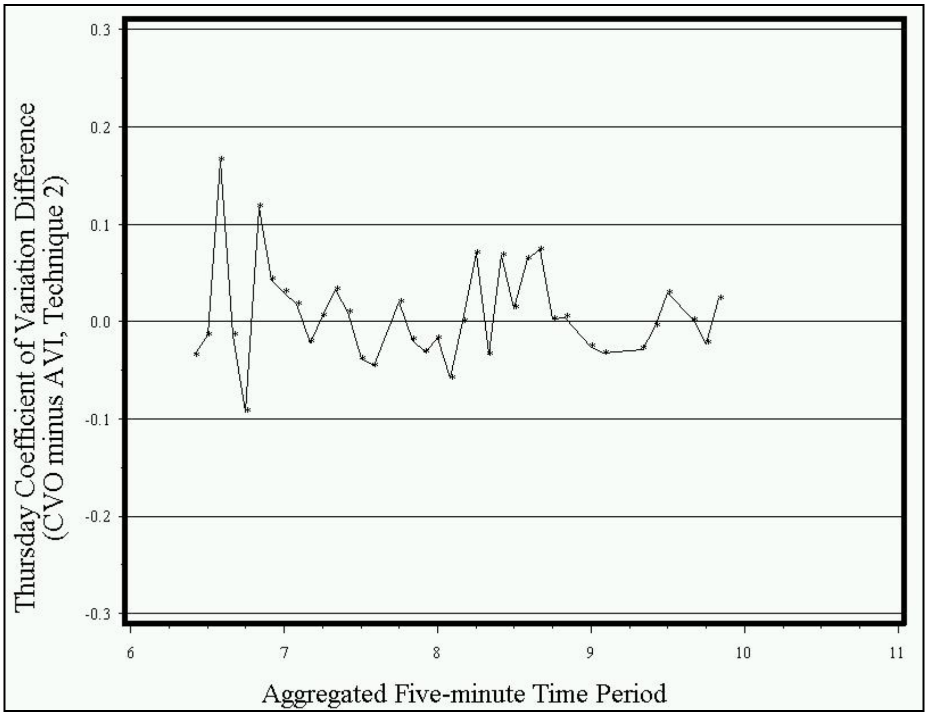

FIGURE 5-18 Thursday Coefficient of Variation Difference Between AVI and CVO Vehicles with Technique Two

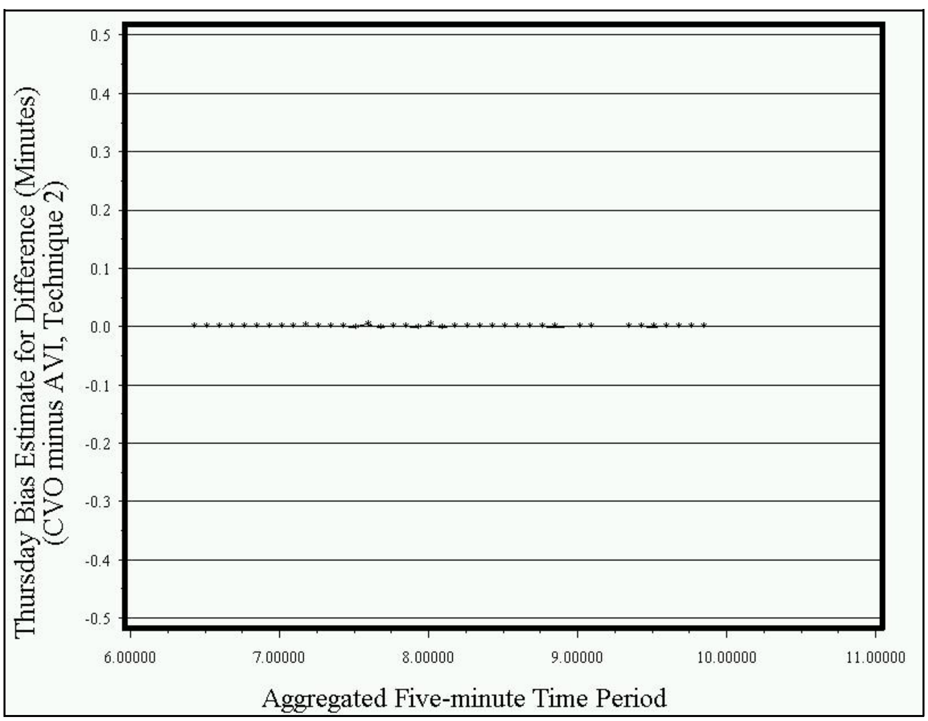

FIGURE 5-19 Thursday Bias Estimate for Differences Between AVI and CVO with Technique Two

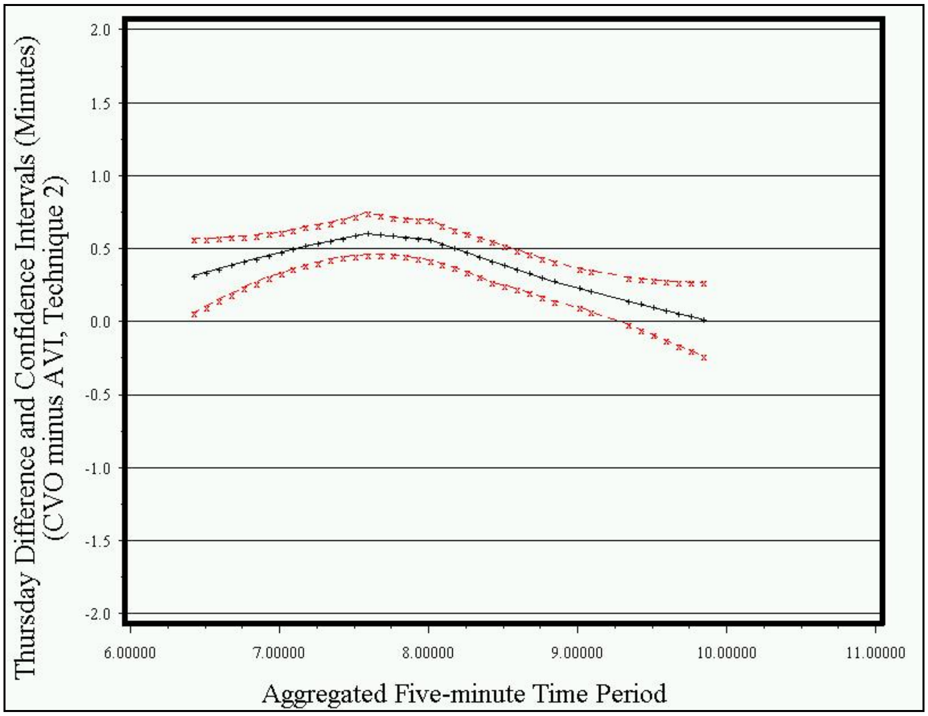

FIGURE 5-20 Thursday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

Table 5-24 presents the summary statistics for the fit bias estimates for technique two across days. The mean difference is approximately zero as found in all comparisons in this chapter. The values in Table 5-24 are again shown to their calculated values and then shown in parentheses to the appropriately rounded number of significant digits. Table 5-25 presents the percent differences between AVI and CVO data for Thursday by congestion level from technique two. The largest percent difference in the mean travel time estimates is 8.53 percent and it occurs during the congested period (≤30 mph). The largest percent difference of c.v. was also found during the most congested conditions at 23.73 percent difference. Table B-14 through Table B-17 in Appendix B contain similar tables for the remaining days of data collection for comparison. In addition, Tables B-18 through B-21 present average statistics of mean, variance, and c.v. for all days for each data type.

TABLE 5-24 Summary Statistics for Bias Estimate for Technique Two Across Days

Day	Bias Estimate Statistics Calculated Value (Rounded)				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	40	5.55×10^{-6} (0.00)	0.0012 (0.00)	-0.0039 (0.00)	0.0043 (0.00)
Tuesday	41	1.24×10^{-6} (0.00)	0.00018 (0.00)	-0.0004 (0.00)	0.0009 (0.00)
Wednesday	49	-4.62×10^{-6} (0.00)	0.025 (0.03)	-0.055 (0.06)	0.09 (0.09)
Thursday	39	6.19×10^{-6} (0.00)	0.00106 (0.00)	-0.00204 (0.00)	0.00408 (0.00)
Friday	45	0.0001 (0.00)	0.0022 (0.00)	-0.0059 (0.01)	0.0064 (0.01)

TABLE 5-25 Percent Differences Between AVI and CVO for Thursday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Thursday	Mean	All data	39	7.70	5.20	-5.03	17.88
		≥65 mph	3	6.09	2.30	3.54	8.03
		31 to 64 mph	9	5.76	4.36	0.3	14.22
		≤30 mph	27	8.53	5.56	-5.03	17.88
	Variance	All data	37	126.95	383.50	-94.79	–
		≥65 mph	3	78.07	73.28	-6.50	122.62
		31 to 64 mph	8	64.69	236.32	-49.57	646.10
		≤30 mph	26	151.75	439.94	-94.79	–
	Coefficient of Variation	All data	37	19.63	83.87	-77.79	398.17
		≥65 mph	3	23.31	25.92	-6.62	38.42
		31 to 64 mph	8	4.95	56.35	-33.17	139.14
		≤30 mph	26	23.73	95.39	-77.79	398.17

Note: Cells with differences greater than one thousand are indicated with a "–."

Table 5-26 presents the average percent differences between AVI and CVO data for the week using technique two. The largest percent difference of the mean of AVI and CVO data is 7.90 percent and this occurs during free-flow conditions. These differences are intuitive as it would be expected that commercial vehicles would require longer to traverse the corridor than AVI-equipped vehicles. From Table 5-26 for the week of data, the actual differences between CVO and AVI data are larger during congested conditions, while the percent difference is larger during free-flow conditions. This difference occurs because of the division by the AVI travel time in the percent difference calculation. It is also due to the fact that the differences between the two sources are at most on the average of 0.5 minute (thirty seconds) so that a percent difference may not adequately represent these small differences. The largest difference in c.v. occurred during the most congested period indicating that commercial vehicles have a higher variability than the AVI-equipped vehicles.

Table 5-27 presents the percent differences between the two techniques relative to congestion level. Once again, variance percent differences are very large (greater than one thousand). Mean estimates are within 0.4 percent for all the data collected along the corridor for all days. It is found that technique two provides relatively lower percent differences between AVI and CVO data as shown in comparing Table 5-22 and Table 5-26.

TABLE 5-26 Average Percent Differences Between AVI and CVO for the Week of Data for Technique Two

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	6.12	72.04	11.43
≥65 mph	7.90	47.75	11.21
31 to 64 mph	4.22	28.67	1.63
≤30 mph	6.35	89.63	14.69

TABLE 5-27 Percent Differences Between Techniques One and Two Comparing CVO and AVI Data

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	0.39	–	–
≥65 mph	-18.07	–	–
31 to 64 mph	12.23	–	–
≤30 mph	4.32	–	912.91

Note: Cells with differences greater than one thousand are indicated with a "–."

As with previous comparisons between the AVI and test vehicle data, the application of loess to provide differences between AVI and CVO data sources was more successful with technique two. The variance and c.v. percent differences were not as large with the technique two models. These smaller percent differences are hypothesized to be due in part to the two loess estimations that are performed when using technique one for travel time differences. Technique one is valuable for nonparametric travel time estimation on individual data sources.

CONCLUDING REMARKS

The loess nonparametric statistical smoothing technique was applied to the AVI, test vehicle, and CVO data sources. The procedure provides an easily understood method of local least squares for providing predicted mean values of nonparametric functions with large ITS data sets. Two techniques were used to compare differences between the AVI and test vehicle data and then the CVO and AVI data.

The first technique included calculating the loess smoother through the original data, aggregating to five-minute periods, and then smoothing the differences between the data sources. The second technique included calculating five-minute aggregations of the observed data, taking differences between the data sources, and fitting predicted values through the differences. As demonstrated with the figures and tables presented in this chapter and in Appendix B, the second technique qualitatively provides a smoother model of the difference between the two data sources.

The relationships produced with technique one comparing AVI and test vehicles had a percent error in variance of greater than one thousand minutes squared with all data for the entire week, while technique two had a similar percent error of -107 percent. Similar results were found between the two techniques for CVO and AVI comparisons. It is hypothesized that averaging the observed data in technique two and then performing loess on the differences smooths the data more to provide the smaller percent differences in the variance estimates as compared to technique one. Technique two also requires less computation for transportation applications including system monitoring because only one loess smoothing is performed.

Technique one is valuable when travel time estimates are desired over time for an individual data source.

The first objective of the chapter was to compare the AVI and test vehicle data. The differences between the mean predicted values were within one percent for the entire test corridor from instrumented vehicles that were AVI-equipped. When smoothing the differences of AVI and test vehicle data sources, four of the five final profiles for technique one showed variability in the difference for Thursday as shown in Figure 5-9. Conversely, for technique two, all of the resulting loess plots show a very smooth relationship for Thursday as shown in Figure 5-12. The loess predicted values from technique two were also within two percent between AVI and test vehicles. The largest c.v. difference between AVI and test vehicles was 37.6 percent, and it occurred during the congested period (≤30 mph) for technique two. The outlier differences are hypothesized to be due to when the drivers marked the checkpoints. A paired *t*-test analysis also provided statistical evidence that there was measurement error introduced by different drivers. These results indicate that with the implementation of adequate AVI infrastructure, an AVI system can provide useful system monitoring without the need for instrumented vehicle data collection.

It is important to note that ANOVA results on the AVI data found that, while the mean travel time may differ statistically by day of week and time period, the ratio of the standard deviation to the mean (c.v.) does not have a statistical difference. This result appears to indicate that variability about the mean is constant. This is valuable information for situations when it may be difficult to obtain the variability on the travel time estimate (i.e., when inductance loop detectors are used).

The second objective of this chapter was to compare the CVO and AVI data. Differences up to 7.9 percent were found with the second loess technique (Table 5-26). This occurred during free-flow conditions (≥65 mph). This is intuitive, as commercial vehicles have different operating characteristics than AVI-equipped vehicles. During congested periods (≤30 mph), the difference was 6.4 percent. The c.v. difference between commercial vehicles and AVI vehicles was up to 14.7 percent difference during congested periods (≤30 mph). The c.v. difference was 11.2 percent during free-flow (≥65 mph) conditions. When comparing CVO and AVI data sources, four of the five technique one profiles show a smooth relationship as shown in Figure 5-17. The technique two results were similar with four of the five profiles showing a smooth profile for the Thursday data as shown in Figure 5-20. Only the Wednesday data does not produce a smooth relationship between the predicted travel time difference and time. It is uncertain why the Wednesday data do not result in a smoother differences plot (Figure B-127) since the mean and c.v. of the differences are within two percent of the weekly averages. This day of data appears to be an anomaly of the trends in the other days of data. Overall, technique two appears to provide less percent error than technique one, and it is recommended for analyses in which travel time differences between data sources are desired. Clearly, commercial vehicles have different operating characteristics than commuter travelers. This research has shown that if the same data are available, and the relationship between CVO and AVI data is known, then it may be appropriate to adjust AVI vehicle estimates for CVO use.

The third objective of this chapter was to investigate the use of the loess nonparametric statistical smoothing technique for the AVI, test vehicle, and CVO data sources. The loess statistical procedure was successful for estimating the travel time mean and variance for subsequent comparisons between the data sources used in this chapter. Loess provides an easily understood statistical method for nonparametric locally weighted smoothing that would allow estimation of travel time mean and variability estimates from ITS data. Further, as ITS data become more numerous from emerging data sources and technologies (e.g., cellular telephones) statistical techniques such as loess algorithms will become more valuable for travel time characteristic estimation for systems monitoring and multi-modal analysis (*16*). The following chapter will perform similar analyses on data collected from the San Antonio corridor, which was instrumented with inductance loops.

CHAPTER VI

INVESTIGATION OF TRAVEL TIME ESTIMATION FOR SYSTEM MONITORING AND MULTI-MODAL ANALYSES USING INDUCTANCE LOOP DETECTOR DATA

This chapter discusses the analyses performed on the data collected along the IH-35 corridor in San Antonio, Texas. The emphasis is on the estimation of mean travel time from three data sources. Specifically, the following objectives are addressed:

1. Investigate the difference between two common techniques used for travel time estimation from inductance loop detectors. The most appropriate method will be used in subsequent analyses throughout the chapter.
2. Investigate the extent that deployed ITS detector techniques, such as inductance loop detectors, can be used for system planning and performance monitoring. More specifically, the accuracy of travel time estimates from inductance loop detectors will be studied. Inductance loop detector and test vehicle travel time characteristic estimates will be compared to satisfy this objective.
3. Investigate how well travel time estimates from loop detectors replicate travel conditions for commercial vehicle operations. Inductance loop detectors are used to monitor and provide information to commuter drivers based on data from all vehicles in the traffic stream, yet the difference between travel time estimates from inductance loop detectors and actual travel time estimates from CVO data is unknown. CVO and inductance loop detector travel time estimates will be compared to satisfy this objective.
4. Compare travel time estimates of test vehicle data with CVO travel time estimates along the corridor. These two methods will be compared because they both provide a direct measurement of travel time from which travel time estimates can be computed rather than extrapolated travel time estimates from inductance loop detectors.
5. Investigate the use of the loess statistical procedure for locally weighted smoothing to obtain travel time estimates for inductance loops, test vehicle, and CVO data sources.

COMPARISON OF TWO COMMON TRAVEL TIME ESTIMATION TECHNIQUES FROM INDUCTANCE LOOP DETECTOR SPOT SPEEDS

Two common methods of travel time estimation from inductance loop detector spot speeds were previously presented in Chapter II. The first travel time estimation technique assumes that the spot speed obtained from the loop detector is valid for half the distance to the next adjacent detector. This is the method that is commonly used at traffic management centers to obtain travel time estimates from spot speeds. Note that this could be any detector technology that provides spot speeds from which travel time estimates are computed (e.g., video camera, acoustic). The second travel time estimation technique uses the average speed from the two adjacent detectors and uses that speed to estimate the travel time along the link of interest (*10*).

In each case, the spot speed is assumed to be constant over the link over which travel time is desired.

For the comparison analyses presented in this chapter, the algebraic relationships presented in Chapter II are revisited in this section. Figure 6-1 illustrates a sample corridor over which travel time is desired with both the estimation techniques. With X_1=X_2=O and n=6 detectors, Equation 2-3 for the half the distance estimation technique reduces to Equation 6-1. Similarly, Equation 2-4 for the average-speed technique (technique two) reduces to Equation 6-2.

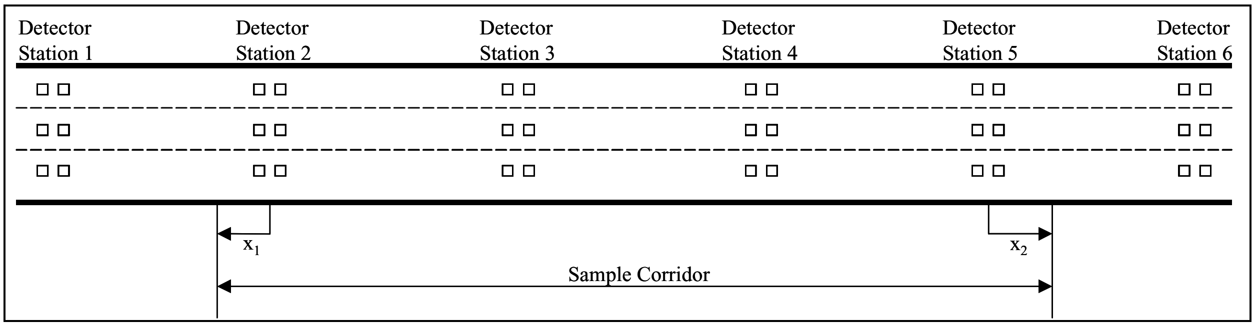

FIGURE 6-1 Sample Corridor Used to Illustrate Two Travel Time Estimation Techniques from Dual Inductance Loop Detector Spot Speed Data

$$TT_1 = \sum_{i=2}^{4} \left(\frac{l_{i,i+1}}{2S_i} + \frac{l_{i,i+1}}{2S_{i+1}} \right) \tag{6-1}$$

where: i = Detector station i;
$l_{i,,i+1}$ = Distance between detector station i and $i+1$;
S_i = Spot speed at detector location i;
TT_1 = Travel time computed with technique 1.

$$TT_2 = \sum_{i=2}^{4} \frac{l_{i,i+1}}{\left(S_i + S_{i+1}\right)/2} \tag{6-2}$$

The inductance loop spot speed data from the San Antonio corridor were aggregated to 5 minutes. The speed data were averaged across lanes at each of the loop detector stations. Averages across all three lanes were used because spot speed estimates do not monitor individual vehicles, and the travel time data collected for the test vehicles did not record the lane in which each vehicle was driving.

Corridor travel times were estimated by composite linear functions as shown in the example of Figure 6-2. With this travel time estimation method, linear interpolation between the five-minute discrete aggregation was performed based on when the vehicle arrived at the link. An example is shown in Figure 6-2. Table 6-1 presents the average percent differences between the two travel time techniques shown in Equation 6-1 and Equation 6-2 for the comparison corridor. Data for Thursday are not presented because one loop detector station had missing data for the first two hours of the data collection period. The percent difference between the two travel time estimation techniques was less than two percent.

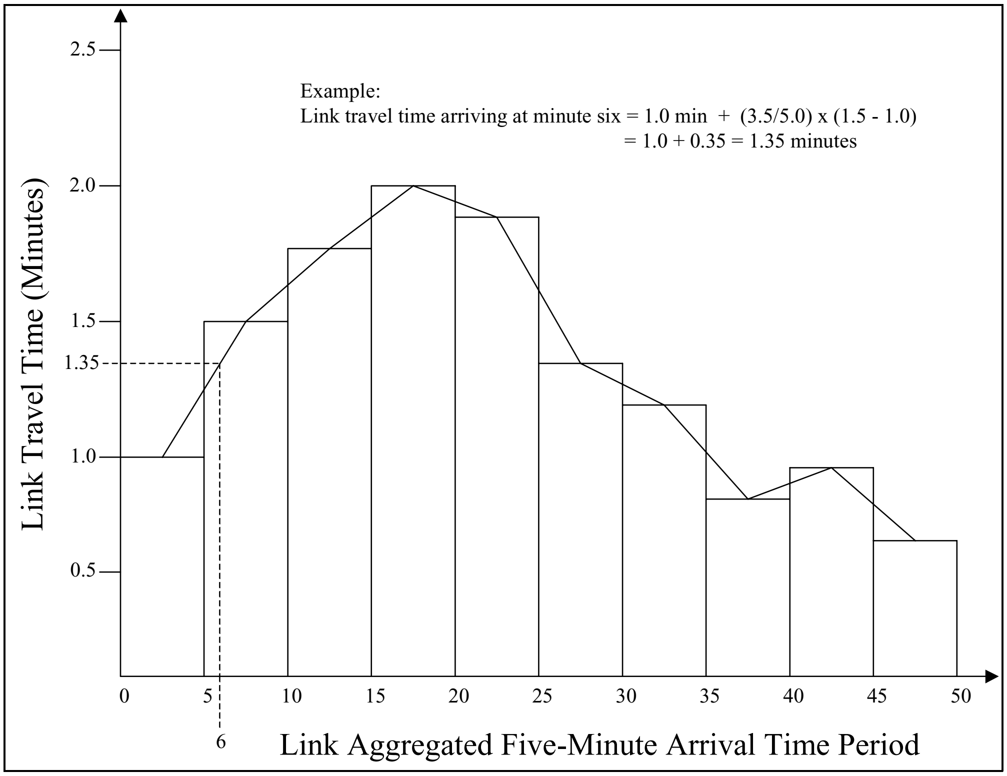

FIGURE 6-2 Step Functions with Composite Linear Functions for Comparison of Travel Time Estimation with Loop Detector Data

TABLE 6-1 Percent Differences Between Two Travel Time Estimation Techniques with Loop Detector Data

Day of Week	Travel Time Estimation Difference
Monday	1.66%
Tuesday	0.65%
Wednesday	0.72%
Friday	0.35%

Based upon the similarity between the results of the two travel time estimation techniques from this analysis, the analysis throughout this chapter uses the half the distance travel time estimation technique to estimate travel time from loop detectors to compare to test vehicle and CVO data. In addition, the location of the field video cameras was oriented for the use of this estimation method and a downstream detector was not available to the south of the southern-most loop detector, precluding the use of the average-speed technique.

CORRIDOR TRAVEL TIME ESTIMATION FROM INDUCTANCE LOOP DETECTORS USING LOESS

The loess technique was subsequently used to obtain travel time mean estimates from inductance loop detectors for comparison to CVO and test vehicle data. The first step was to generate plots of the link arrival time by total link travel time at each of the four detectors. Figure 6-3 shows the Monday data for detector 152.005. Figure C-1 through Figure C-15 show similar plots for each detector and day of data available. Figure 6-3 also displays the linear interpolation of the predicted travel time values from loess. Visual inspection of Figure 6-3, and similar figures in Appendix C, reveals the relatively large range in estimated travel times during the congested period. This large range of travel time estimates occurred because three lanes of data are included.

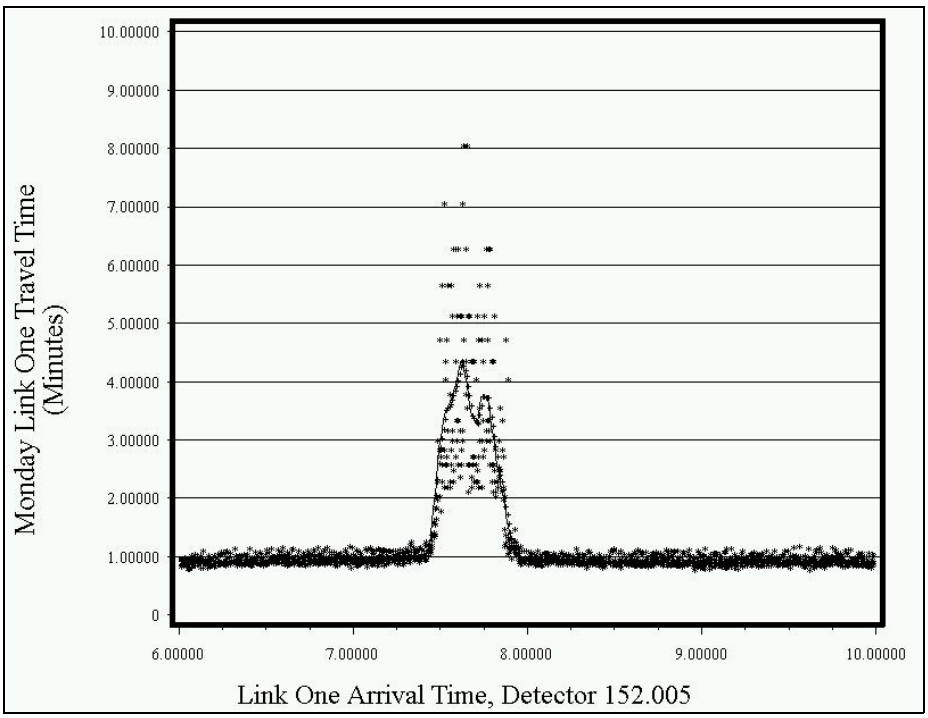

FIGURE 6-3 Loess Travel Time Predicted Values for Monday Inductance Loop Data from Detector 152.005

The loess technique was used for the inductance loop detectors in the same manner described in detail in Chapter V. Table 6-2 presents the statistical properties of the loess statistical smoothing, including the number of observations, smoother value, and the generalized cross-validation mean squared error for the local quadratic fit. In general, approximately four percent of the data were used in the local smoothing.

TABLE 6-2 Statistical Properties of Inductance Loop Detector Travel Time Estimates at Each Link

Day	Inductance Loop Detector	Number of Observations	Smoother Value	GCV MSE
Monday	152.005	1394	0.0512	0.1964
Tuesday		1380	0.0481	0.2265
Wednesday		1335	0.0700	0.1714
Friday		1387	0.0242	0.0166
Monday	152.590	1408	0.0175	0.0790
Tuesday		1424	0.0185	0.0280
Wednesday		1394	0.0218	0.0343
Friday		1424	0.0228	0.0196
Monday	153.048	927	0.0477	0.0358
Tuesday		939	0.0156	0.0058
Wednesday		919	0.0244	0.0094
Friday		462	0.0504	0.0020
Monday	153.614	1425	0.0194	0.0285
Tuesday		1427	0.0445	0.0167
Wednesday		1388	0.0801	0.0131
Friday		1429	0.1095	0.0133

The smoother value, γ, for loess was necessary for estimating the corridor travel time plots with the inductance loop data. After these values were obtained for each link and day, this information was used to estimate the mean travel time of vehicles traversing the corridor. Equation 6-3 was used to estimate the travel time through the corridor. Figure 6-4 graphically illustrates the method in which the corridor travel time was estimated for a given day with the individual link data from the inductance loop detectors. The steps to perform this recursive computation of the corridor travel time estimate are as follows.

1. The first T_A was selected as 6:00 a.m.
2. The smoothing value percentage of points, γ, around the study corridor arrival time (T_A) were selected.

3. A quadratic locally weighted fit was performed on these data (as performed with the loess statistical technique described in Chapter V). The data were weighted locally with the function used by loess that was presented in Equation 5-3.
4. With the local quadratic equation, the link one travel time (TT_1) was estimated.
5. Equation 6-3 is used recursively to calculate the time of arrival at each link following the vehicle through the corridor.
6. The corridor travel time was then estimated with Equation 6-4. It can be shown that steps five and six approach an approximation of the true travel time. A theoretical justification may be found elsewhere (*67*).
7. Return to step one and add 0.01 hour (36 seconds) to previous beginning time. The first time through, the time is 6.00 (T_A), so the second time is 6.01, and so on. The steps were repeated with T_A ranging from 6.00 to 10.00 (i.e., 6:00 a.m. to 10:00 a.m.).

$$T_i = T_A + \sum_{j=1}^{i-1} TT_j \, , \; i = 2 \; to \; 5 \tag{6-3}$$

where: T_i = Time of arrival at link i;
T_A = Study corridor arrival time (i.e., time of arrival at link 1); and
TT_j = Sum of travel time over links 1 to *i-1*. As shown in Figure 6-4, $TT_j = f(T_i)$

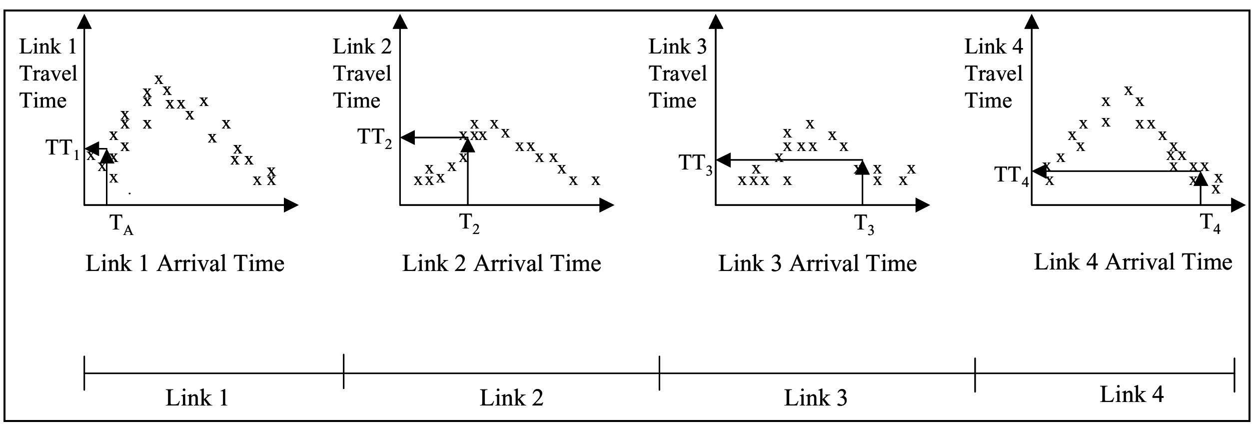

FIGURE 6-4 Graphical Illustration of Recursive Corridor Travel Time Estimation from Inductance Loop Detector Data

$$TT_C = TT_5 - T_A \tag{5-4}$$

where: TT_5 = Time of arrival at link 5 (i.e., through link 4 and the study corridor);
T_A = Study corridor arrival time (i.e., time of arrival at link 1); and
TT_C = Estimated corridor travel time from link 1 to 4.

Figure 6-5 shows the resulting corridor travel time estimate for the Wednesday travel time data from the inductance loop detector data by corridor arrival time (T_A). The linear interpolation between each loess estimate is shown. The travel time estimates are within the free-flow periods (i.e., speeds ≥60 mph) from about 6:00 a.m. to 7:30 a.m. and then again from about 8:15 a.m. to 10:00 a.m. Figure C-16 through Figure C-18 present similar graphics for the remaining days of data collection. After these travel time profiles were created, analysis comparing the travel time mean estimates from inductance loop data and the instrumented test vehicles was performed. These comparisons are made in the following sections.

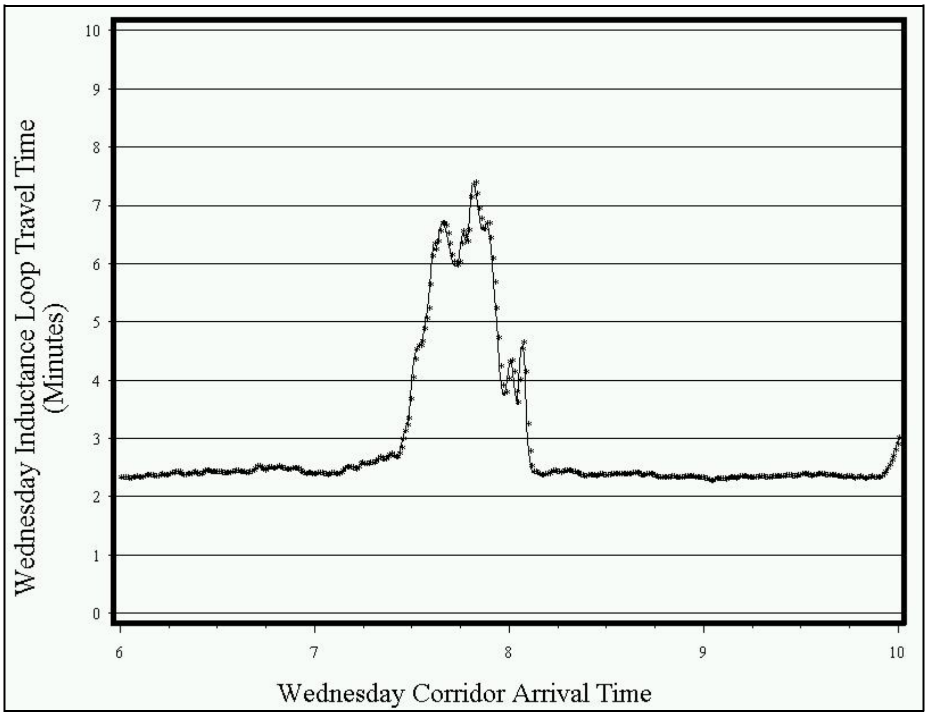

FIGURE 6-5 Study Corridor Travel Time Estimate from Inductance Loop Detector Data for Wednesday

INDUCTANCE LOOP TRAVEL TIME ESTIMATES COMPARED TO INSTRUMENTED TEST VEHICLES

Analysis of Variance

ANOVA was performed for the inductance loops and instrumented test vehicle data sources on the fixed effects shown in Equation 5-6 and Equation 5-7. The travel time estimates including the mean, standard deviation, and coefficient of variation (c.v.) were aggregated to five-minute periods. The travel time estimates were investigated over half-hour periods to examine the travel time characteristics over time. All statistical tests were performed at the α=0.05 level of significance. The fixed effects model shown in Equation 5-6 was used to produce the results shown in Table 6-3 while the fixed effects model shown in Equation 5-7 was used to produce the results in Table 6-4. It was found that the mean travel time was statistically different for each data source by day of week and time period. Time period was found to be statistically different at the α=0.05 level of significance for each travel time characteristic including the c.v. ($p<0.0001$) for the travel time estimates from inductance loop detectors. The c.v. of the test vehicle data was not found to be statistically different for the day of the week ($p=0.6715$) or time period ($p=0.4617$). These results indicate that the inductance loop travel time mean estimates did vary by time period. It is interesting to note that the test vehicle c.v. does not vary statistically. Therefore, the ratio of the standard deviation to the mean is relatively constant by day of the week and time period.

TABLE 6-3 ANOVA Results on Travel Time Characteristics from Inductance Loop and Test Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Value (Degrees of Freedom)	
		Day of Week	Time Period
Inductance Loops	Average	**<0.0001 (3)**	**<0.0001 (28)**
	Standard Deviation	0.0938 (3)	**<0.0001 (28)**
	Coefficient of Variation	0.6025 (3)	**<0.0001 (28)**
Test Vehicle	Average	**0.0015 (4)**	**<0.0001 (33)**
	Standard Deviation	0.6340 (4)	**0.0129 (32)**
	Coefficient of Variation	0.6715 (4)	0.4617 (32)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Table 6-4 presents ANOVA results for the travel time characteristics of interest by comparing the inductance loop and test vehicle data sources with the model shown in Equation 5-7. Interaction effects were found between the data source and time period (p=0.0009) and there was a statistical difference in the mean travel time across days (p<0.0001). Upon graphing the significant interaction effects, the differences between the inductance loops and test vehicles were 100 percent larger during congested time periods than uncongested time periods, causing the interaction effects to be present by time period. The ratio of the standard deviation to the mean (c.v.) was found to be statistically different by data source (p<0.0001) and time period (p=0.0015). The c.v. was not statistically different by day of week (p=0.5441). Generally, these results indicate that the mean and ratio of the standard deviation to the mean (c.v.) between the two data sources were statistically different. These results are expected, as the mean and variance from aggregated loop detector travel time estimates are not related to those of individual test vehicles. The following section will explore the differences in more detail.

TABLE 6-4 ANOVA Results on Travel Time Characteristics Comparing Inductance Loop and Test Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Values (Degrees of Freedom)				
		Data Source	Day of Week	Time Period	Interaction of Data Source and Day of Week	Interaction of Data Source and Time Period
Inductance Loop and Test Vehicle	Average	–	**<0.0001 (4)**	–	0.9139 (3)	**0.0009 (27)**
	Standard Deviation	**0.0003 (1)**	0.2757 (4)	**<0.0001 (34)**	0.3850 (3)	0.7905 (26)
	Coefficient of Variation	**<0.0001 (1)**	0.5441 (4)	**0.0015 (34)**	0.4391 (3)	0.2824 (26)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Loess Statistical Smoothing

The sections that follow will describe the procedure and results of using loess for comparisons of travel time data sources for Wednesday data. Related statistics and figures for other days of data collection are presented in Appendix C.

Figure 6-5 presented the inductance loop travel time estimate over time for Wednesday. Similarly, Figure 6-6 shows the corridor travel time estimate from the test vehicles on Wednesday. Figure 6-7 illustrates the difference between the inductance loop and test vehicle travel time estimates for Wednesday along the corridor. Relatively larger differences of up to 1.7 minutes during the congested periods can be seen. Figure C-19 through Figure C-22 contain similar plots for the remaining days of test vehicle data used in the analysis. Data presented in these figures were then aggregated to 5 minutes for subsequent analysis.

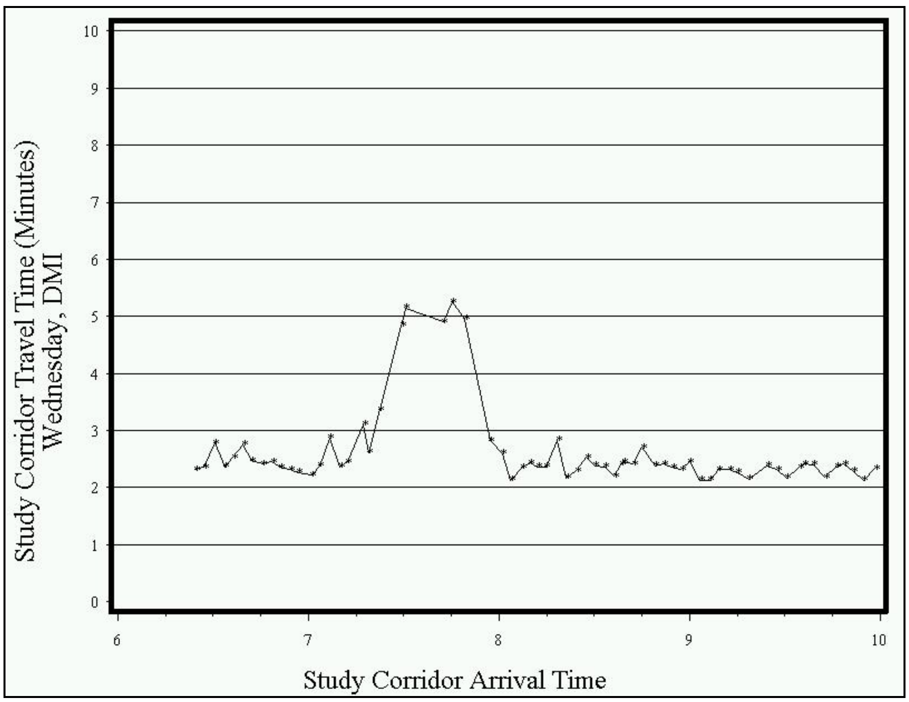

FIGURE 6-6 Study Corridor Travel Time Estimate from Test Vehicle Data for Wednesday

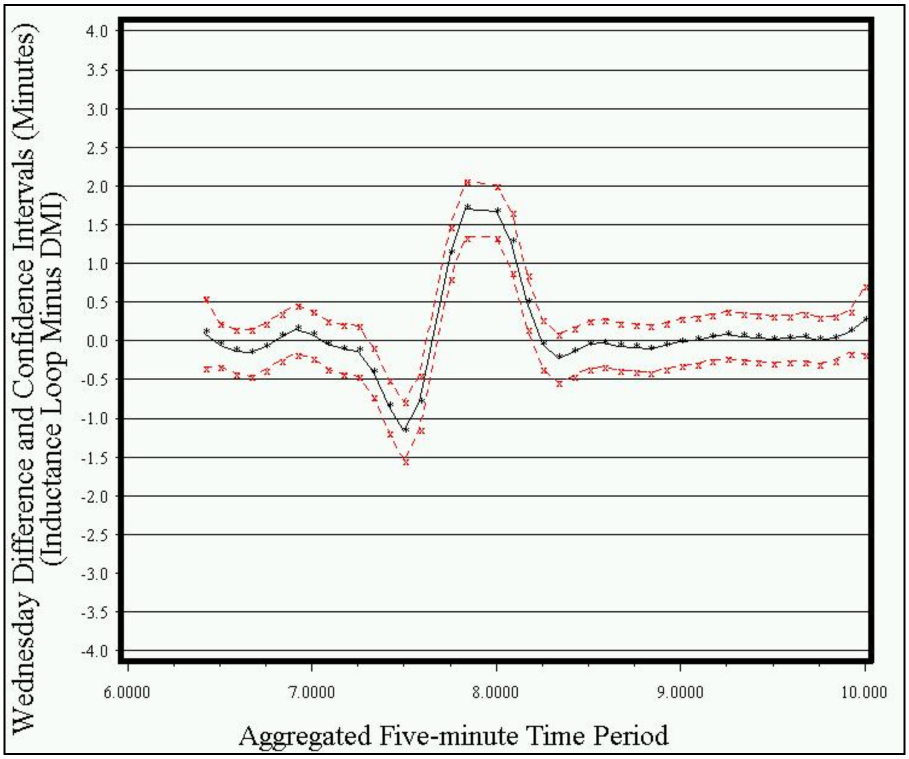

FIGURE 6-7 Wednesday Difference Between Inductance Loop and Test Vehicle and Confidence Intervals Including Correction for Estimated Bias

Five-minute differences of the inductance loop and test vehicle travel time estimates were calculated. Table 6-5 presents the loess statistical properties for each day of data for the differences between the inductance loop and test vehicle five-minute travel time averages. Smoother values range from 18.6 percent to 21.9 percent of the data used in the local smoothing of the quadratic fits performed with loess. Note that the Thursday data are not included in the analyses, as one inductance loop detector was missing data.

TABLE 6-5 Statistical Properties for Each Day of Data for Differences Between Inductance Loop and Test Vehicle

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	43	0.2018	0.2964	Quadratic
Tuesday	46	0.1859	0.1124	Quadratic
Wednesday	42	0.2018	0.0979	Quadratic
Friday	39	0.2190	0.0851	Quadratic

Figure 6-7 presents the difference and confidence intervals around the differences between the inductance loop and test vehicle travel time estimates for the Wednesday data. Figure 6-8 shows the bias estimate for the differences for the Wednesday data. Table 6-6 presents a summary of the estimated bias as computed from Equation 5-6. The average estimated fit bias is approximately zero and the maximum of -0.82 minute (49 seconds) occurs on Tuesday. Figure 6-9 presents the coefficient of variation difference between the inductance loop and test vehicle five-minute aggregated data. Figure C-23 to Figure C-43 in Appendix C present graphs of inductance loop variance, test vehicle variance, difference in variance, difference in c.v., fit bias estimate, and final plots of predicted differences between the two data sources along with confidence intervals adjusted for fit bias for the remaining days of analysis. The data in Figure 6-9 are generally below 0.0, indicating that the test vehicles have larger variability in the five-minute aggregated data than the inductance loop data.

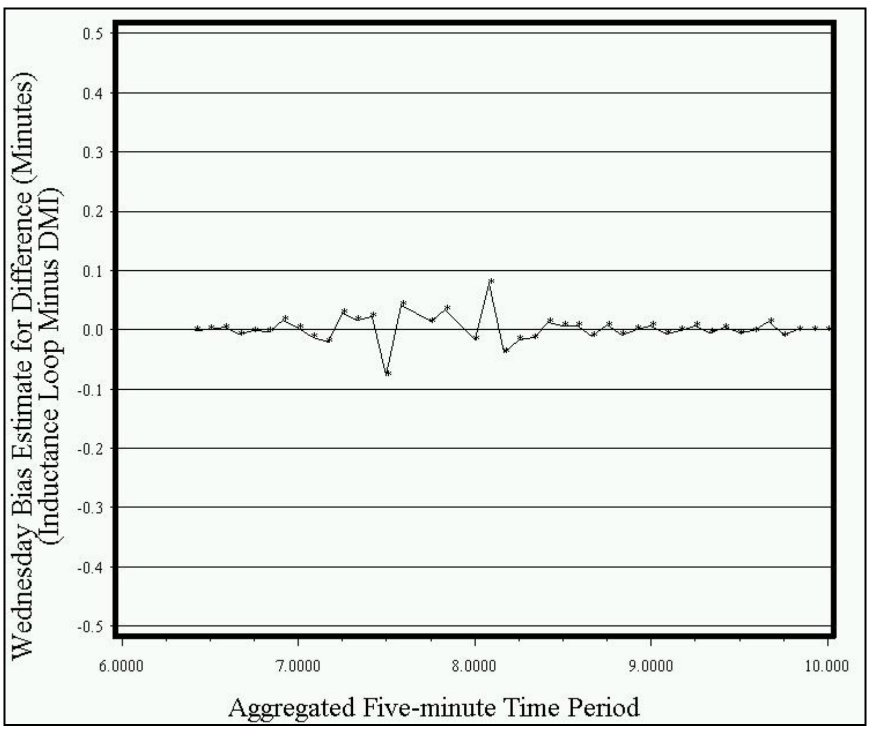

FIGURE 6-8 Wednesday Bias Estimate for Differences Between Inductance Loop and Test Vehicles

TABLE 6-6 Summary Statistics for Bias Estimate for Differences Between Inductance Loop and Test Vehicles

Day	Bias Estimate Statistics				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	43	0.00	0.04	-0.07	0.15
Tuesday	46	0.00	0.03	-0.82	0.09
Wednesday	42	0.00	0.02	-0.08	0.08
Friday	39	0.00	0.02	-0.05	0.05

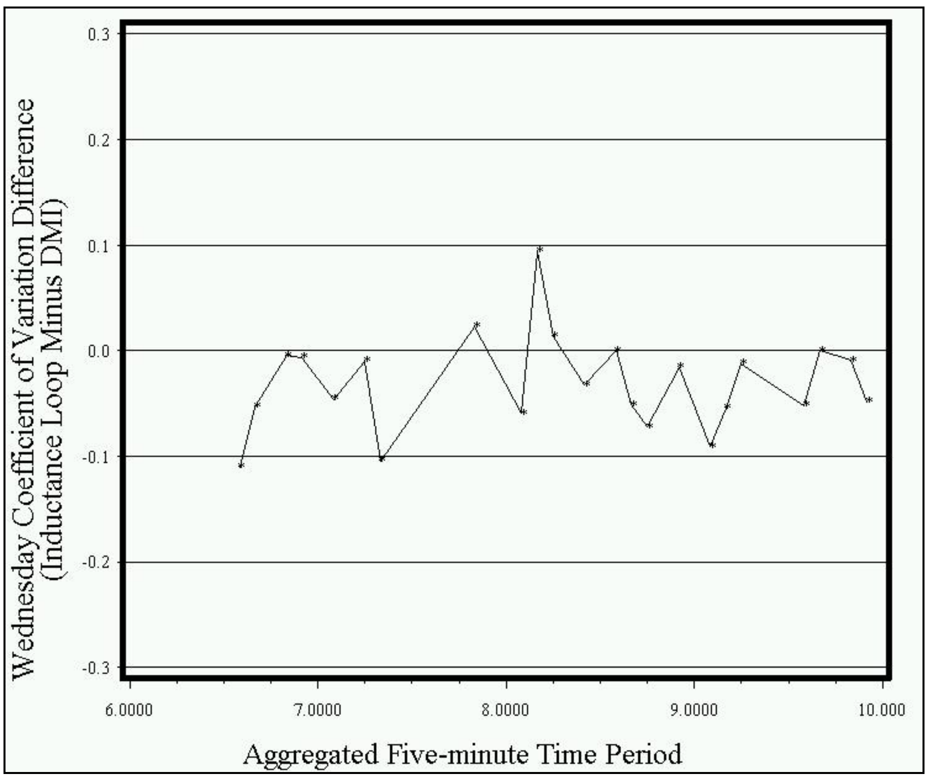

FIGURE 6-9 Wednesday Coefficient of Variation Difference Between Inductance Loop and Test Vehicles

Table 6-7 presents percent differences between inductance loop and test vehicle travel time characteristic estimates for the Wednesday data. The average percent difference between the inductance loop and test vehicle data across the entire data collection period is 2.8 percent. The largest percent difference between the two data sources was experienced during free-flow conditions (≥60 mph) at 5.5 percent. During congested conditions (≤30 mph) the percent difference average was 3.3 percent on Wednesday. Table C-1 through Table C-3 in Appendix C present similar information for the other days of data collected in San Antonio, Texas. Table 6-8 presents a summary of the percent differences between inductance loops and test vehicles for the entire week of data. The largest difference of 5.83 percent between inductance loop and test vehicle data was during free-flow conditions (≥60 mph). During congested conditions, the average difference between the two data sources was 2.5 percent. The c.v. difference during congested conditions was 617.11 percent. From a practical perspective, the implication in this result is that there is a relatively large variability in c.v. that is present in the inductance loop detector data. This result is intuitive in that, while the means are comparable, there is no relationship between the variability of the aggregated loop detector and the variability in individual vehicles.

TABLE 6-7 Percent Differences Between Inductance Loop and Test Vehicles for Wednesday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All Data	42	2.8	18.20	-36.8	75.37
		≥60 mph	25	5.51	15.05	-3.45	75.37
		31 to 59 mph	13	-2.54	19.08	-20.93	56.38
		≤30 mph	4	3.25	32.74	-36.8	33.33
	Variance	All Data	23	-0.41	1.60	-4.03	3.71
		≥60 mph	15	-0.16	1.22	-2.18	3.71
		31 to 59 mph	7	-1.42	1.67	-4.03	0.00
		≤30 mph	1	2.88	N.A.	2.88	2.88
	Coefficient of Variation	All Data	22	-43.73	102.80	-96.17	382.07
		≥60 mph	14	-39.88	124.38	-92.94	382.07
		31 to 59 mph	7	-65.51	35.54	-96.17	-4.04
		≤30 mph	1	54.93	N.A.	54.93	54.93

TABLE 6-8 Percent Differences and Number of Observations Between Inductance Loop and Test Vehicles for the Week of Data

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	3.03	-1.10	-3.37
≥60 mph	5.83	0.17	-46.86
31 to 59 mph	0.02	-3.17	-51.09
≤30 mph	2.49	2.09	617.11

INDUCTANCE LOOP TRAVEL TIME ESTIMATES COMPARED TO COMMERCIAL VEHICLE TRAVEL TIME ESTIMATES

Analysis of Variance

Similar to the previous section, ANOVA was computed for the inductance loop and CVO travel time data using Equation 5-6 and Equation 5-7. The travel time estimates including the mean, standard deviation, and c.v. were aggregated to five-minute periods. The travel time estimates were investigated over half-hour time periods to examine statistical differences. All statistical tests were performed at the $\alpha=0.05$ level of significance. The fixed effects model shown in Equation 5-6 was used to produce the results discussed in Table 6-9 while the fixed effects model shown in Equation 5-7 was used to produce the results discussed in Table 6-10. The inductance loop travel time estimates were statistically different across days ($p<0.0001$) while the average travel time estimate for commercial vehicles was not statistically significant ($p=0.3002$). The thirty-minute time aggregation was always significant for both data sources for all travel time characteristics except c.v. for the commercial vehicle data ($p=0.9322$). The inductance loop detector mean estimates are statistically different across days, but the standard deviation relative to the mean (c.v.) does not vary from day to day. It also demonstrates that the commercial vehicle data do not vary statistically from day to day in mean or c.v. estimates. In general, these results indicate that statistical differences across time periods were often found, while across days statistical differences were not found for the travel time characteristics for inductance loops and CVO. It is intuitive that differences are found across different time periods.

TABLE 6-9 ANOVA Results on Travel Time Characteristics from Inductance Loop and Commercial Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Value (Degrees of Freedom)	
		Day of Week	Time Period
Inductance Loops	Average	**<0.0001 (3)**	**<0.0001 (28)**
	Standard Deviation	0.0938 (3)	**<0.0001 (28)**
	Coefficient of Variation	0.6025 (3)	**<0.0001 (28)**
CVO	Average	0.3002 (4)	**<0.0001 (23)**
	Standard Deviation	0.9398 (4)	**0.0028 (23)**
	Coefficient of Variation	0.8536 (4)	0.9322 (23)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

TABLE 6-10 P-Values and Degrees of Freedom for Travel Time Characteristics Comparing Inductance Loop and Commercial Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Values (Degrees of Freedom)				
		Data Source	Day of Week	Time Period	Interaction of Data Source and Day of Week	Interaction of Data Source and Time Period
Inductance Loop and CVO	Average	—	**<0.0001 (4)**	—	0.9394 (3)	**0.0011 (19)**
	Standard Deviation	**0.0001 (1)**	0.3540 (4)	**<0.0001 (32)**	0.8344 (3)	0.2301 (19)
	Coefficient of Variation	**<0.0001 (1)**	0.8410 (4)	**0.0017 (32)**	0.8319 (3)	0.0265 (19)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Table 6-10 displays ANOVA results for the travel time characteristics of interest by comparing the inductance loop travel time data with CVO as shown in Equation 5-7. The null hypothesis (H_o) is that the loop detector and CVO travel time characteristic estimate is the same. All tests were performed at the α=0.05 level of significance. Interaction effects were found between the data source and time period. Upon graphing the interaction effects, the differences between the inductance loops and CVO data were approximately 100 percent during congested time periods, causing the interaction effects to be present by time period. The c.v. was found to be statistically different between data sources ($p<0.0001$) and time period ($p=0.0017$). Coefficient of variation was not significantly different by day of the week ($p=0.8410$). Generally, the mean and c.v. between the two data sources were statistically different. As expected, these results indicate that the travel time mean, standard deviation, and c.v. from inductance loop detectors and CVO are statistically different. The following section will explore these differences further.

Loess Statistical Smoothing

The loess statistical smoothing technique was used in a similar manner to compare the inductance loop travel time estimates with the commercial vehicle data. Figure 6-10 provides an illustration of a travel time profile for the Wednesday data used in comparison to the inductance loop travel time profiles. Figure C-44 to Figure C-47 in Appendix C provide similar graphs for the remaining days of data.

Table 6-11 provides the statistical properties for each day of data for differences between the inductance loop and commercial vehicle predicted travel time estimates using loess. Quadratic fits provided the minimum generalized cross-validation mean square error, and the smoother values indicate that from 18.5 to 37.2 percent of the data were used in the local fit.

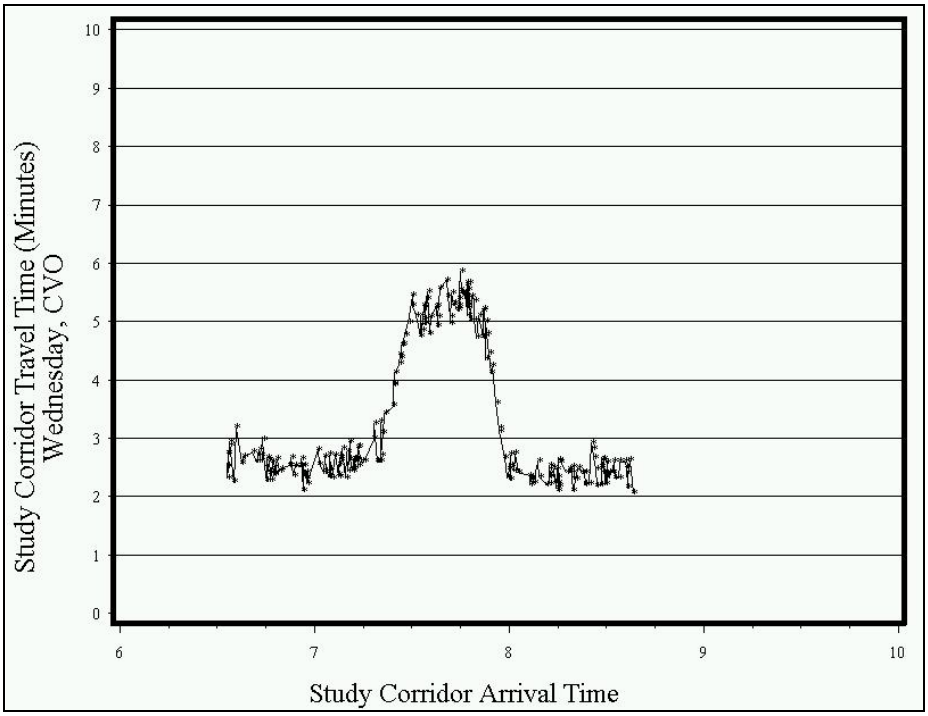

FIGURE 6-10 Study Corridor Travel Time Estimate from CVO for Wednesday

TABLE 6-11 Statistical Properties for Each Day of Data for Differences Between Inductance Loop and CVO

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	38	0.193	0.0746	Quadratic
Tuesday	31	0.1853	0.07	Quadratic
Wednesday	26	0.2931	0.132	Quadratic
Friday	20	0.3719	0.0933	Quadratic

Figure 6-11 shows the difference and confidence intervals around the differences between the inductance loop and commercial vehicle travel time estimates for the Wednesday data. Figure 6-12 shows the small fit bias estimates for the differences for the Wednesday data. The maximum difference of approximately 1.8 minutes occurs at about 8:10 a.m. during the congested period. This difference is hypothesized to be due to the difficulty of estimating travel times from inductance loop detector spot speeds, especially during congested conditions. Table 6-12 presents a summary of the estimated bias by aggregated five-minute period. The average estimated fit bias is zero, and the maximum of -0.05 minute (three seconds) occurs on Tuesday. The data in Table 6-12 are significant to the 0.01 level as shown in the values that are rounded in the parentheses. Figure 6-13 illustrates the coefficient of variation difference between the inductance loop and test vehicle five-minute aggregated data. The maximum difference in c.v. is 0.10. Figure C-48 to Figure C-64 in Appendix C present graphs of commercial vehicle variance, difference in variance, difference in c.v., bias estimate, and final plots of predicted differences between the two data sources along with confidence intervals adjusted for fit bias for the remaining days of analysis. The data in Figure 6-13 tend to be below 0.0 during free-flow conditions.

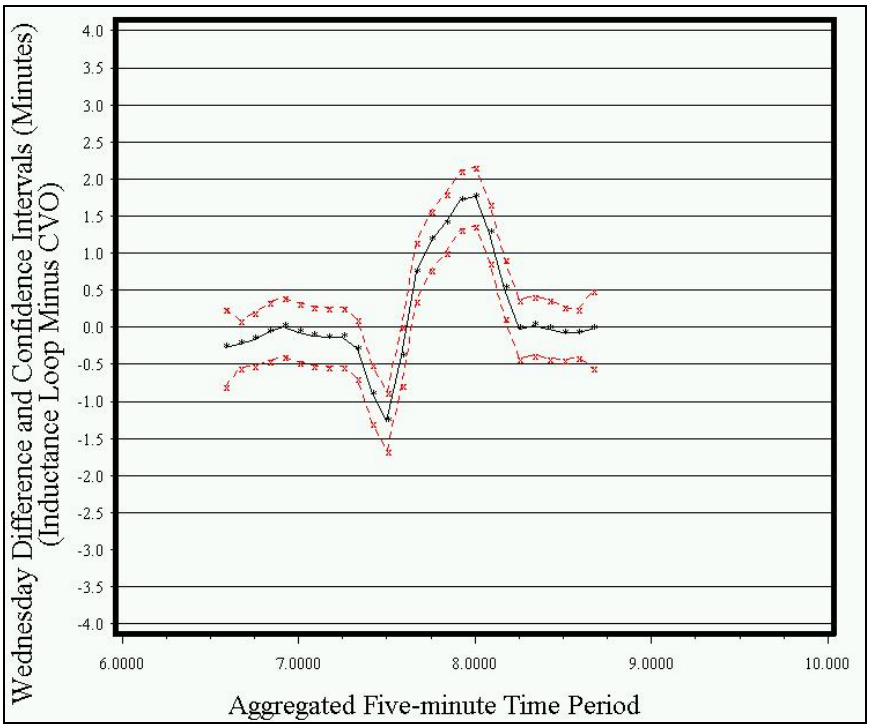

FIGURE 6-11 Wednesday Difference Between Inductance Loop and CVO and Confidence Intervals Including Correction for Estimated Bias

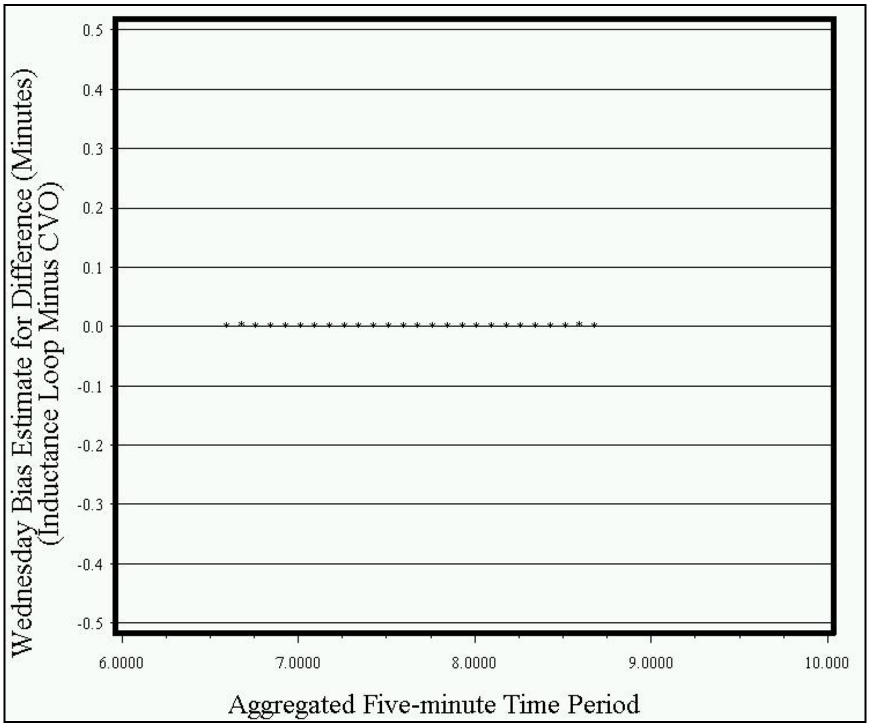

FIGURE 6-12 Wednesday Bias Estimate for Differences Between Inductance Loop and CVO

TABLE 6-12 Summary Statistics for Bias Estimate for Differences Between Inductance Loops and CVO

Day	Bias Estimate Statistics Calculated Value (Rounded)				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	38	0.0001 (0.00)	0.00031 (0.00)	-0.00146 (0.00)	0.000385 (0.00)
Tuesday	31	0.0008 (0.00)	0.01072 (0.01)	-0.01994 (-0.02)	0.0533 (0.05)
Wednesday	26	0.00006 (0.00)	0.000297 (0.00)	0.00031 (0.00)	0.00117 (0.00)
Friday	20	0.000112 (0.00)	0.000515 (0.00)	-0.000507 (0.00)	0.001917 (0.00)

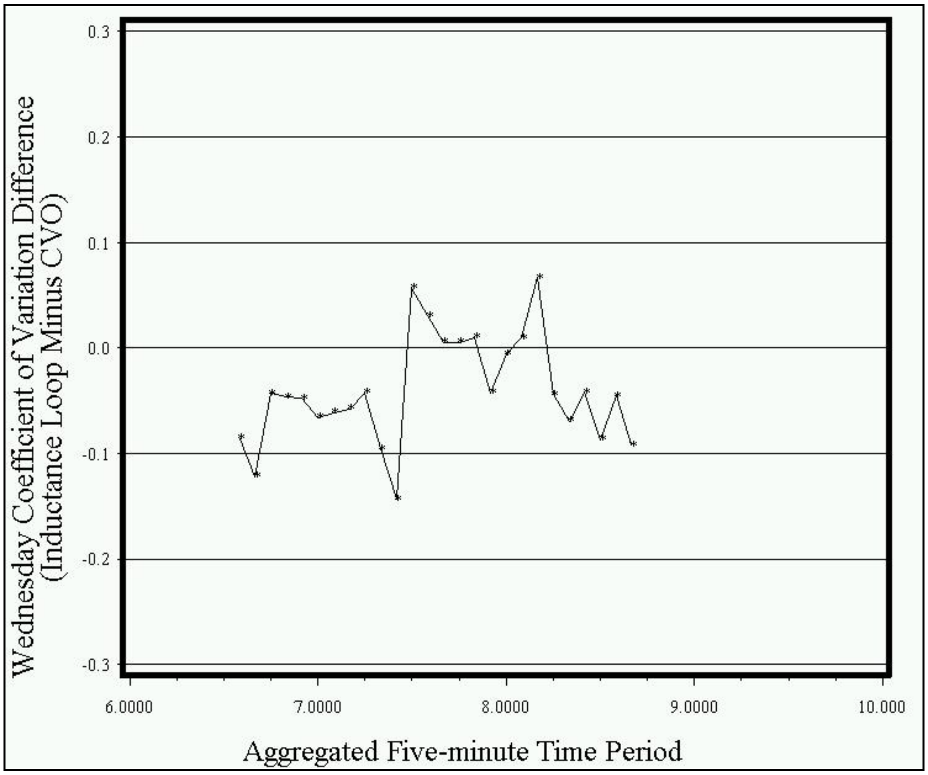

FIGURE 6-13 Wednesday Coefficient of Variation Difference Between Inductance Loop and CVO

Table 6-13 displays the percent differences between inductance loop and CVO for Wednesday by congestion level. The average percent difference between the inductance loop and commercial vehicle data across the entire day of data is 4.1 percent. The largest difference between the two data sources is during congested conditions (≤30 mph) at 14.0 percent. During free-flow conditions (≥60 mph) the percent difference is 2.2 percent on the Wednesday data. These results imply that the CVO mean travel time estimate is more accurately estimated by the inductance loop detector estimate during free-flow conditions and is more difficult to accurately estimate during congested conditions. In contrast, in the Houston study corridor, the largest difference between CVO and AVI-equipped vehicles was largest at 7.9 percent during free-flow conditions as shown in Table 5-26. This is attributed to the larger variance difference of CVO drivers in Houston as computed at 47.8 minutes squared in Table 5-26 compared to the one percent difference in Table 6-14. Table C-4 through Table C-6 in Appendix C present similar information for the other days of data collected in San Antonio, Texas. Table 6-14 presents a summary of the percent differences between the inductance loops and commercial vehicles for the week of data. The largest difference is 5.1 percent during congested conditions. During congested conditions, the c.v. difference is 233.0 percent. This indicates the larger variability in the inductance loop detector travel time estimates that can occur during congested conditions.

TABLE 6-13 Percent Differences Between Inductance Loop and CVO for Wednesday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All Data	26	4.09	21.79	-33.21	64.74
		≥60 mph	6	2.22	4.07	-0.56	10.38
		31 to 59 mph	16	2.3	26.45	-33.21	64.74
		≤30 mph	4	14.03	16.57	-10	26.63
	Variance	All Data	26	-0.47	3.13	-8.41	9.63
		≥60 mph	6	-0.48	1.97	-2.25	3.35
		31 to 59 mph	16	-0.9	3.74	-8.41	9.63
		≤30 mph	4	1.25	0.58	0.58	1.97
	Coefficient of Variation	All Data	26	-45.52	67.21	-96.11	128.39
		≥60 mph	6	-50.95	88.12	-94.61	128.39
		31 to 59 mph	16	-61.75	55.54	-96.11	106.76
		≤30 mph	4	27.54	26.27	10.27	66.65

TABLE 6-14 Percent Differences Between Inductance Loop and CVO for the Week of Data

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	2.74	-0.03	-21.88
≥60 mph	2.14	-0.88	-78.82
31 to 59 mph	2.43	-0.64	-58.3
≤30 mph	5.05	4.1	232.99

COMMERCIAL VEHICLE TRAVEL TIME ESTIMATES COMPARED TO INSTRUMENTED TEST VEHICLES

Analysis of Variance

ANOVA was performed for the CVO and test vehicle data on the fixed effects shown in Equation 5-6 and Equation 5-7. These results were shown previously in Table 6-3 and Table 6-9. It was found that the CVO travel time characteristics do not vary across days, but the mean and standard deviation does vary by time period. For commercial vehicle shipping and logistics applications, it would appear that planning shipments for a particular weekday is less important than the time of day (i.e., avoiding congested conditions). It was also found that for the test vehicle data in San Antonio, there is a daily and temporal variation in the mean travel time estimate while the c.v. remains relatively constant. The implication of this result is that the variability about the test vehicle is relatively constant across days and time periods; therefore, for this test corridor, it appears that the variability could be assumed constant, given a mean travel time estimate.

Table 6-15 presents ANOVA results for travel time characteristics comparing the CVO and test vehicle data sources. The null hypothesis (H_o) is that the CVO and test vehicle value is the same. The interaction effects were not significant for any of the analyses performed. Further, the results indicate that the CVO and test vehicle travel time means are not statistically different ($p=0.3883$). However, day of week ($p=0.0017$) and time period ($p<0.0001$) were statistically different between the two data sources for the travel time mean. The data source ($p=0.7300$), day of week ($p=0.8996$), and time period ($p=0.1721$) were not found to be statistically different for the ratio of the standard deviation to the mean (c.v.). These results indicate that the CVO and test vehicles in San Antonio are not statistically different. Though one would expect differences in the CVO and test vehicle estimates, Figure 6-7 (test vehicle) and Figure 6-11 (CVO) indicate for the Wednesday data there is only a 1.8 percent difference. Therefore, the CVO and test vehicles are traveling with similar travel times during uncongested conditions. Because the congested period ($\leq$30 mph) only lasts approximately thirty minutes, large differences between CVO and the test vehicles are not found. This is intuitive as the congestion is not long enough to affect the acceleration characteristics of the commercial vehicles.

TABLE 6-15 ANOVA Results for Travel Time Characteristics Comparing CVO and Test Vehicle Data Sources

Data Source	Travel Time Variable Tested	P-Values (Degrees of Freedom)				
		Data Source	Day of Week	Time Period	Interaction of Data Source and Day of Week	Interaction of Data Source and Time Period
CVO and Test Vehicle	Average	0.3883 (1)	**0.0017 (4)**	**<0.0001 (33)**	0.9986 (4)	1.00000 (23)
	Standard Deviation	0.7619 (1)	0.7756 (4)	**<0.0001 (32)**	0.3773 (4)	0.8127 (23)
	Coefficient of Variation	0.7300 (1)	0.8996 (4)	0.1721 (32)	0.2534 (4)	0.8759 (23)

Note: Bold values indicate a statistical difference at the α=0.05 level of significance.

Loess Statistical Smoothing

The loess statistical smoothing of the CVO and test vehicle data are discussed in this section. This section will focus on the analysis of the differences between the two data sources from five-minute aggregated data. Table 6-16 presents the statistical properties for each day of data for differences between CVO and test vehicles. The GCV MSE ranges from 0.0439 for the Wednesday data to 0.2211 with the Monday data, and the number of observations range from twenty to thirty-seven. An average of eight percent of the data were used in the smoothing of the estimate differences.

TABLE 6-16 Statistical Properties for Each Day of Data for Differences Between CVO and Test Vehicles

Day	Number of Observations	Smoother Value	GCV MSE	Fit Type
Monday	37	0.3097	0.2211	Quadratic
Tuesday	29	0.4663	0.0484	Linear
Wednesday	24	0.3912	0.0439	Linear
Thursday	24	0.8931	0.0465	Linear
Friday	20	0.9692	0.0323	Linear

Figure 6-14 presents the estimated differences and confidence intervals between the CVO and test vehicle data for Wednesday from the loess statistical technique. The lack of a statistical difference between the CVO and test vehicle data is illustrated in Figure 6-14 because the maximum difference at 7:45 a.m. is only about 0.2 minutes (12 seconds) over the length of the study corridor. Figure 6-15 shows the bias estimate over time. Summary statistics for bias estimates for the differences between CVO and test vehicles are shown in Table 6-17. The average bias is zero, while the maximum estimated bias occurs on Monday at -0.187 minute (11 seconds). The calculated values for bias are shown in Table 6-17. The values in parentheses are rounded to the appropriate number of significant digits. Figure 6-16 illustrates the c.v. difference between the CVO and test vehicles over time with the Wednesday data. The average percent difference between the CVO and test vehicle c.v. values is approximately 170 percent.
Figure C-65 to Figure C-81 in Appendix C present similar figures for each day of data collection including differences in variance, differences in c.v., bias estimates, and predicted differences including confidence intervals corrected for estimated bias.

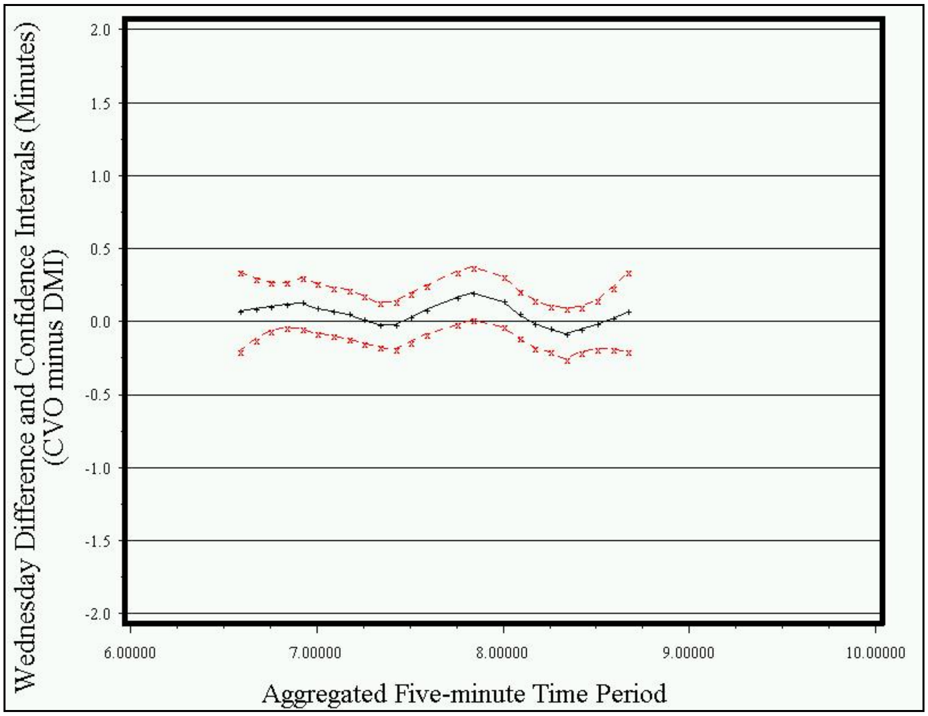

FIGURE 6-14 Wednesday Difference Between CVO and Test Vehicles and Confidence Intervals Including Correction for Estimated Bias

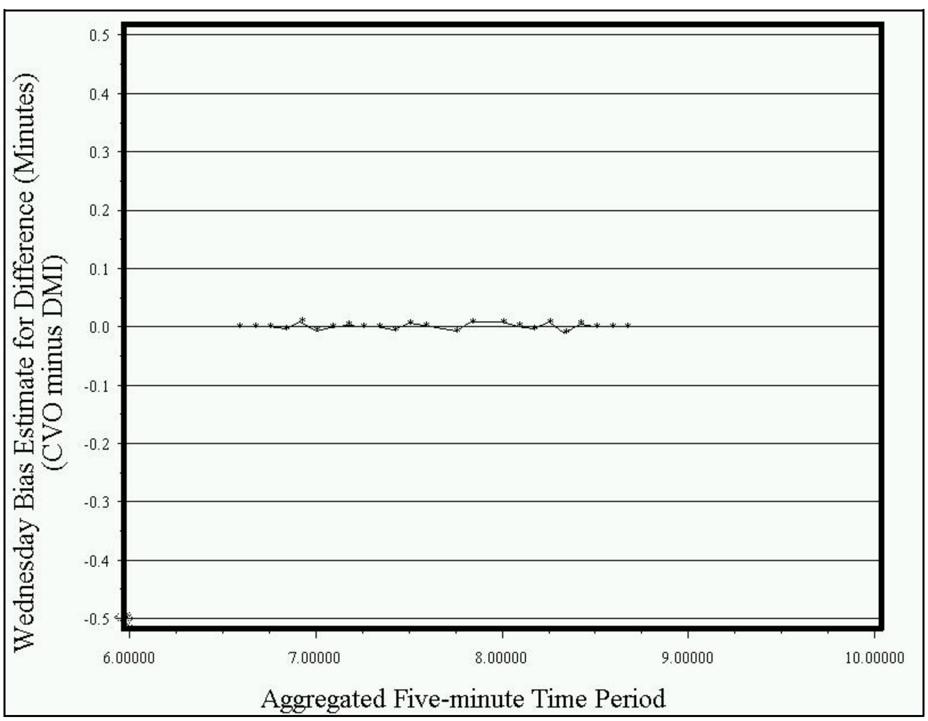

FIGURE 6-15 Wednesday Bias Estimate for Differences Between CVO and Test Vehicles

TABLE 6-17 Summary Statistics for Bias Estimate for Differences Between CVO and Test Vehicles

Day	Bias Estimate Statistics Calculated Value (Rounded)				
	Number of Observations	Mean (minutes)	Standard Deviation (minutes)	Minimum (minutes)	Maximum (minutes)
Monday	37	0.000905 (0.00)	0.05227 (0.05)	-0.187 (-0.19)	0.184 (0.18)
Tuesday	29	-0.000176 (0.00)	0.00196 (0.00)	-0.0044553 (0.00)	0.0032836 (0.00)
Wednesday	24	0.000524944 (0.00)	0.0051272 (0.01)	-0.0104793 (-0.01)	0.00857 (0.01)
Thursday	24	$-8.28\text{x}10^{-6}$ (0.00)	0.000864 (0.00)	-0.00136 (0.00)	0.0027216 (0.00)
Friday	20	-0.0000179 (0.00)	0.00008228 (0.00)	-0.000306 (0.00)	0.00008104 (0.00)

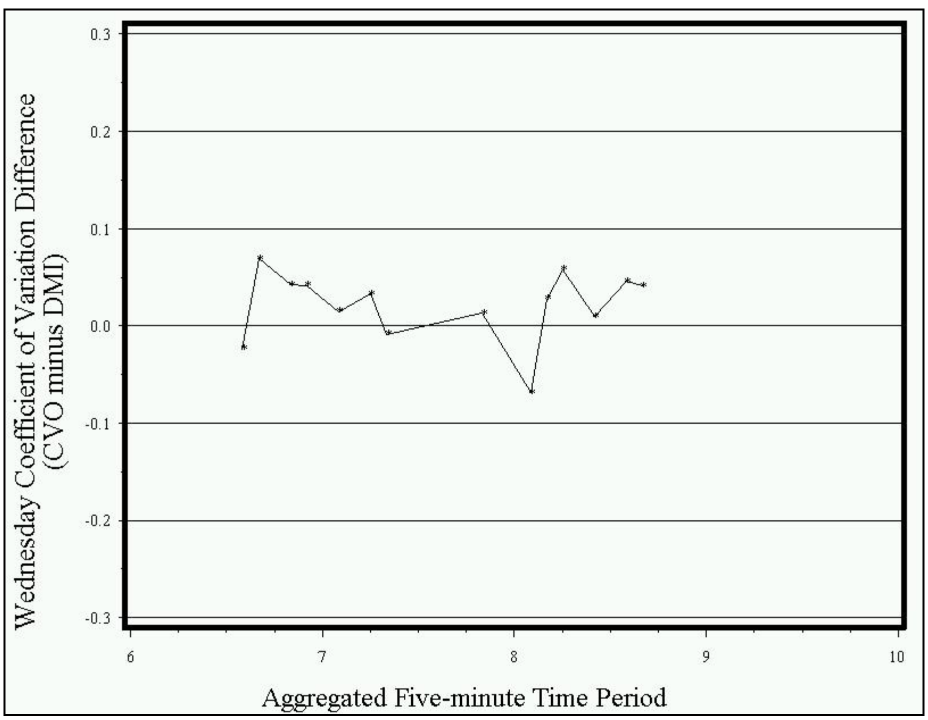

FIGURE 6-16 Wednesday Coefficient of Variation Difference Between CVO and Test Vehicles

Table 6-18 presents the percent differences between CVO and test vehicles for Wednesday by congestion level. The largest percent difference between the CVO and test vehicle data occurs during free-flow conditions (≥60 mph) at 4.1 percent. It is hypothesized that the difference is largest during uncongested periods because both passenger cars and CVO are able to travel at speeds unrestricted by congestion, and the commercial vehicles simply do not travel at the same speed of the test vehicles. The absolute difference is also very small at approximately 0.5 minute (nine seconds) maximum as shown in Figure 6-14. As described in the previous chapter, the percent error metric may exemplify these small differences across congested and uncongested conditions. For all data collected, the average percent difference is 1.8 for the mean estimated travel time. Coefficient of variation differences were highest during free-flow conditions as well. This is intuitive as vehicles are less constrained during the free-flow conditions; therefore, there is more variability in the travel. Table C-7 to Table C-10 contain similar results for the percent differences between CVO and test vehicles for each additional day of data collection.

TABLE 6-18 Percent Differences Between CVO and Test Vehicles for Wednesday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All Data	24	1.76	6.39	-15.75	10.78
		≥60 mph	9	4.06	4.3	-3.14	10.78
		31 to 59 mph	11	-0.25	7.66	-15.75	9.56
		≤30 mph	4	2.13	6.07	-5.37	8.48
	Variance	All Data	14	0.41	1.47	-3.26	3.42
		≥60 mph	8	0.22	1.46	-3.26	1.55
		31 to 59 mph	5	0.63	1.76	-1.15	3.42
		≤30 mph	1	0.08	–	0.8	0.8
	Coefficient of Variation	All Data	13	169.85	271.28	-49.31	918.31
		≥60 mph	7	216.36	342.97	-49.31	918.31
		31 to 59 mph	5	132.45	184.41	-21.04	437.09
		≤30 mph	1	31.28	–	31.28	31.28

Table 6-19 further quantifies the percent differences found between CVO and test vehicles for the week of data collected by congestion level. Throughout the data collection period, there was a percent difference of 2.4 between CVO and test vehicles. This difference was higher during free-flow periods (5.6 percent) and only 1.8 percent during the most congested periods (≤30 mph). The highest percent difference in the ratio of the standard deviation to the mean (c.v.) occurred during free-flow conditions (≥60 mph) at 259.2 percent. This difference may be attributed to the change to floating-car test vehicle data collection during free-flow conditions from the chase-car method during congested conditions. Finally, for reference,

Table C-11 to Table C-14 in Appendix C provide average statistics for each data source for all days by congestion level.

TABLE 6-19 Average Percent Differences Between CVO and Test Vehicles for the Week of Data

Congestion Level	Mean	Variance	Coefficient of Variation
All Data	2.38	-0.93	165.22
≥60 mph	5.58	0.58	259.18
31 to 59 mph	0.50	-1.68	110.48
≤30 mph	1.78	-3.01	81.40

CONCLUDING REMARKS

Two common techniques for estimating travel time from inductance loop detectors were compared on a sample corridor to investigate the percent difference in the travel time estimates. It was found that both methods provided results that were within two percent during the time periods during which data were collected. For the remaining analysis throughout the chapter, the technique that assumes the spot speed from the detector is valid for one-half the distance to the next adjacent detector was used since the differences were small. In addition, video cameras in the field were located to correspond with links defined by this technique, and a downstream detector was not available for use in the average-speed technique.

Comparison of estimated travel time characteristics from inductance loop detectors and instrumented test vehicles were then compared based upon five-minute aggregated data. The loess nonparametric technique was used in the comparative analysis. Statistical differences were found between the data sources by day of the week in average travel time estimates, but the c.v. was not statistically different across days. For the week of data available, the largest percent difference in corridor travel time mean between the two data sources was experienced during free-flow conditions (≥60 mph) at 5.8 percent. During congested conditions (≤30 mph) the average percent difference was 2.5 percent. The c.v. difference during congested conditions was large at 617.1 percent. This indicates that there is a relatively large difference in the ratio of standard deviation to the mean in the inductance loop detector data. This demonstrates that the loop detector estimate of travel time variance is not related to individual vehicle variance.

The inductance loop detector data were also compared to the commercial vehicle data with five-minute aggregated data. The results indicated that the mean travel time estimates across days were statistically different across days, while the variability relative to the mean (c.v.) was not statistically different. The largest percent difference between the two data sources for the week of data was 5.1 percent during congested conditions. During congested conditions, the c.v. difference is 233.0 percent. Once again, these results indicate the larger variability that occurs in the inductance loop detector data, especially during congested conditions.

The mean and c.v. travel time estimates from the CVO and test vehicle data were not found to be statistically different. Throughout the data collection period, there was a percent difference of 2.4 between the CVO and test vehicles. This difference was higher during free-flow periods (5.6 percent) and only 1.8 percent during the most congested periods. The highest percent difference in c.v. occurred during free-flow conditions ($\geq$65 mph) at 259.2 percent. Though differences between CVO and test vehicles, on average 2.4 percent, were not statistically different, there may still be benefit to providing real-time information specific to CVO because over longer corridors these differences may become significant. It should be noted that CVO travel time mean and c.v. were not statistically different by day of the week, but the mean estimate was statistically significant by time period. For all data for the week combined, the corridor travel time for CVO was 2.4 minutes during free-flow conditions (speeds $\geq$60 mph) and 6.0 minutes during congested periods (speeds $\leq$30 mph). For commercial vehicle shipping and logistics applications, when time allows, it would appear that planning shipments for a particular weekday may be less of a concern than the time of day the shipment is sent in order to avoid congested conditions.

The loess technique was again successfully used in this chapter for the estimation of travel time mean and variance from which comparisons of different data sources were performed. This technique provides an easily understood statistical method for nonparametric smoothing that would allow estimation of travel time mean and variability estimates from ITS data sources for transportation applications such as systems monitoring and multi-modal analysis.

CHAPTER VII

CONCLUSIONS AND RECOMMENDATIONS

This report describes relevant literature, survey results, and subsequent research into estimating travel time characteristics from ITS data for real-time and off-line transportation applications. Though the data used in this report are from AVI and inductance loop detectors, the methodologies presented for link and corridor travel time mean and variance estimation are applicable to any detector technology. Future technologies that provide travel time data (e.g., cellular telephones) can also use these methods. These future technologies, and advances on existing methods, will likely provide increased and more reliable data. As sample sizes increase, estimates of travel time mean, and the variance around the travel time estimate, will improve. Some of the key findings and subsequent conclusions are provided below, along with a discussion of further research recommendations.

TRUCKING COMPANY SURVEY RESULTS

Chapter II described the relevant literature in the areas of travel time mean and variance estimation as well as results from a survey of trucking companies and trucking professionals to obtain insight into motor carrier information needs and how ITS can assist in providing these information needs. Unfortunately, the response to the telephone survey was very low and the responses cannot be expected to be representative of all trucking companies. However, some valuable insight was provided by the survey results including the indication that particular speeds are not as important as whether the traffic is moving or not. It was indicated that the technologies (e.g., GPS, wireless data communications) would need to reduce in cost and increase in durability and coverage area before they would be beneficial. There was also an indication that the cost of stopping at scales is minimal and well within the overall delay of a trip expected from traffic or weather conditions, and that transponders would not be beneficial especially because there is a concern for proprietary information being released.

ITS DATA REDUCTION AND QUALITY CONTROL

Chapter III included a detailed description of the application of data reduction, imputation, and quality control techniques to screen for outliers in inductance loop detector data obtained from the TransGuide® ATMS in San Antonio, Texas. This report represents the first application of the screening rules and imputation methods described for the analysis of travel time mean and variance estimation. Screening rules and imputation methods are essential when reducing inductance loop detector data and the techniques described in this report, which are based upon previous research, appear to work well. Standard techniques were also used to screen for outliers in the AVI data; however, imputation of missing data was not performed because standard techniques for AVI data imputation are not documented. As shown in the statistical results that are discussed below, the AVI data provide a more reliable data source for travel time mean and variance estimation.

INVESTIGATION OF TRAVEL TIME ESTIMATES FOR SYSTEM MONITORING AND MULTI-MODAL ANALYSES USING AVI DATA

Chapter V introduced the loess nonparametric statistical technique for estimating and comparing AVI, instrumented test vehicle, and CVO data source corridor travel time estimates. The loess procedure was found to provide an easily understood method of local least squares for providing predicted mean values of nonparametric functions with large ITS data sets.

The first objective of Chapter V was to compare the AVI and instrumented test vehicle corridor travel time data using five-minute aggregated data. The differences between the mean predicted values were within two percent for the entire corridor from each data source. ANOVA indicated that there was no statistical difference in the travel time mean or standard deviation from each data source at the α=0.05 level of significance. In addition, each data source was independently studied. While the ANOVA of the test vehicle and AVI data sources separately indicated that there was a statistical difference in the travel time mean by day of week and time period, the ratio of the standard deviation to the mean (c.v.) did not indicate a statistical difference. This is valuable information for situations when it may be difficult to obtain the variability on the travel time estimate (i.e., when inductance loop detectors are used) as it could be assumed constant if known for a particular day and time period.

The average c.v. difference between AVI and test vehicles was 11.8 percent while the largest difference occurred during the congested period ($\leq$35 mph) at 37.6 percent. The difference between AVI and instrumented test vehicles travel time mean was generally within two percent. The instrumented test vehicles used in the study also carried AVI tags onboard. A paired *t*-test analysis provided statistical evidence that there was measurement error introduced by different drivers. The paired *t*-test analysis can also be used to identify drivers who are not performing the test vehicle data collection correctly. Currently, there is no methodology for performing this evaluation of drivers. In conclusion, these results indicate that with the implementation of an adequate AVI infrastructure and appropriate level of tag reads, an AVI system can replace traditional data collection techniques used for system monitoring. The additional benefit is that data can be collected dynamically, all year long, rather than at selected times.

CVO and AVI data from the Houston test corridor were subsequently compared. A statistical difference was found between the CVO and AVI travel time mean and standard deviation at the α=0.05 level of significance. The c.v. between the two data sources was not found to be statistically different. The AVI vehicles were traversing the corridor an average of 6.1 percent faster than the commercial vehicles. The coefficient of variation was 11.4 percent different between AVI and commercial vehicles. These results are intuitive, as commercial vehicles have different operating characteristics than AVI-equipped vehicles even though ATMSs generally provide traveler information to CVO and commuters based on information from AVI-equipped vehicles. For just-in-time delivery and fleet operations that operate under strict constraints, the differences found between AVI and commercial vehicles could become significant. It may be reasonable to provide travel time maps and information in real-time specifically for commercial vehicles.

The research found that the loess statistical procedure is useful in providing travel time estimates and confidence intervals for a nonparametric function. The procedure is simple to understand and implement, and it provides results that can be produced in a user-friendly manner with minimal programming. The loess statistical procedure could be used to automate the real-time travel time mean and confidence intervals for multi-modal and system monitoring. Loess could also be used to analyze historical archived data for off-line performance monitoring.

INVESTIGATION OF TRAVEL TIME ESTIMATES FOR SYSTEM MONITORING AND MULTI-MODAL ANALYSES USING INDUCTANCE LOOP DETECTOR DATA

Two methods were presented in Chapter II and then in Chapter VI for determining travel time mean estimates from inductance loop detector spot speed estimates. The first estimation technique assumes that the spot speed is valid for half the distance to the next adjacent detector while the second method uses the average speed from the two adjacent detectors and uses that speed to estimate the travel time along the link of interest. It was found that both methods provided results that were within two percent during the time period over which the data were collected. For the remaining analyses throughout the report, the first method was used. A method using loess to obtain mean corridor travel time estimates from link travel time estimates obtained from the inductance loop detector spot speeds was also presented in Chapter VI.

Comparisons of estimated travel time characteristics from inductance loop detectors and instrumented test vehicles were then compared based upon five-minute aggregated data. The loess technique was used in the comparative analysis. The average percent difference between inductance loop and test vehicle mean corridor travel time was three percent, while during uncongested conditions ($\geq$60 mph) the difference was 5.8 percent. The c.v. difference during congested conditions was large at 617 percent while during uncongested conditions it was 46.8 percent. These results provided a statistical difference at the α=0.05 level of significance. This indicates that there is a relatively large difference in the ratio of the standard deviation to the mean in the inductance loop detector travel time estimates. With these results, this report has assisted in quantifying the high variability that is found in inductance loop detector travel time estimates, especially during congested conditions.

Five-minute aggregate estimates of travel time characteristics from the inductance loop detectors were then compared to the commercial vehicles with the San Antonio data. During congested conditions, the high variability in the inductance loop detector data was again discovered. During congested conditions, the c.v. difference between the two data sources was 233.0 percent. This result was statistically different at the α=0.05 level of significance. The largest percent difference in travel time mean between the two data sources for the week of data was 5.1 percent during congested conditions. It is clear from these results that, due to the large variability in the loop detector data, it is difficult to get an accurate estimate of the variability about the corridor mean. When providing data for real-time traveler and CVO information needs, this would result in the need for large confidence intervals around the mean travel time.

Finally, a comparison of five-minute aggregate estimates of travel time characteristics from CVO and the instrumented test vehicles was performed with the San Antonio data. The largest difference between the CVO and test vehicles was found during free-flow periods at 5.6 percent and the difference was only 1.8 percent during the most congested periods. The highest percent difference in the ratio of the standard deviation to the mean (c.v.) also occurred during free-flow conditions at 259.2 percent. These results indicate that the commercial vehicles have different operating conditions than the instrumented test vehicles, especially during free-flow conditions, which further suggests that providing real-time traveler information specific to commercial vehicles may be useful for shipping logistics.

RECOMMENDATIONS FOR FUTURE RESEARCH

Though this research provided several contributions to the transportation literature in the area of link and corridor travel time mean and variance estimation, there are several areas in which future work is needed.

Though the number of responses to the trucking surveys was limited, valuable insight was provided including the indication that the trucking industry is concerned about how proprietary information may be released and used from ITS technologies applied to CVO. There is also a concern for the high costs and relatively low durability of these systems. These issues must be considered in the development of ITS applications that will provide information to truckers in order for these systems to be of use to the trucking industry.

This report used data obtained along two corridors–one in Houston instrumented with AVI detectors at 0.5-mile spacings, and one in San Antonio with detectors at 0.5-mile spacings. The corridor in Houston was two miles in length and the corridor in San Antonio was 2.5 miles in length. There is a need for similar work that studies link and corridor travel time mean and variance estimates over longer corridors with varying congestion levels.

Future similar work should also be performed along a corridor in which detectors capable of measuring spot-mean speed for conversion to travel time estimates (e.g., inductance loop detectors) and detectors capable of directly measuring space-mean travel time (e.g., AVI) are located along the same corridor. This would provide the added benefit of a direct comparison of the two sources of travel time mean and variance. Future work should also include lane-by-lane analysis of the ITS data especially from inductance loop detectors to better quantify the lane-by-lane variability in the travel time estimates.

This study was successful in instrumenting test vehicles with a distance-measuring instrument (DMI) for the collection of travel time data with chase vehicles. There is a need to compare DMI-instrumented test vehicles with test vehicles instrumented with the global positioning system (GPS). Both methods have their advantages and disadvantages, yet these tradeoffs have not been fully quantified.

There is a need for further characterizing CVO travel time mean and variance under varying traffic conditions both temporally and spatially. CVO transportation needs for just-in-time deliveries and goods movement logistics are a considerable economic factor both nationally and internationally. Additional investigation of travel time mean and variance estimates for statewide shipping is also needed. Multi-modal information needs can benefit from further work in this area.

REFERENCES

1. Turner, S.M., W.L. Eisele, R.J. Benz, and D.J. Holdener. *Travel Time Data Collection Handbook*. Report No. FHWA-PL-98-035, FHWA, U.S. Department of Transportation, 1998.
2. Turner, S.M. Advanced Techniques for Travel Time Data Collection. In *Transportation Research Record 1551*, TRB, National Research Council, Washington, DC, 1996, pp. 51-58.
3. Lomax, T.J., S.M. Turner, S. Shunk, H.S. Levinson, R.H. Pratt, P.N. Bay, and G.B. Douglas. *NCHRP Report 398: Quantifying Congestion: Final Report*. TRB, National Research Council, Washington, DC, 1997.
4. Lomax, T., S.M. Turner, S. Shunk, H.S. Levinson, R.H. Pratt, P.N. Bay, and G.B. Douglas. *NCHRP Report 398: Quantifying Congestion: User's Guide*. TRB, National Research Council, Washington, DC, 1997.
5. Schrank, D.L. and T.J. Lomax. *2001 Urban Mobility Report*. Texas Transportation Institute, College Station, TX, 2001, (http://mobility.tamu.edu).
6. *Manual of Transportation Engineering Studies*. Institute of Transportation Engineers, Prentice-Hall, Englewood Cliffs, NJ, 1994.
7. Berry, Donald S. and F.H. Green. Techniques for Measuring Over-all Speeds in Urban Areas. In *Highway Research Board Proceedings,* Volume 29, HRB, National Research Council, Washington, DC, 1949, pp. 311-318.
8. Berry, D.S. Evaluation of Techniques for Determining Over-all Travel Time. In *Highway Research Board Proceedings,* Volume 31, HRB, National Research Council, Washington, DC, 1952, pp. 429-440.
9. Rakha, H. and M. Van Aerde. Accuracy of Vehicle-Probe Estimates of Link-Travel Time and Instantaneous Speed. In *Proceedings of the 1995 Annual Meeting of ITS America,* ITS America, Washington, DC, 1995, pp. 385-392.
10. Ferrier, P.J. *Comparison of Vehicle Travel Times and Measurement Techniques Along the I-35 Corridor in San Antonio, Texas*. Master of Science Thesis, Texas A&M University, College Station, TX, August 1999.
11. Quiroga, C. Assessment of Dynamic Message Sign Travel Time Information Accuracy. In *Proceedings for the North American Travel Monitoring Conference and Exposition* [CD-ROM], Middleton, WI, August 2000.
12. Lindveld, C. and R. Thijs. On-Line Travel Time Estimation Using Inductive Loop Data: The Effect of Instrumentation Peculiarities. In *Proceedings of the 6th ITS World Congress* [CD-ROM], Toronto, Ontario, Canada, 1999.
13. Van Grol, Rik, K. Lindveld, S. Manfredi, and M. Danech-Pajouh. DACCORD: On-Line Travel Time Estimation/Prediction Results. In *Proceedings of the 6th ITS World Congress* [CD-ROM], Toronto, Ontario, Canada, 1999.
14. Lindveld, C., R. Thijs, P.H. Bovy, and N.J. Van der Zijpp. Evaluation of On-Line Travel Time Estimators and Predictors. In *Transportation Research Board 1719*, TRB, National Research Council, Washington, DC, 2000, pp. 45-53.

15. Riley, J.D. *Evaluation of Travel Time Estimates Derived From Automatic Vehicle Identification Tags in San Antonio, Texas*. Master of Science Thesis, Virginia Polytechnic Institute and State University, Blacksburg, VA, June 1999.
16. Eisele, W.L., L.R. Rilett, K.B. Mhoon, and C.H. Spiegelman. Using Intelligent Transportation Systems (ITS) Travel Time Data for Multi-Modal Analysis and System Monitoring. In *Transportation Research Board 1768*, TRB, National Research Council, Washington, DC, 2001, pp. 148-156.
17. Eisele, W.L. and L.R. Rilett. A Statistical Comparison of Travel Time Estimates Obtained from Intelligent Transportation Systems and Instrumented Test Vehicles. To be published in forthcoming *Transportation Research Record*, Transportation Research Board, Washington, DC, 2002.
18. Eisele, W.L. and L.R. Rilett. Estimating Corridor Travel Time Mean, Variance, and Covariance with Intelligent Transportation System Link Travel Time Data. In *Proceedings of the 81st Annual Meeting of the Transportation Research Board* [CD-ROM], Washington, DC, January 2002.
19. Eisele, W.L. Estimating Travel Time Mean and Variance Using Intelligent Transportation Systems Data for Real-time and Off-line Transportation Applications. Ph.D. Dissertation, Texas A&M University, May 2001.
20. Chen, L. and A. May. Traffic Detector Errors and Diagnostics. In *Transportation Research Record 1132*, TRB, National Research Council, Washington, DC, 1987, pp. 82-93.
21. Nihan, N., L. Jacobson, J. Bender, and G. Davis. *Detector Data Validity*. Washington State Transportation Commission, Olympia, WA, March 1990.
22. Jacobson, L.N., N.L. Nihan, and J.D. Bender. Detecting Erroneous Loop Detector Data in a Freeway Traffic Management System. In *Transportation Research Record 1287*, TRB, National Research Council, Washington, DC, 1990, pp. 151-166.
23. Cleghorn, D., F. Hall, and D. Garbuio. Improved Data Screening Techniques for Freeway Traffic Management Systems. In *Transportation Research Record 1320*, TRB, National Research Council, Washington, DC, 1991, pp. 17-23.
24. Nihan, N.L. Aid to Determining Freeway Metering Rates and Detecting Loop Errors. *ASCE Journal of Transportation Engineering*, Volume 123, No. 6, 1997, pp. 454-458.
25. Coifman, B. Using Dual Loop Speed Traps to Identify Detection Errors. In *Transportation Research Record 1683*, TRB, National Research Council, Washington, DC, 1999, pp. 47-58.
26. Wang, Y. and N. Nihan. Freeway Traffic Speed Estimation Using Single Loop Outputs. In *Transportation Research Record 1727*, TRB, National Research Council, Washington, DC, 2000, pp. 120-126.
27. Coifman, B. Improved Velocity Estimation Using Single Loop Detectors. *Transportation Research A*, Volume 35, Number 10, 2001, pp. 863-880
28. Turner, S.M, W.L. Eisele, B.J. Gajewski, L.P. Albert, and R.J. Benz. *ITS Data Archiving: Case Study Analyses of San Antonio TransGuide® Data.* Federal Highway Administration Report No. FHWA-PL-99-024. August 1999.
29. Turner, S.M., L.P. Albert, B.J. Gajewski, and W.L. Eisele. Archived ITS Data Quality: Preliminary Analysis of San Antonio TransGuide Data. In *Transportation Research Record 1719*, TRB, National Research Council, Washington, DC, 2000, pp. 77-84.

30. Petty, K.F., P. Bickel, M. Ostland, J. Rice, F. Schoenberg, J. Jiang, and Y. Ritov. Accurate Estimation of Travel Times from Single-Loop Detectors. *Transportation Research A*, Volume 32, Number 1, 1998, pp. 1-17.
31. Sun, C., S. Ritchie, and K. Tsai. Algorithm Development for Derivation of Section-Related Measures of Traffic System Performance Using Inductive Loop Detectors. In *Transportation Research Record 1643*, TRB, National Research Council, Washington, DC, 1998, pp. 171-180.
32. Sun, C., S. Ritchie, K. Tsai, and R. Jayakrishnan. Use of Vehicle Signature Analysis and Lexicographic Optimization for Vehicle Reidentification on Freeways. *Transportation Research C7*, 1999, pp. 167-185.
33. Sun, C. and S. Ritchie. Individual Vehicle Speed Estimation Using Single Loop Inductive Waveforms. *ASCE Journal of Transportation Engineering*, Volume 125, No. 6, 1997, pp. 531-538.
34. Sisiopiku, V.P. and N.M. Rouphail. Toward the Use of Detector Output for Arterial Link Travel Time Estimation: A Literature Review. In *Transportation Research Record 1457,* TRB, National Research Council, Washington, DC, 1994, pp. 158-165.
35. Sisiopiku, V.P., N.M. Rouphail, and A. Santiago. Analysis of Correlation Between Arterial Travel Time and Detector Data from Simulation and Field Studies. In *Transportation Research Record 1457,* TRB, National Research Council, Washington, DC, 1994, pp. 166-173.
36. Palacharla, P.V. and P.C. Nelson. Application of Fuzzy Logic and Neural Networks for Dynamic Travel Time Estimation. *International Transactions in Operational Research*, Volume 6, Number 1, 1999, pp. 145-160.
37. Hallenbeck, M., T. Boyle, and J. Ring. *Use of Automatic Vehicle Identification Techniques for Measuring Traffic Performance and Performing Incident Management*. Washington State Department of Transportation Report No. WA-RD273.1, October 1992.
38. Levine, S.Z. and W.R. McCasland. Monitoring Freeway Traffic Conditions with Automatic Vehicle Identification Systems. *ITE Journal*, March 1994, pp. 23-28.
39. Balke, K.N., G.L. Ullman, W.R. McCasland, C.E. Mountain, and C.L. Dudek. *Benefits of Real-Time Travel Information in Houston, Texas*. Southwest Region University Transportation Center, Research Report SWUTC/60010-1, Texas A&M University, College Station, TX, January 1995.
40. Gaynor, J.M. and D.W. Borchardt. A Successful Return to Ramp Metering. In *Proceedings of the 7th Annual Meeting and Exposition of ITS America* [CD-ROM], ITS America, Washington, DC, 1997.
41. Turner, S.M., G.A. Carlin, and R.H. Henk. *Quantifying the Benefits of High-Occupancy Vehicle Facilities Using Automatic Vehicle Identification Technology*. Southwest Region University Transportation Center, Research Report SWUTC/465020-1, Texas A&M University, College Station, TX, November 1995.
42. Holdener, D.J. and S.M. Turner. Probe Vehicle Sample Sizes for Real-Time Information: The Houston Experience. In *Proceedings of the 6th Annual Meeting of ITS America*, ITS America, Houston, TX, 1996, pp. 287-295.
43. Carlin, G.A. Travel Time Variations of Probe Vehicles Using Houston's Automatic Vehicle Identification Traffic Monitoring System. In *Compendium of Technical Papers for*

the 66th ITE Annual Meeting, Institute of Transportation Engineers, Minneapolis, MN, 1996, pp. 13-17.
44. *Transportation in America: Statistical Analysis of Transportation in the United States*. Eno Transportation Foundation, Inc., Washington, DC, Seventeenth Edition, 1999.
45. Eisele, W.L. Travel Time Data Measure Traffic Woes. *Business Geographics Magazine*, April 1998, pp. 24-27.
46. Strauss-Wieder, A. Emerging Trends and Considerations in Freight Transportation: Key Observations from Qualitative Interviews with Shippers and Transportation Providers. In *Proceedings of the Transportation Research Board 79th Annual Meeting* [CD-ROM], Washington, DC, 2000.
47. Golob, T.F. and A.C. Regan. Freight Industry Attitudes Towards Policies to Reduce Congestion. In *Proceedings of the Transportation Research Board 78th Annual Meeting* [CD-ROM], Washington, DC, 1999.
48. Regan, A.C. and T.F. Golob. Freight Operators' Perceptions of Congestion Problems and the Application of Advanced Technologies: Results from a 1998 Survey of 1,200 Companies Operating in California. In *Transportation* Journal, Volume 38, Number 3, 1999, pp. 57-67.
49. Regan, A.C., H.S. Mahmassani, and P. Jaillet. Improving Efficiency of Commercial Vehicle Operations Using Real-Time Information: Potential Uses and Assignment Strategies. In *Transportation Research Record 1493*, TRB, National Research Council, Washington, DC, 1995, pp. 188-198.
50. Holguin-Veras, J. and E. Thorson. An Investigation of the Relationships Between the Trip Length Distributions in Commodity-based and Trip-based Freight Demand Modeling. In *Proceedings of the Transportation Research Board 79th Annual Meeting* [CD-ROM], Washington, DC, 2000.
51. Benz, R.J. and M.A. Ogden. Development and Benefits of Computer-Aided Travel Time Data Collection. In *Transportation Research Record 1551*, TRB, National Research Council, Washington, DC, 1995, pp. 1-7.
52. Benz, R.J. The Development, Benefits, and Use of Computer-Aided Transportation Software (CATS) for Travel Time Data Collection. In *Proceedings of the National Traffic Data Acquisition Conference*, Albuquerque, NM, 1996, pp. 211-229.
53. Thurgood, G.S. Development of a Freeway Congestion Index Using an Instrumented Vehicle. In *Transportation Research Record 1494*, TRB, National Research Council, Washington, DC, 1995, pp. 21-29.
54. Eisele, W.L., S.M. Turner, and R.J. Benz. *Using Acceleration Characteristics in Air Quality and Energy Consumption Analysis*. Southwest Region University Transportation Center, Research Report SWUTC/465100-1, Texas A&M University, College Station, TX, January 1996.
55. Dixon, M.P. and L.R. Rilett. Real-Time Origin-Destination Estimation Using Automatic Vehicle Identification Data. Presented at the *Transportation Research Board 79th Annual Meeting* [CD-ROM], Washington, DC, January 2000.
56. Dixon, M.P. *Incorporation of Automatic Vehicle Identification Data Into the Synthetic OD Estimation Process*. Unpublished Ph.D. Dissertation, Texas A&M University, College Station, TX, May 2000.

57. Brydia, R.E., S.M. Turner, W.L. Eisele, and J.C. Liu. Development of Intelligent Transportation System Data Management. In *Transportation Research Record 1253*, TRB, National Research Council, Washington, DC, 1998, pp. 124-130.
58. Turner, S.M., R.E. Brydia, J.C. Liu, and W.L. Eisele. *ITS Data Management System: Year One Activities*. Research Report 1752-2. Texas Transportation Institute, Texas A&M University, College Station, TX, 1997.
59. Gold, D.L., S.M. Turner, B.J. Gajewski, and C. Spiegelman. Imputing Missing Values in ITS Data Archives for Intervals Under Five Minutes. In *Proceedings of the Transportation Research Board 80h Annual Meeting* [CD-ROM], Washington, DC, 2001.
60. Devore, J. and R. Peck. *Statistics: The Exploration and Analysis of Data*. Duxbury Press, Belmont, CA, Third Edition, 1997.
61. Cleveland, W.S. Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association*, Volume 74, Issue 368, December 1979, pp. 829-836.
62. Cleveland, W.S. and S.J. Devlin. Locally Weighted Regression: An Approach to Regression Analysis by Local Fitting. *Journal of the American Statistical Association*, Volume 83, Issue 403, September 1988, pp. 596-610.
63. Cleveland, W.S., S.J. Devlin, and E. Gross. Regression by Local Fitting: Methods, Properties, and Computational Algorithms. *Journal of Econometrics*, Volume 37, 1988, pp. 87-114.
64. *SAS Users Guide*. Version 8.0. Chapter 38: The Loess Procedure. SAS Institute, Carey, NC, 1999.
65. *SAS Users Guide*. Version 8.0. Chapter 39: Fit Analyses. SAS Institute, Carey, NC, 1999.
66. Ott, R.L. *An Introduction to Statistical Methods and Data Analysis*. Duxbury Press, Belmont, CA, Fourth Edition, 1993.
67. Fu, L. and L. Rilett. Expected Shortest Paths in Dynamic and Stochastic Traffic Networks. *Transportation Research B*, Volume 32, Number 7, 1998, pp. 499-516.

GLOSSARY

Advanced Traffic Management System (ATMS)
: The location, usually centralized, where intelligent transportation systems data are collected and the transportation system is monitored.

Advanced Traveler Information Systems (ATIS)
: The use of intelligent transportation systems technologies and communication methods for providing traveler information to motorists.

Analysis of Variance (ANOVA)
: Statistical method used to determine the statistical significance of dependent variables based upon the independent variable.

Average Car
: A test vehicle technique in which the drivers travel according to their judgement of the average speed of the traffic stream.

Automatic Vehicle Identification (AVI)
: Probe vehicles that are equipped with electronic toll tags that communicate with roadside transceivers to identify unique vehicles and collect travel time data between transceivers.

Fit Bias
: Error introduced by performing least-squares regression.

Central Limit Theorem (CLT)
: If random samples of n measurements are repeatedly drawn from a population with a finite mean μ and a standard deviation σ, then, when n is large, the relative frequency histogram for the sample means (calculated from the repeated samples) will be approximately normal (bell-shaped) with mean μ and standard deviation $\sigma / \sqrt{n}$ (adapted from reference *81*).

Chase Car
: A test vehicle technique in which the driver randomly selects a vehicle to follow in the traffic stream.

Coefficient of Variation (c.v.)
: The standard deviation of a random variable divided by the mean of the random variable over the time period of interest.

Commercial Vehicle Operations (CVO)
: Term that refers to trucking activities including deliveries and logistics.

Computer Aided Transportation Software (CATS)
: Commercially available software used to reduce DMI test vehicle travel time runs.

Distance Measuring Instrument (DMI)
: An electronic device connected to the transmission of a vehicle that can be used to determine travel time along a corridor based upon speed and distance information.

Dynamic Message Sign (DMS)
: Traffic sign capable of having messages to motorists updated and changed as necessary.

Floating Car
: A test vehicle technique in which the driver attempts to safely pass as many vehicles as pass the test vehicle.

Generalized Crossed Validation Mean Squared Error (GCV MSE)
: The minimized error in the loess nonparametric local smoothing that is calculated by estimating the fitted value x_i without including the ith observation.

Global Positioning System (GPS)
: The department of defense system of orbiting satellites that may be used for monitoring location, direction, and speed worldwide.

Headway
: The time between test vehicles traversing the study corridor.

Inductance Loop Detector
: Traffic monitoring equipment located in the pavement composed of a metal loop that produces a magnetic field that detects vehicles when they pass over it.

Intelligent Transportation Systems (ITS)
: Any number of advanced technologies and communication methods applied to traffic management.

Just-in-Time Deliveries
: A type of inventory in which in-stock materials are minimal or non-existent. The materials must arrive at exactly the right time and not too early or too late.

License-Plate Matching
: Travel time estimation technique in which license plates are read at an origin and destination along with the time stamp of the arrival. The difference in time stamps provides the travel time estimate.

Loess
: Nonparametric statistical technique for locally weighted least squares smoothing of a function.

Occupancy
: The percent of a time period in which a vehicle is above an inductance loop detector.

Spot Speed
: The speed provided from an inductance loop detector that is for a single location and must be assumed over a given distance to estimate travel time along a link.

Test Vehicle Travel Time Data Collection Method
: Any number of travel time data collection techniques in which a driver travels along a corridor and records travel time data between checkpoints of interest.

APPENDIX A

Telephone Interview and Discussion Questions

Date: _______ Confidential code number: ______

The Texas Transportation Institute is conducting a survey of commercial vehicle companies regarding their information needs and how various technologies may satisfy these needs. The study is sponsored by the Southwest Region University Transportation Center and is entitled, "Examining Information Needs for Efficient Motor Carrier Transportation Logistics." Your participation in this study is appreciated.

General Questions

1. Coverage area (e.g., statewide, state-to-state, where to where?):

2. Type of operation (truck load versus less than truck load):

3. Number of trips per day:

4. What percentage of trips require just-in-time operation:

5. Major commodities hauled:

6. What percentage of trips require special permits:

7. Fleet characteristics (number of tractors and trailers, body types, semitrailer lengths):

8. Company characteristics (number of drivers by type–company drivers vs. owner operators):

Information Needs and Technologies

9. What type of advanced technology is the company currently using, or planning to use (e.g., transponders, on-board computers and/or traveler information, global positioning systems, automatic toll cards (AVI), others)? What percentage of the fleet is covered, or will be covered, with each?

10. Are your vehicles equipped with any of the following: 2-way radio, cell phone, AM/FM radio, CB (is it left on?), others? What percentage of the fleet is covered with each?

11. What type of information is desired prior to departure on a trip (i.e., at truck stops or at your terminal)? Are these information needs different for rural/urban trips or for highway/arterial trips?

12. What type of information is desired while on route? Are these information needs different for rural/urban trips or for highway/arterial trips? How often would you like the information updated?

13. What is the best way to get this information to your drivers?

14. Do you currently use roadway information provided on the changeable message signs along freeways or on the Internet (e.g., traffic congestion maps)? If so, do you have any comments regarding this information and how it can assist your needs?

15. What causes you the most delay on a typical trip?

16. Are your drivers interested in trip travel time estimates and the reliability (i.e., plus/minus 5-minutes) of that estimate?

17. How willing is your company to pay for a given technology that would address these information needs? What would the company be willing to spend?

18. What benefits would your company see with the installation of such a system (i.e., would it be cost-effective)?

19. What are some of the technical, institutional, or economic hurdles you would see regarding identifying, collecting, and disseminating appropriate information needs for motor carrier logistics?

20. Do you have any additional information needs that intelligent transportation systems (ITS) technologies could provide?

21. Do you have any additional comments?

ADDITIONAL QUESTIONS

Transponder Questions

22. How much time do trucks usually spend at weigh scales in Texas either being weighed or inspected?

23. What is the cost associated with having to stop at scales?

24. How important would it be for the company to make use of transponders for scale bypass (economically and in terms of just-in-time deliveries)?

25. Do you see any benefits in using transponders?

26. In the case of Texas, do you see any benefits in the application of ITS to CVO for purposes of pre-clearance?

27. When and if these technologies are introduced, would the company be willing to pay a flat rate to equip the vehicles with transponders for pre-clearance purposes? What would the company be willing to pay to equip the vehicles?

Additional CVO Trip Discussion Questions

28. Are there any specific locations in your operating area that experience significant congestion and difficulty in your operations?

29. What is the main reason for the congestion in these areas (e.g., roadway geometry, too many vehicles)?

30. How could ITS assist in providing you information regarding congested segments of roadway? When, and how often, would you like to obtain this information?

31. Do any of the following cause you delays? If so, where?
    a. Fog
    b. Flooding
    c. Hydroplaning
    d. Extremely rough road
    e. Steep grade
    f. Bad intersections and interchanges
    g. Frequent accidents

32. Do you make deliveries or pick-ups at ports? What ports?

33. If pick-ups are made at ports, what causes the most delay at the ports (e.g., gate, getting chassis, loading, finding location of wharf or terminal, difficult access to port, paperwork)?

34. Does your company cross international borders during typical operations? If so, where?

35. What causes the most delay at the border crossings? How could this be alleviated with ITS technologies?

36. What causes you the most delay on a typical trip?

37. How do you contact the company or dispatcher if you have a problem / emergency?

38. Do you think that ITS leads to productivity gains or cost savings? How?

39. In general, what do you think are the benefits of applying ITS to CVO?

40. Do you have any concerns regarding the privacy of data collected by transponders or other ITS technologies?

41. Do you have any other comments?

Thank you for your participation in this study!

APPENDIX B

TABLE B-1 P-Values for Sub-Links of US 290 Corridor by Day Comparing AVI and Test Vehicle Data

Day	Link Defined by AVI Antennas	Number of Observations	P-value	Mean Difference (AVI-DMI) (Seconds)	Percent Difference
Monday	AVI #1 to #2	32	0.5879	0.2	-0.5
	AVI #2 to #3	10	0.0396	0.9	1.5
	AVI #3 to #4	10	0.0374	-0.8	-3.5
	AVI #4 to #5	21	0.0187	-0.6	1.3
	AVI #1 to #3	9	0.0060	2.7	2.2
	AVI #3 to #5	8	0.9907	0.0	-0.4
Tuesday	AVI #1 to #2	40	0.0194	-0.6	-0.2
	AVI #2 to #3	10	0.0423	0.9	1.7
	AVI #3 to #4	6	0.7870	0.2	0.6
	AVI #4 to #5	26	0.0172	0.7	1.1
	AVI #1 to #3	9	0.9916	0.0	0.4
	AVI #3 to #5	7	0.0010	0.9	0.7
Wednesday	AVI #1 to #2	39	0.0637	-0.7	-1.3
	AVI #2 to #3	3	0.0945	2.7	7.0
	AVI #3 to #4	3	0.2223	-1.0	-4.5
	AVI #4 to #5	29	0.5456	-0.1	-0.2
	AVI #1 to #3	3	0.2285	1.0	1.6
	AVI #3 to #5	2	<0.0001	-1.0	-1.2
Thursday	AVI #1 to #2	33	0.0018	-1.3	-2.2
	AVI #2 to #3	9	0.0176	1.4	2.3
	AVI #3 to #4	10	0.1412	-0.3	-1.3
	AVI #4 to #5	24	0.0863	1.2	1.2
	AVI #1 to #3	11	0.4419	-0.3	-0.2
	AVI #3 to #5	10	0.6833	0.1	0.4

TABLE B-1 (continued)

Friday	AVI #1 to #2	29	0.9321	0.2	-0.2
	AVI #2 to #3	15	0.0018	0.6	2.6
	AVI #3 to #4	10	0.1369	-0.8	1.6
	AVI #4 to #5	26	0.0317	0.5	0.8
	AVI #1 to #3	14	0.0576	1.7	1.2
	AVI #3 to #5	11	0.9723	0.0	-0.1

TABLE B-2 Percent Differences Between AVI and Test Vehicles for Monday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All data	49	-0.98	5.47	-12.61	13.34
		≥65 mph	15	-0.16	3.20	-6.32	6.00
		31 to 64 mph	13	-3.50	5.31	-12.61	4.69
		≤30 mph	21	0.00	6.48	-10.74	13.34
	Variance	All data	25	–	–	–	99.40
		≥65 mph	10	58.38	54.91	-59.21	99.33
		31 to 64 mph	7	–	–	–	99.40
		≤30 mph	8	-654.71	–	–	99.12
	Coefficient of Variation	All data	25	-82.60	386.11	–	92.33
		≥65 mph	10	50.09	44.29	-24.88	92.33
		31 to 64 mph	7	-254.93	694.04	–	92.01
		≤30 mph	8	-97.69	201.53	-434.12	90.41

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-3 Percent Differences Between AVI and Test Vehicles for Tuesday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All data	53	1.57	5.34	-12.39	15.25
		≥65 mph	11	0.64	3.02	-6.84	3.79
		31 to 64 mph	14	0.68	6.05	-12.39	11.91
		≤30 mph	28	2.38	5.71	-7.83	99.95
	Variance	All data	30	–	–	–	99.95
		≥65 mph	9	–	–	–	99.66
		31 to 64 mph	6	7.65	102.54	-172.27	99.90
		≤30 mph	15	-619.55	–	–	99.95
	Coefficient of Variation	All data	30	-543.68	–	–	97.83
		≥65 mph	9	–	–	–	93.91
		31 to 64 mph	6	18.37	58.16	-64.79	97.04
		≤30 mph	15	-92.15	220.35	-679.27	97.83

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-4 Percent Differences Between AVI and Test Vehicles for Wednesday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All data	57	1.36	6.30	-16.39	18.42
		≥65 mph	14	-1.51	5.20	-16.39	2.66
		31 to 64 mph	11	-0.31	6.77	-13.33	10.43
		≤30 mph	32	3.19	6.12	-8.52	18.42
	Variance	All data	31	-346.14	–	–	99.93
		≥65 mph	5	-561.44	–	–	87.87
		31 to 64 mph	6	-873.78	–	–	84.22
		≤30 mph	20	-134.02	323.38	–	99.93
	Coefficient of Variation	All data	31	-45.86	153.10	-593.94	97.43
		≥65 mph	5	-37.08	213.34	-418.51	64.92
		31 to 64 mph	6	-112.82	243.77	-593.94	59.46
		≤30 mph	20	-27.97	100.10	-300.01	97.43

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-5 Percent Differences Between AVI and Test Vehicles for Friday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All data	46	1.10	7.05	-15.95	15.22
		≥65 mph	3	-1.83	0.97	-2.90	-1.00
		31 to 64 mph	20	2.69	7.32	-12.25	15.22
		≤30 mph	23	0.09	7.13	-15.95	12.15
	Variance	All data	18	31.01	142.36	-499.56	99.50
		≥65 mph	3	86.47	10.01	74.96	93.16
		31 to 64 mph	5	51.49	62.39	49.50	99.37
		≤30 mph	10	4.13	185.65	-499.56	99.50
	Coefficient of Variation	All data	18	40.56	61.36	-156.17	92.71
		≥65 mph	3	65.47	12.33	51.37	74.26
		31 to 64 mph	5	44.68	42.68	-8.92	91.82
		≤30 mph	10	31.03	77.15	-156.17	92.71

TABLE B-6 Percent Differences Between AVI and Test Vehicles for Monday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All data	49	-0.48	8.75	-22.97	22.78
		≥65 mph	12	-0.55	5.51	-9.27	8.85
		31 to 64 mph	15	-1.55	10.08	-19.98	22.78
		≤30 mph	22	0.28	9.48	-22.97	16.34
	Variance	All data	25	-85.45	218.21	-747.89	100.00
		≥65 mph	7	-147.04	258.74	-647.41	92.29
		31 to 64 mph	10	5.50	113.39	-223.13	100.00
		≤30 mph	8	-145.26	263.89	-747.89	57.34
	Coefficient of Variation	All data	25	-12.43	76.54	-196.42	100.00
		≥65 mph	7	-34.26	91.49	-196.42	72.03
		31 to 64 mph	10	24.43	62.51	-86.77	100.00
		≤30 mph	8	-39.40	68.11	-171.65	32.57

TABLE B-7 Percent Differences Between AVI and Test Vehicles for Tuesday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All data	53	1.97	7.69	-15.66	26.17
		≥65 mph	14	-0.37	5.29	-15.66	5.16
		31 to 64 mph	11	3.82	8.68	-5.32	26.17
		≤30 mph	28	2.42	8.25	-10.92	18.99
	Variance	All data	30	-72.10	320.79	–	100.00
		≥65 mph	10	82.77	27.74	12.11	100.00
		31 to 64 mph	5	1.96	77.37	-78.26	100.00
		≤30 mph	15	-200.04	417.53	–	98.10
	Coefficient of Variation	All data	30	3.10	101.15	-350.26	100.00
		≥65 mph	10	69.82	25.93	18.94	100.00
		31 to 64 mph	5	13.79	55.55	-27.80	100.00
		≤30 mph	15	-44.94	119.11	-350.26	86.99

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-8 Percent Differences Between AVI and Test Vehicles for Wednesday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All data	57	1.33	7.19	-17.91	18.96
		≥65 mph	14	-1.83	6.95	-17.32	7.51
		31 to 64 mph	11	1.08	6.37	-7.59	13.95
		≤30 mph	32	2.80	7.19	-17.91	18.96
	Variance	All data	31	-125.51	381.28	–	99.99
		≥65 mph	5	-157.60	351.26	-731.88	84.51
		31 to 64 mph	6	45.17	67.70	-59.88	99.49
		≤30 mph	20	-168.70	436.94	–	99.99
	Coefficient of Variation	All data	31	-11.24	105.19	-294.15	98.80
		≥65 mph	5	-21.62	92.70	-149.65	59.03
		31 to 64 mph	6	40.19	44.83	-17.56	92.72
		≤30 mph	20	-24.00	118.72	-294.15	98.80

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-9 Percent Differences Between AVI and Test Vehicles for Friday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All data	46	0.70	8.14	-19.05	17.66
		≥65 mph	7	-4.1	8.73	-19.05	4.87
		31 to 64 mph	16	5.19	7.39	-12.93	17.66
		≤30 mph	23	-0.96	7.25	15.83	12.18
	Variance	All data	18	-23.97	168.20	-474.44	99.80
		≥65 mph	4	79.84	20.84	49.00	93.24
		31 to 64 mph	4	79.96	27.41	40.27	99.65
		≤30 mph	10	-107.07	189.15	-474.44	99.80
	Coefficient of Variation	All data	18	16.73	72.57	-130.96	95.48
		≥65 mph	4	59.38	19.74	30.61	74.23
		31 to 64 mph	4	63.19	31.92	21.33	93.83
		≤30 mph	10	-18.92	79.36	-130.96	95.48

TABLE B-10 Percent Differences Between AVI and CVO for Monday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All data	40	6.04	4.90	-5.44	15.98
		≥65 mph	6	7.37	1.82	5.49	9.78
		31 to 64 mph	10	4.80	5.93	-5.44	15.65
		≤30 mph	24	6.22	5.00	-3.40	15.98
	Variance	All data	37	–	–	-99.72	–
		≥65 mph	6	–	–	-63.20	–
		31 to 64 mph	8	–	–	-89.44	–
		≤30 mph	23	224.76	722.41	-99.72	–
	Coefficient of Variation	All data	37	80.28	268.55	-94.84	–
		≥65 mph	6	222.25	345.96	-44.17	867.41
		31 to 64 mph	8	169.52	435.01	-69.15	–
		≤30 mph	23	12.20	131.75	-94.84	403.03

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-11 Percent Differences Between AVI and CVO for Tuesday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All data	41	5.27	5.33	-11.08	13.25
		≥65 mph	4	6.19	4.39	0.20	9.77
		31 to 64 mph	9	4.40	5.39	-7.36	11.89
		≤30 mph	28	5.42	5.56	-11.08	13.25
	Variance	All data	40	–	–	-87.72	–
		≥65 mph	4	527.28	823.42	-68.36	–
		31 to 64 mph	8	902.74	–	2.72	–
		≤30 mph	28	–	–	-87.72	–
	Coefficient of Variation	All data	40	195.71	350.73	-68.67	–
		≥65 mph	4	101.39	160.28	-46.75	328.54
		31 to 64 mph	8	140.39	192.55	-9.42	495.33
		≤30 mph	28	224.99	402.62	-68.67	–

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-12 Percent Differences Between AVI and CVO for Wednesday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All data	49	6.43	5.94	-11.41	20.19
		≥65 mph	8	5.87	2.09	2.76	8.84
		31 to 64 mph	9	4.66	4.12	-0.45	14.01
		≤30 mph	32	7.07	6.91	-11.41	20.19
	Variance	All data	47	–	–	-97.29	–
		≥65 mph	7	–	–	-72.86	–
		31 to 64 mph	9	968.35	–	-54.34	–
		≤30 mph	31	–	–	-97.29	–
	Coefficient of Variation	All data	47	–	–	-85.59	–
		≥65 mph	7	–	–	-49.99	–
		31 to 64 mph	9	158.64	188.31	-34.56	459.54
		≤30 mph	31	73.20	328.56	-85.59	–

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-13 Percent Differences Between AVI and CVO for Friday by Congestion Level for Technique One

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All data	45	5.18	4.06	-3.18	17.98
Friday	Mean	≥65 mph	2	6.78	0.08	6.72	6.83
Friday	Mean	31 to 64 mph	18	4.42	3.34	0.39	133.33
Friday	Mean	≤30 mph	25	5.61	4.63	-3.18	17.98
Friday	Variance	All data	40	636.65	–	-97.12	–
Friday	Variance	≥65 mph	2	–	–	–	–
Friday	Variance	31 to 64 mph	16	257.39	550.16	-97.12	–
Friday	Variance	≤30 mph	22	486.74	–	-97.00	–
Friday	Coefficient of Variation	All data	40	77.28	187.29	-83.59	717.91
Friday	Coefficient of Variation	≥65 mph	2	574.53	202.78	431.14	717.91
Friday	Coefficient of Variation	31 to 64 mph	16	42.73	114.86	-83.59	307.36
Friday	Coefficient of Variation	≤30 mph	22	57.21	169.95	-82.88	708.07

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-14 Percent Differences Between AVI and CVO for Monday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All data	40	5.05	6.27	-17.56	16.07
Monday	Mean	≥65 mph	5	7.45	2.69	3.34	10.80
Monday	Mean	31 to 64 mph	10	4.50	5.98	-6.75	14.63
Monday	Mean	≤30 mph	25	4.79	6.92	-17.56	16.07
Monday	Variance	All data	37	60.95	107.60	-63.38	459.93
Monday	Variance	≥65 mph	5	45.36	68.95	-58.97	117.79
Monday	Variance	31 to 64 mph	9	48.86	57.48	-58.17	110.26
Monday	Variance	≤30 mph	23	69.07	129.22	-63.38	459.93
Monday	Coefficient of Variation	All data	37	13.82	36.41	-45.48	124.04
Monday	Coefficient of Variation	≥65 mph	5	8.49	29.50	-38.02	37.15
Monday	Coefficient of Variation	31 to 64 mph	9	12.84	24.57	-37.18	36.15
Monday	Coefficient of Variation	≤30 mph	23	15.37	42.22	-45.58	124.04

TABLE B-15 Percent Differences Between AVI and CVO for Tuesday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All data	41	4.85	6.47	-16.95	16.51
		≥65 mph	7	6.94	3.45	0.29	10.99
		31 to 64 mph	6	1.26	9.62	-16.95	11.93
		≤30 mph	28	5.10	6.19	-11.06	16.51
	Variance	All data	40	61.33	162.54	-67.02	895.22
		≥65 mph	7	37.05	72.52	-55.26	161.08
		31 to 64 mph	5	-2.44	23.41	-29.11	21.27
		≤30 mph	28	78.79	188.92	-67.02	895.22
	Coefficient of Variation	All data	40	13.39	51.60	-46.43	228.06
		≥65 mph	7	6.07	28.42	-38.16	45.58
		31 to 64 mph	5	-6.45	10.33	-19.20	6.34
		≤30 mph	28	18.77	59.45	-46.43	228.06

TABLE B-16 Percent Differences Between AVI and CVO for Wednesday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wednesday	Mean	All data	49	6.99	6.24	-11.93	24.06
		≥65 mph	8	7.91	7.01	2.38	24.06
		31 to 64 mph	9	5.44	4.11	0.28	14.76
		≤30 mph	32	7.19	6.63	-11.93	21.48
	Variance	All data	47	98.51	352.10	-88.85	–
		≥65 mph	7	30.06	68.31	-53.89	135.53
		31 to 64 mph	9	39.99	79.43	-79.81	141.79
		≤30 mph	32	130.96	429.26	-88.85	–
	Coefficient of Variation	All data	47	13.50	65.93	-70.79	318.05
		≥65 mph	7	4.23	27.51	-34.13	40.21
		31 to 64 mph	9	6.87	36.16	-57.40	49.59
		≤30 mph	31	17.51	78.19	-70.79	318.05

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE B-17 Percent Differences Between AVI and CVO for Friday by Congestion Level for Technique Two

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All data	45	6.01	5.86	-1.73	29.86
		≥65 mph	5	11.13	10.59	4.46	29.86
		31 to 64 mph	15	4.13	4.20	-0.76	14.02
		≤30 mph	25	6.12	5.13	-1.73	19.90
	Variance	All data	40	12.48	75.07	-75.31	315.11
		≥65 mph	4	55.23	75.93	-24.85	148.97
		31 to 64 mph	14	-7.73	55.65	-61.50	163.40
		≤30 mph	22	17.57	84.13	-75.31	315.11
	Coefficient of Variation	All data	40	-3.18	29.01	-54.16	96.02
		≥65 mph	4	13.97	27.11	-17.01	44.98
		31 to 64 mph	14	-10.05	24.19	-43.49	55.71
		≤30 mph	22	-1.93	31.72	-54.16	96.02

TABLE B-18 Travel Time Characteristic Averages for All Days and All Data Sources

Travel Time Variable	Data Source	Number of Observations	Mean
Mean	AVI	287	4.02
	Test Vehicles	262	4.07
	CVO	226	4.92
Variance	AVI	272	0.17
	Test Vehicles	142	0.31
	CVO	225	0.27
Coefficient of Variation	AVI	272	0.09
	Test Vehicles	142	0.08
	CVO	225	0.09

TABLE B-19 Travel Time Characteristic Averages for All Days for AVI Data by Congestion Level for All Days Together

Travel Time Variable	Congestion Level	Number of Observations	Mean
Mean	≥65 mph	58	1.81
	31 to 64 mph	88	2.46
	≤30 mph	141	5.90
Variance	≥65 mph	54	0.02
	31 to 64 mph	83	0.07
	≤30 mph	135	0.30
Coefficient of Variation	≥65 mph	54	0.08
	31 to 64 mph	83	0.10
	≤30 mph	135	0.09

TABLE B-20 Travel Time Characteristic Averages for All Days for Test Vehicle Data by Congestion Level for All Days Together

Travel Time Variable	Congestion Level	Number of Observations	Mean
Mean	≥65 mph	64	2.24
	31 to 64 mph	68	2.46
	≤30 mph	130	5.81
Variance	≥65 mph	38	0.10
	31 to 64 mph	34	0.04
	≤30 mph	70	0.55
Coefficient of Variation	≥65 mph	38	0.06
	31 to 64 mph	34	0.06
	≤30 mph	70	0.10

TABLE B-21 Travel Time Characteristic Averages for CVO Data by Congestion Level for All Days Together

Travel Time Variable	Congestion Level	Number of Observations	Mean
Mean	≥65 mph	40	2.71
	31 to 64 mph	49	2.85
	≤30 mph	137	6.31
Variance	≥65 mph	40	0.08
	31 to 64 mph	49	0.08
	≤30 mph	136	0.39
Coefficient of Variation	≥65 mph	40	0.09
	31 to 64 mph	49	0.09
	≤30 mph	136	0.09

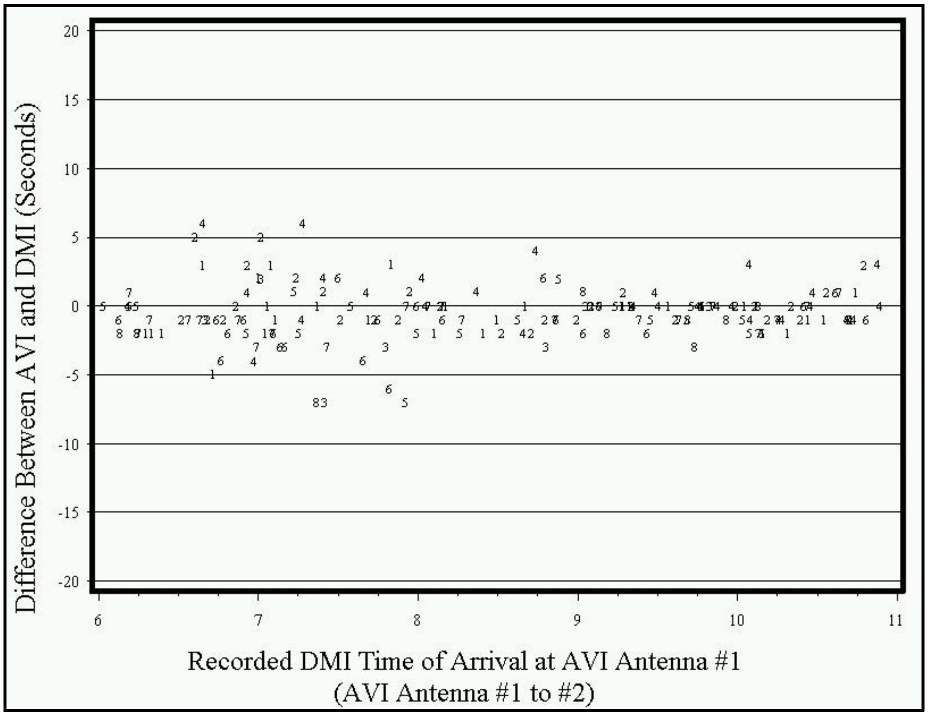

FIGURE B-1 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #1 to #2

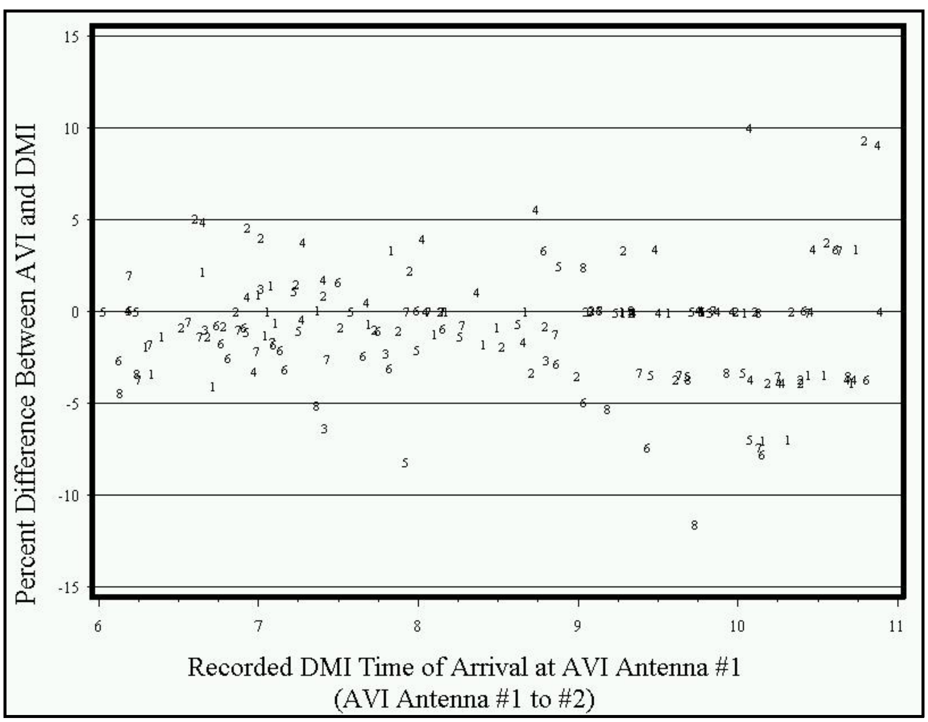

FIGURE B-2 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #1 to #2

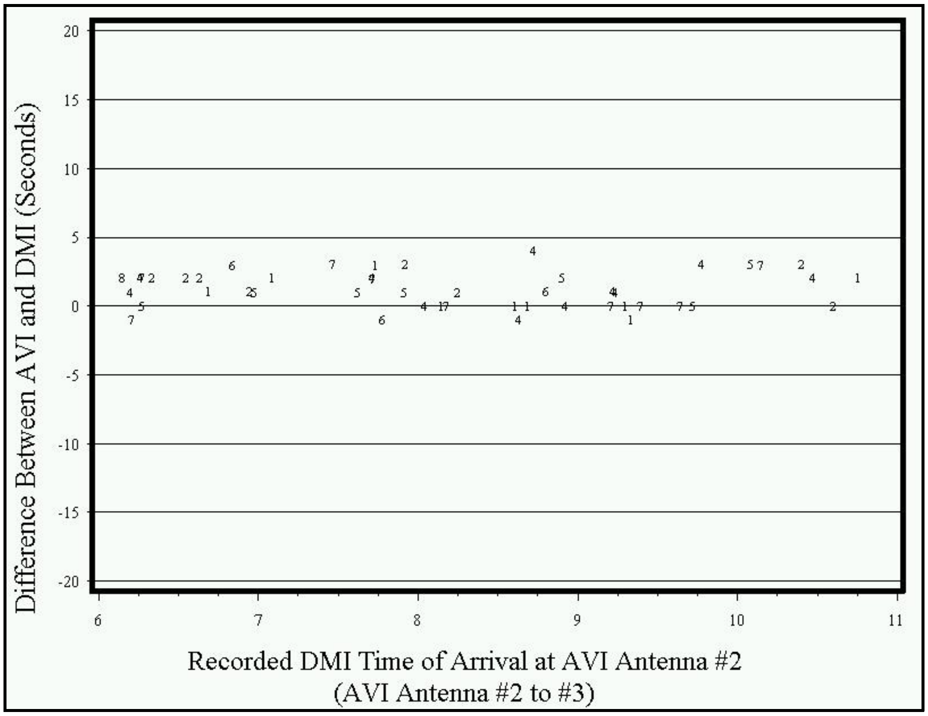

FIGURE B-3 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #2 to #3

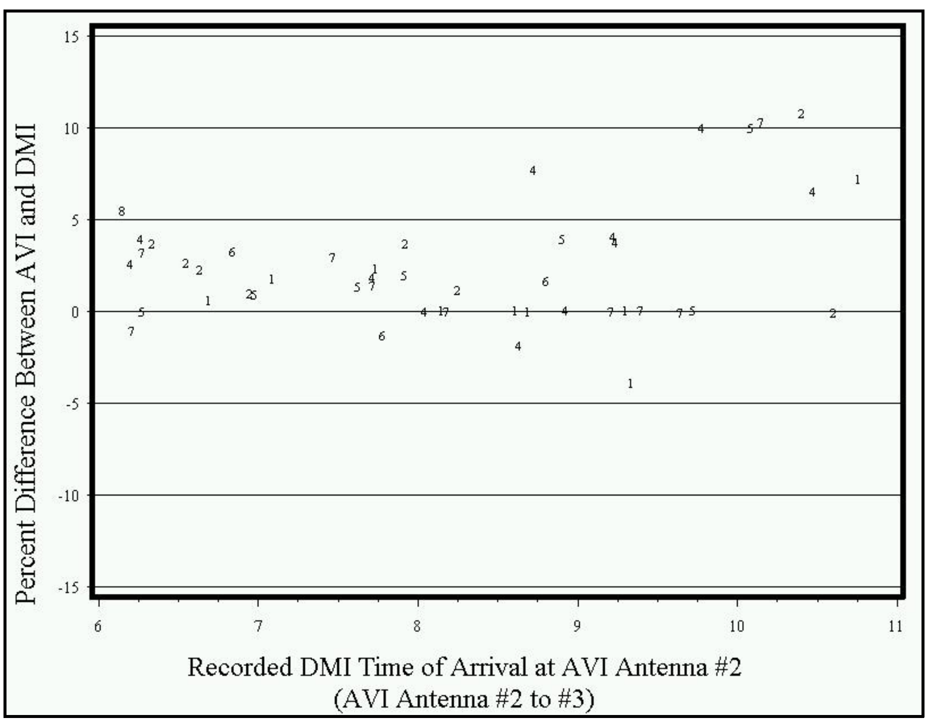

FIGURE B-4 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #2 to #3

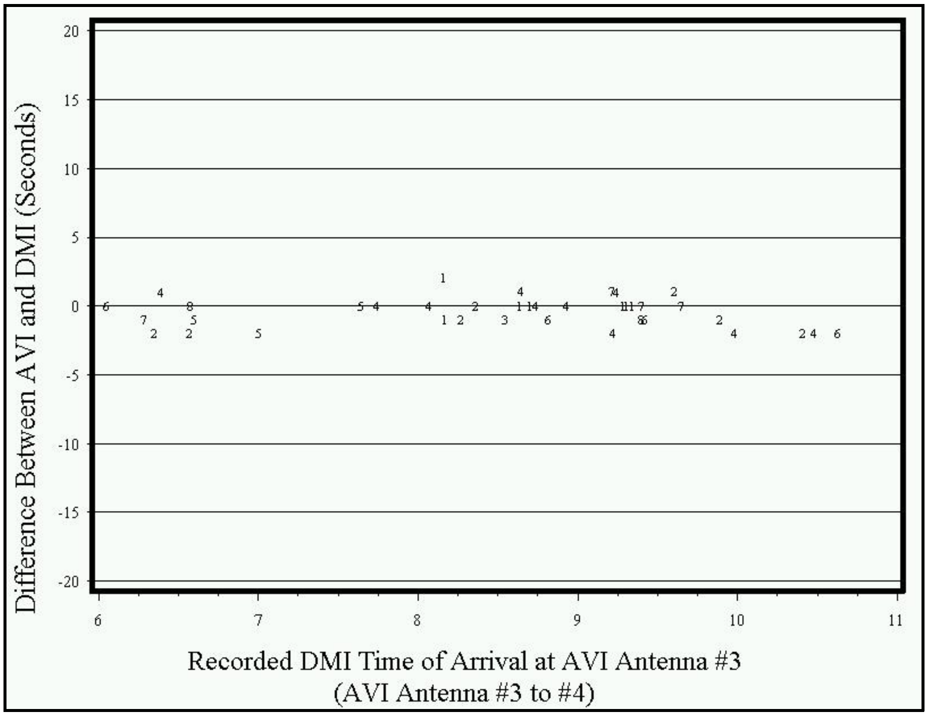

FIGURE B-5 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #3 to #4

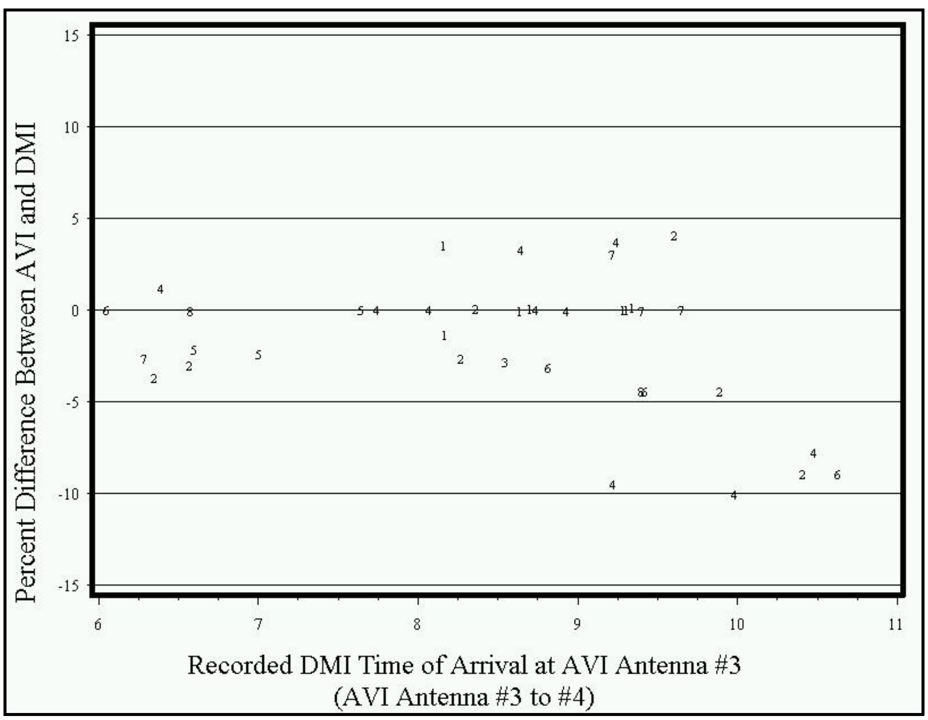

FIGURE B-6 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #3 to #4

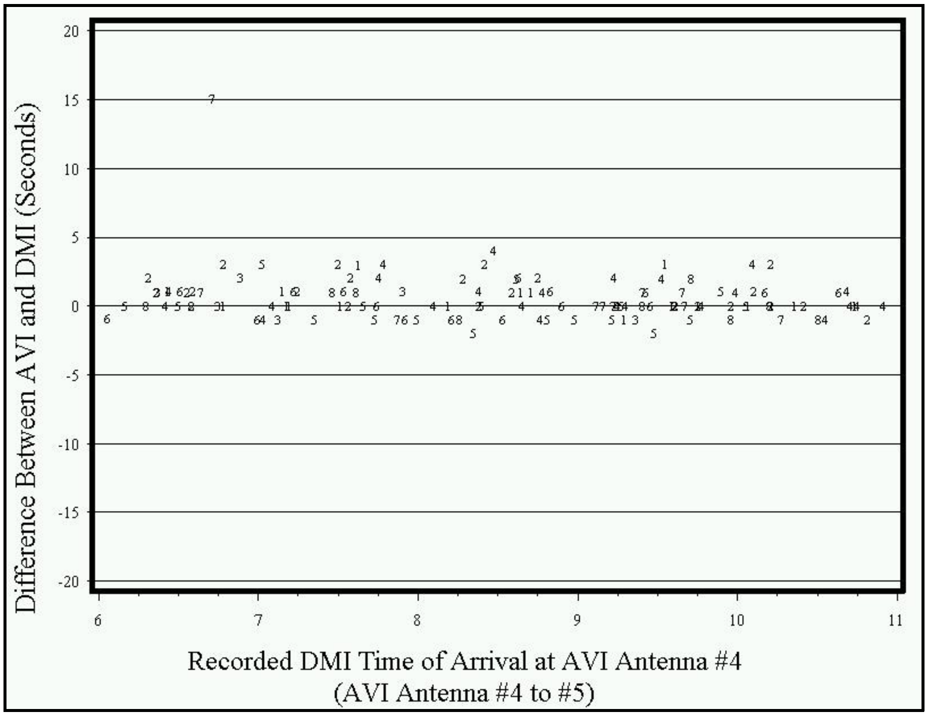

FIGURE B-7 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #4 to #5

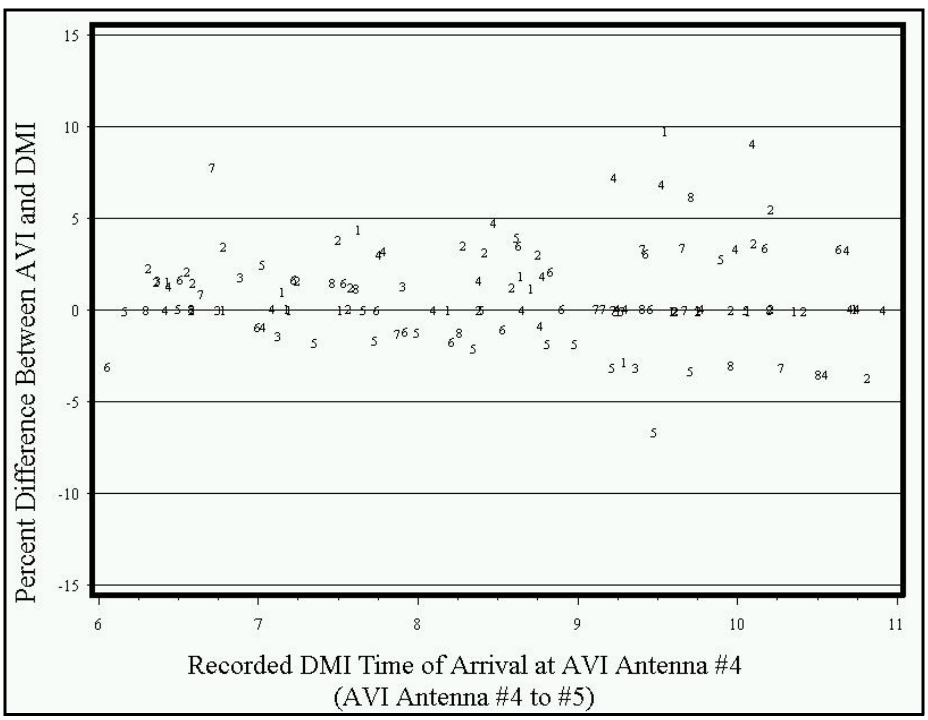

FIGURE B-8 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #4 to #5

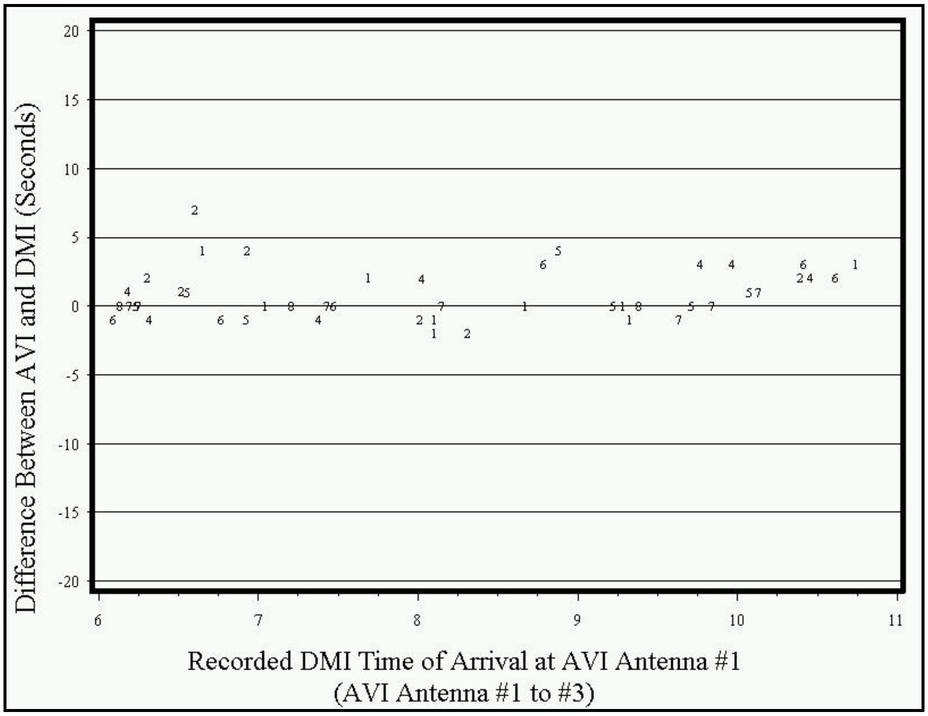

FIGURE B-9 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #1 to #3

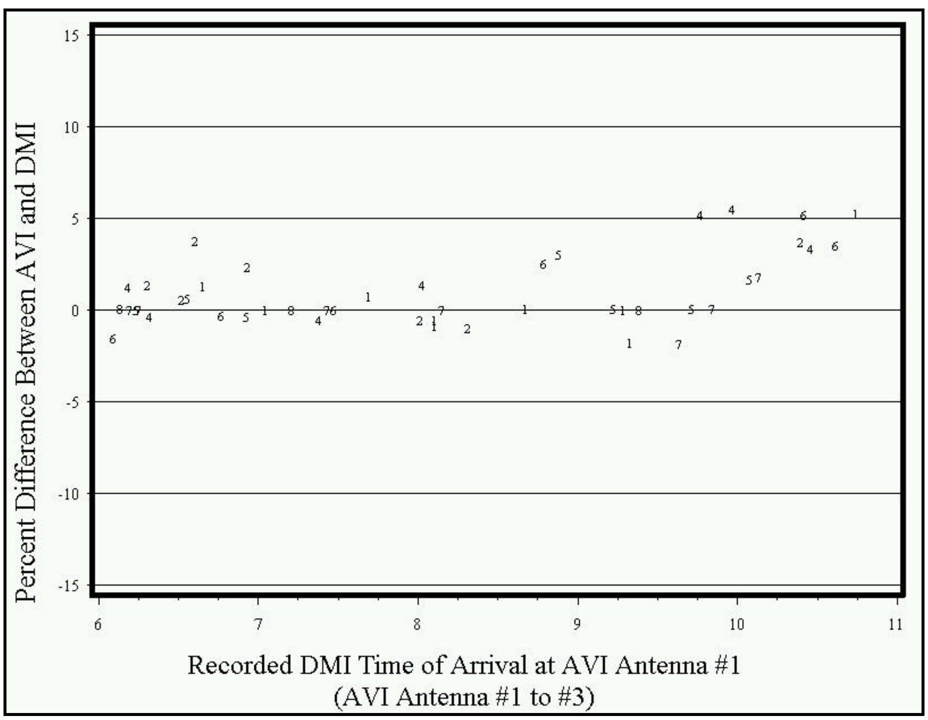

FIGURE B-10 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #1 to #3

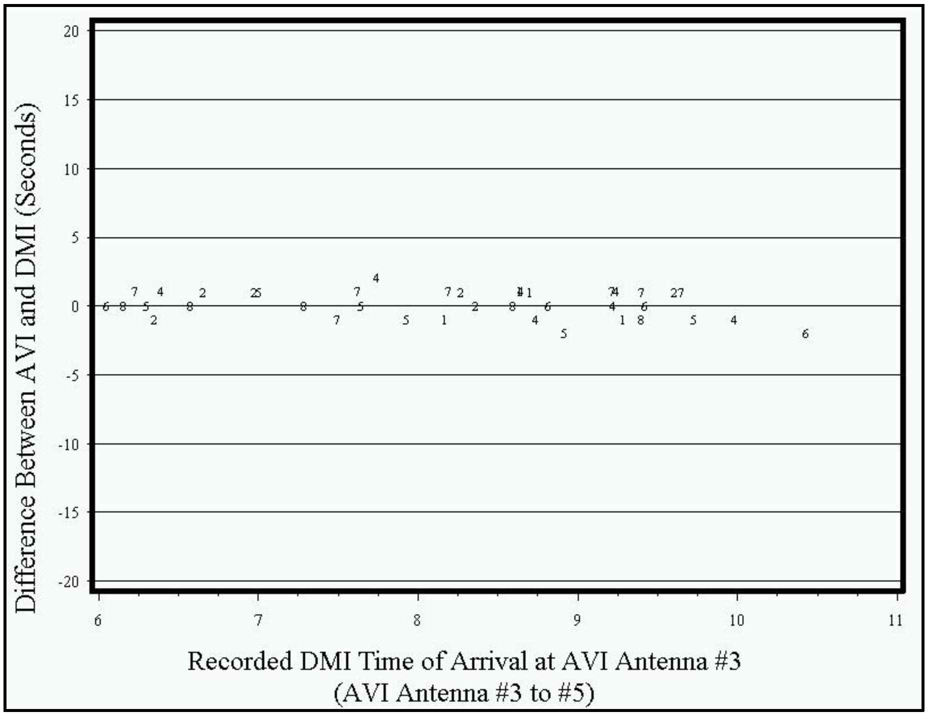

FIGURE B-11 Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #3 to #5

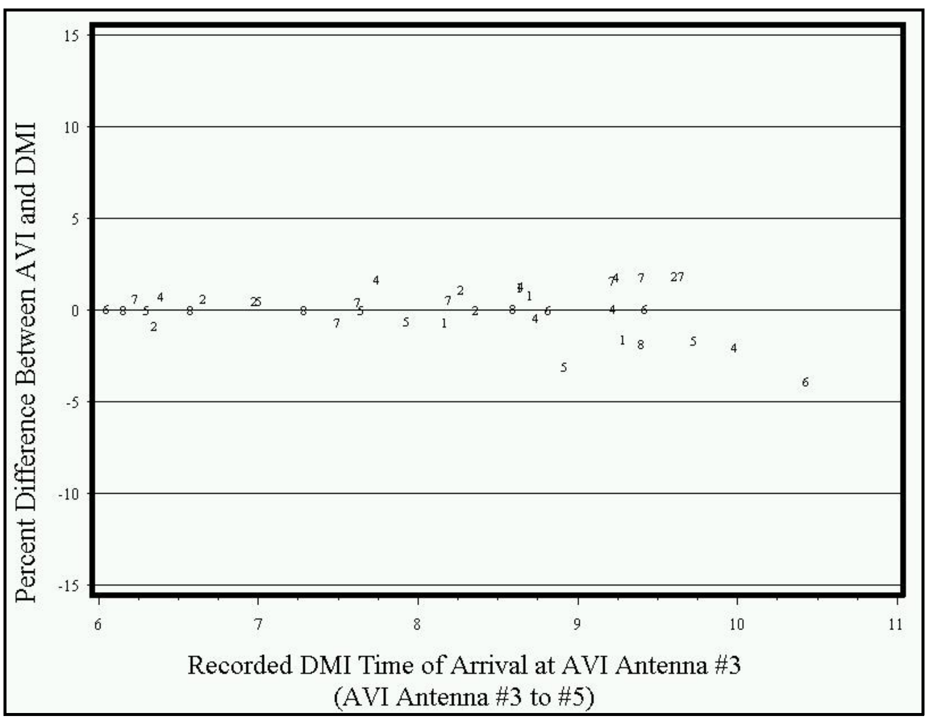

FIGURE B-12 Percent Difference Between AVI and Test Vehicle (DMI) Travel Time Estimates by Driver from AVI Antenna #3 to #5

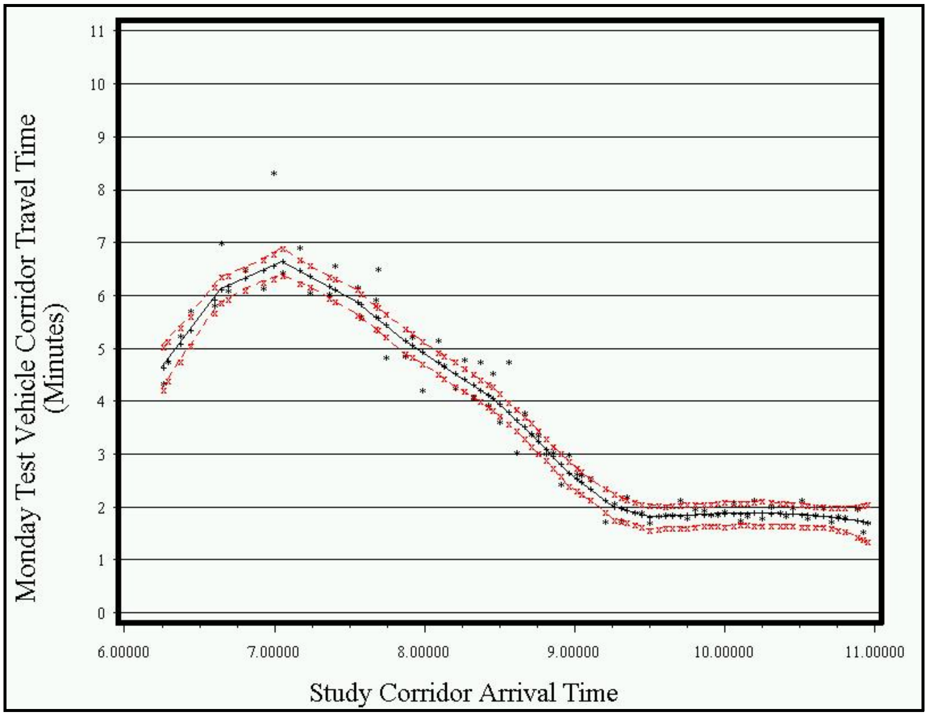

FIGURE B-13 Monday Corridor Travel Time by Time of Arrival for Test Vehicle Data Showing Loess Estimation and Confidence Interval

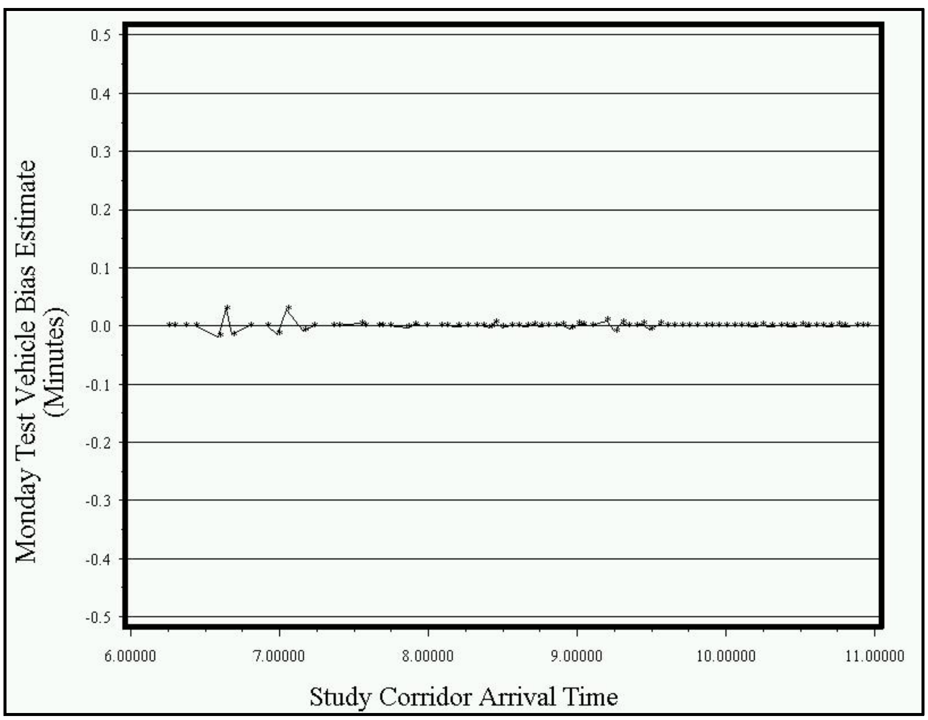

FIGURE B-14 Monday Bias Estimate by Time of Arrival for Test Vehicle (DMI) Data

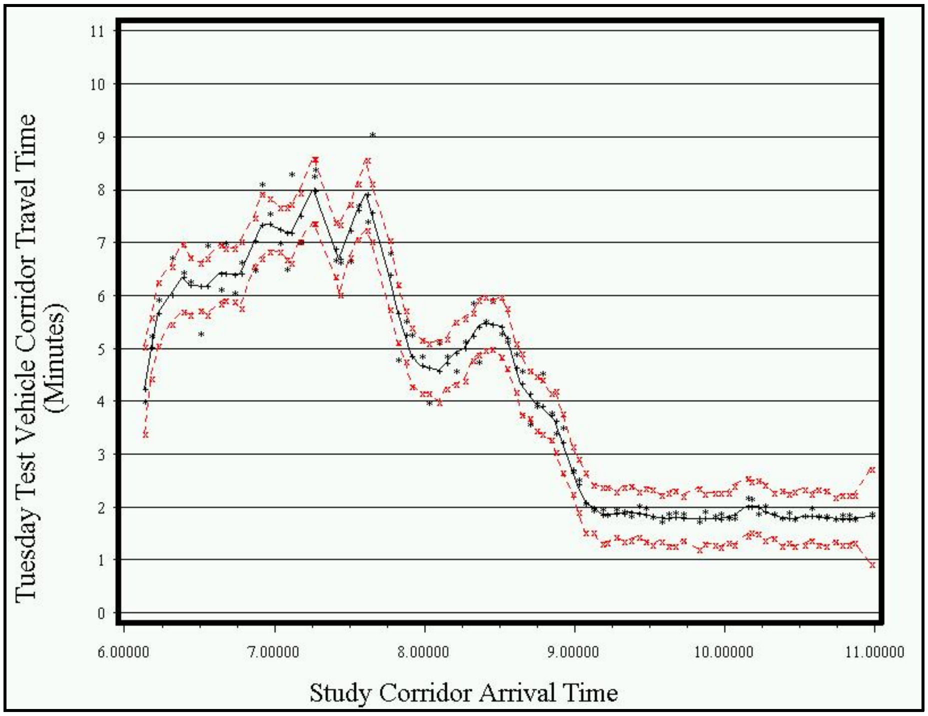

FIGURE B-15 Tuesday Corridor Travel Time by Time of Arrival for Test Vehicle Data Showing Loess Estimation and Confidence Interval

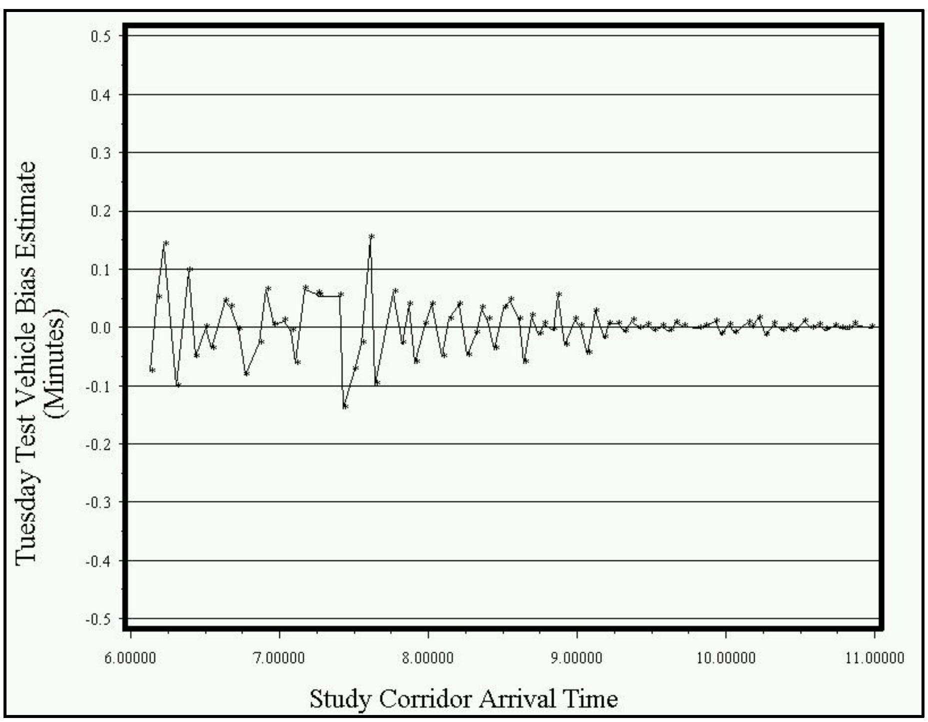

FIGURE B-16 Tuesday Bias Estimate by Time of Arrival for Test Vehicle (DMI) Data

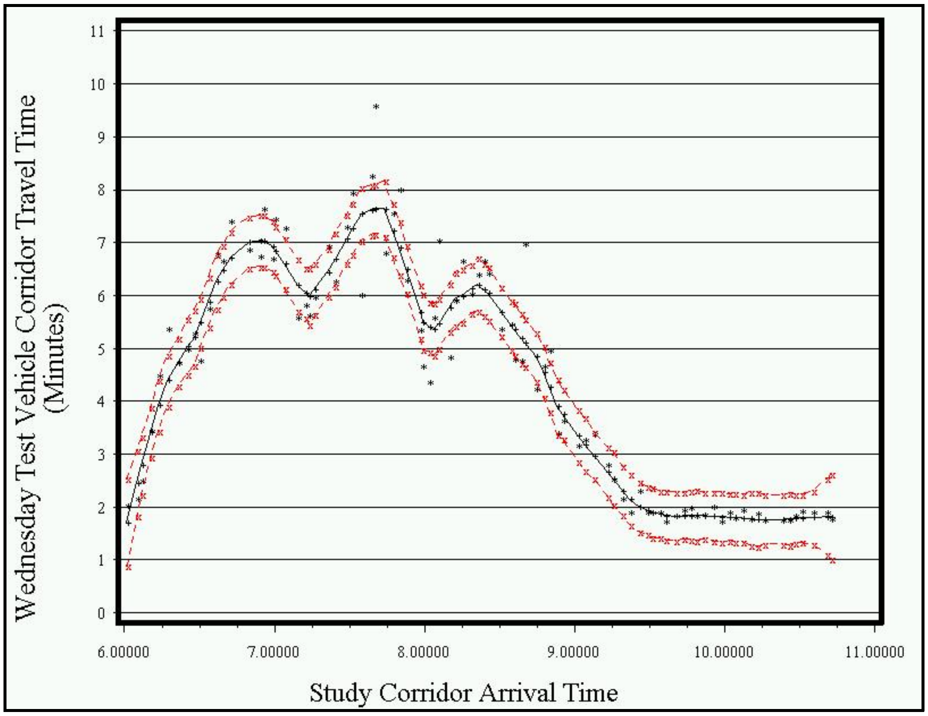

FIGURE B-17 Wednesday Corridor Travel Time by Time of Arrival for Test Vehicle Data Showing Loess Estimation and Confidence Interval

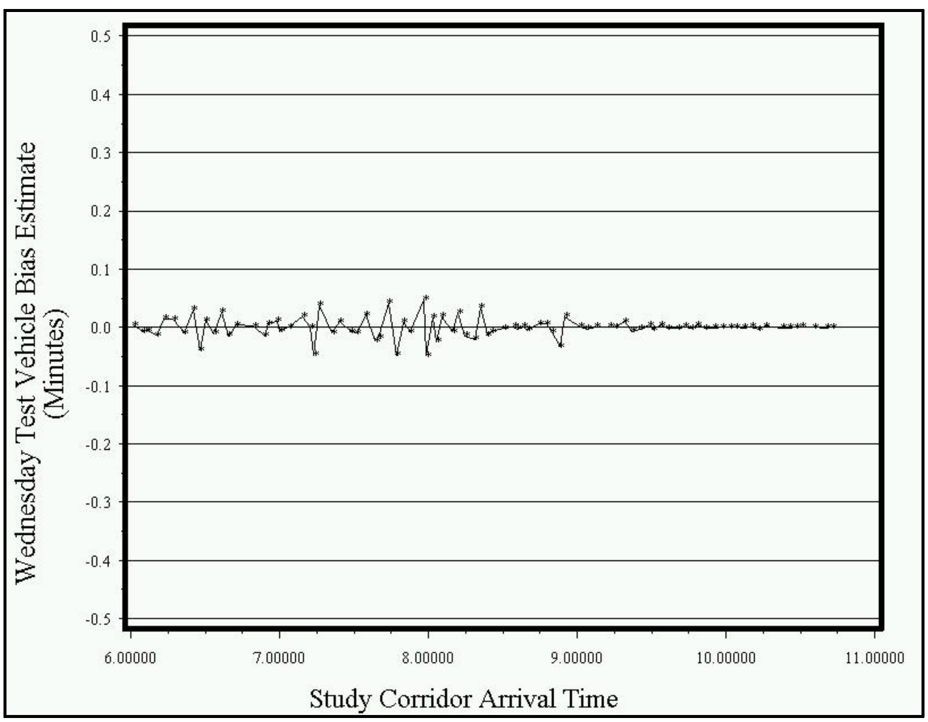

FIGURE B-18 Wednesday Bias Estimate by Time of Arrival for Test Vehicle (DMI) Data

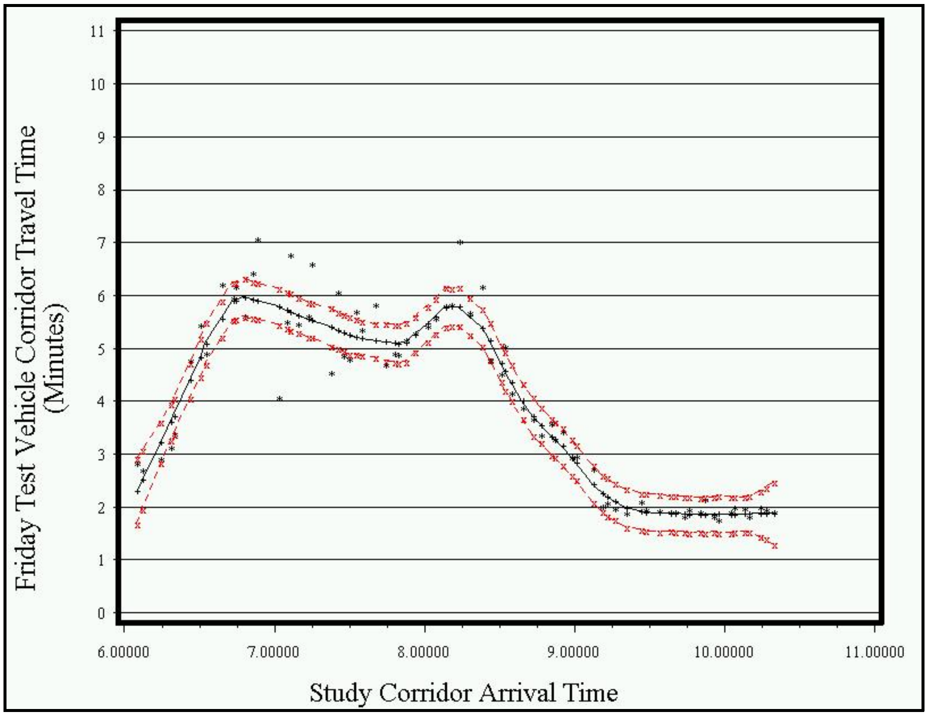

FIGURE B-19 Friday Corridor Travel Time by Time of Arrival for Test Vehicle Data Showing Loess Estimation and Confidence Interval

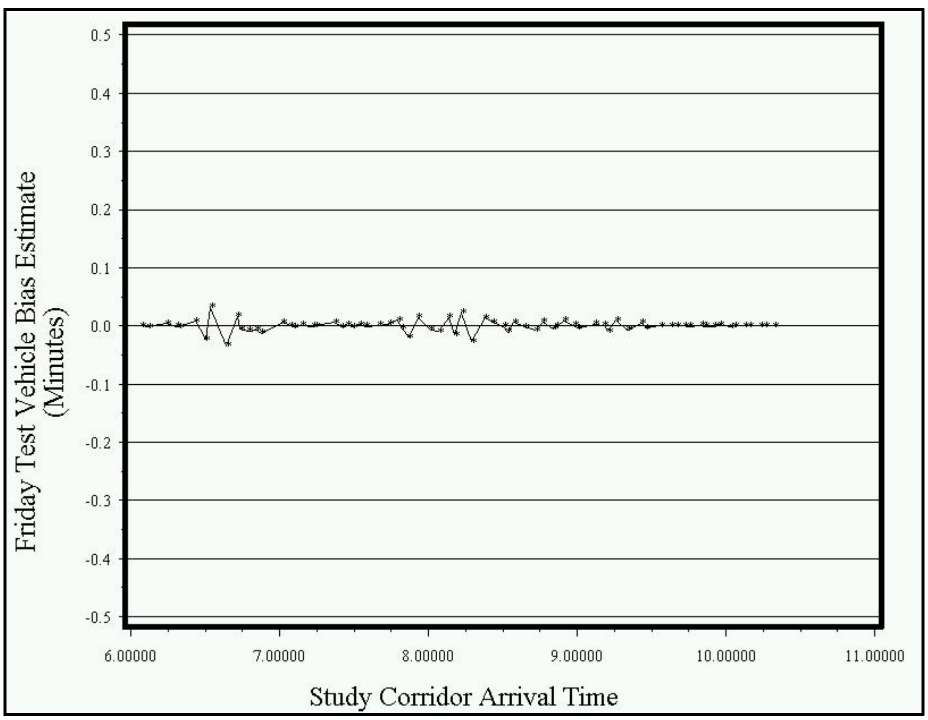

FIGURE B-20 Friday Bias Estimate by Time of Arrival for Test Vehicle (DMI) Data

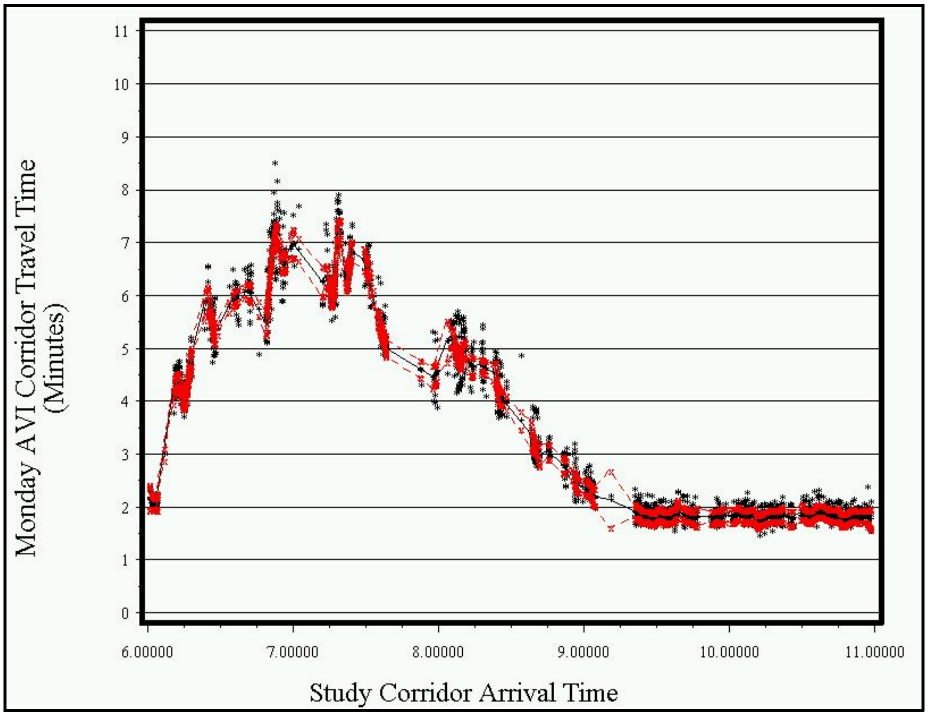

FIGURE B-21 Monday Corridor Travel Time by Time of Arrival for AVI Data Showing Loess Estimation and Confidence Interval

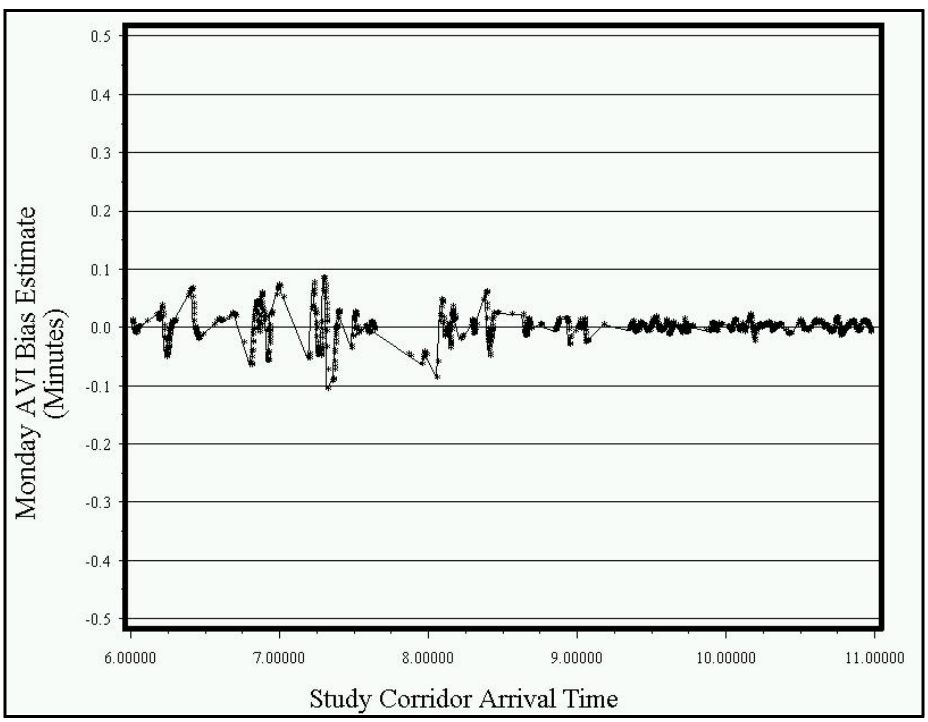

FIGURE B-22 Monday Bias Estimate by Time of Arrival for AVI Data

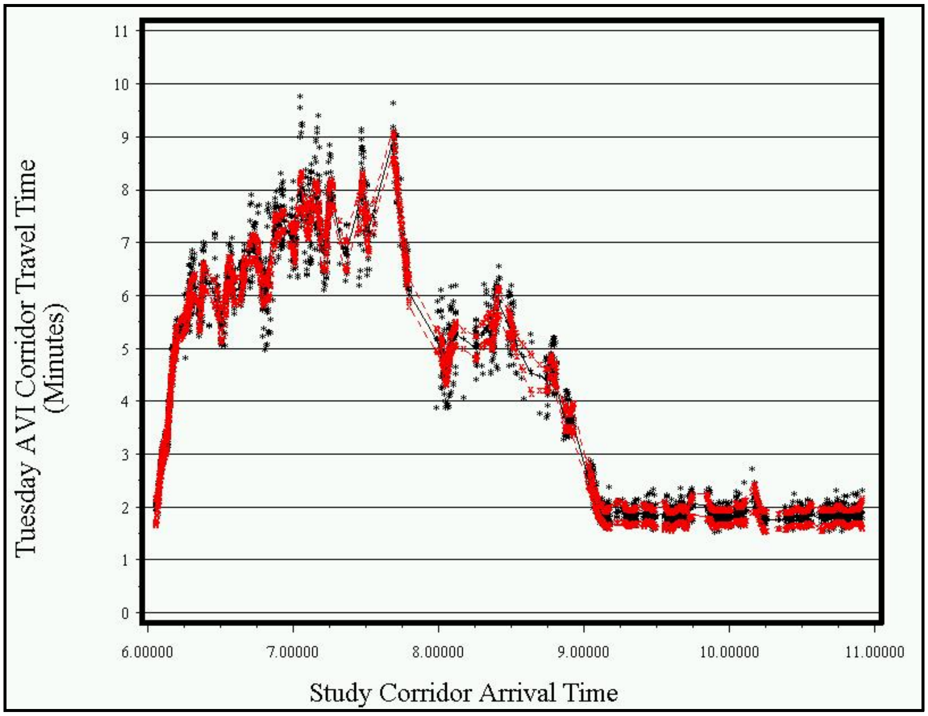

FIGURE B-23 Tuesday Corridor Travel Time by Time of Arrival for AVI Data Showing Loess Estimation and Confidence Interval

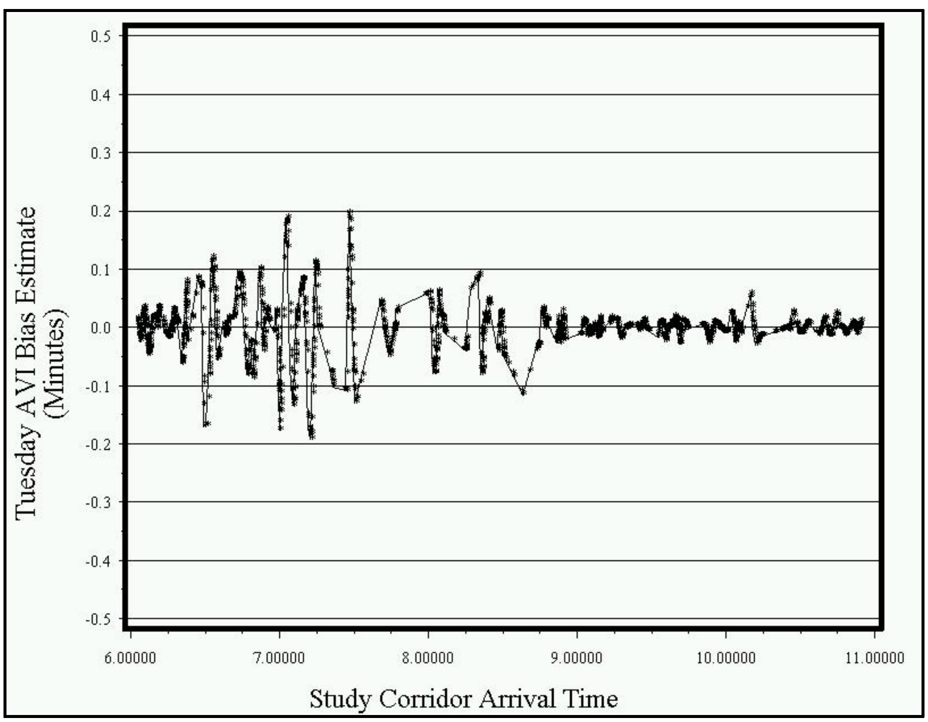

FIGURE B-24 Tuesday Bias Estimate by Time of Arrival for AVI Data

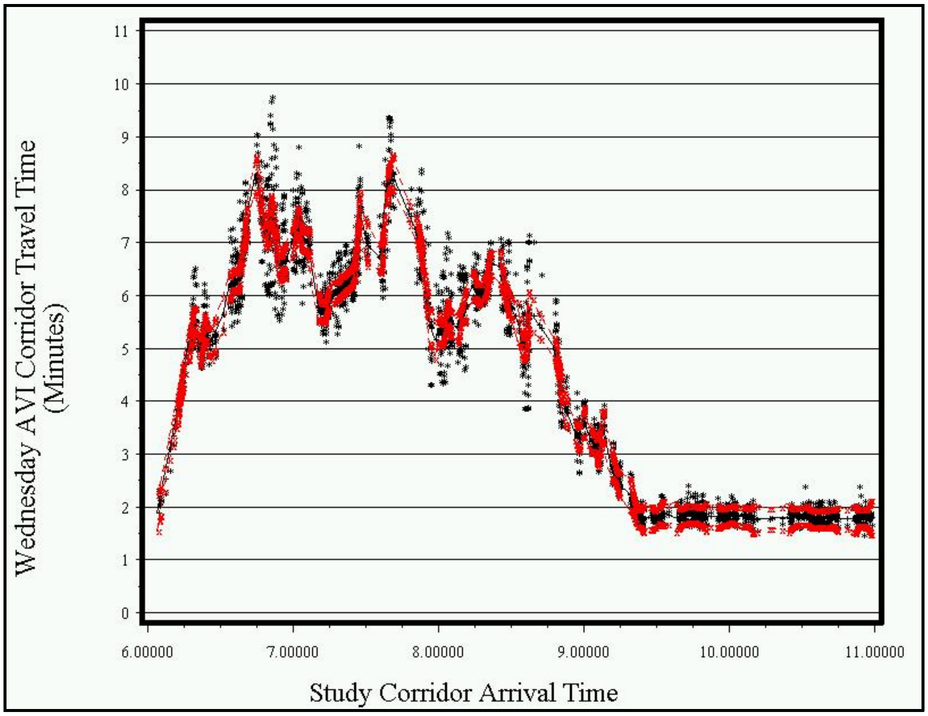

FIGURE B-25 Wednesday Corridor Travel Time by Time of Arrival for AVI Data Showing Loess Estimation and Confidence Interval

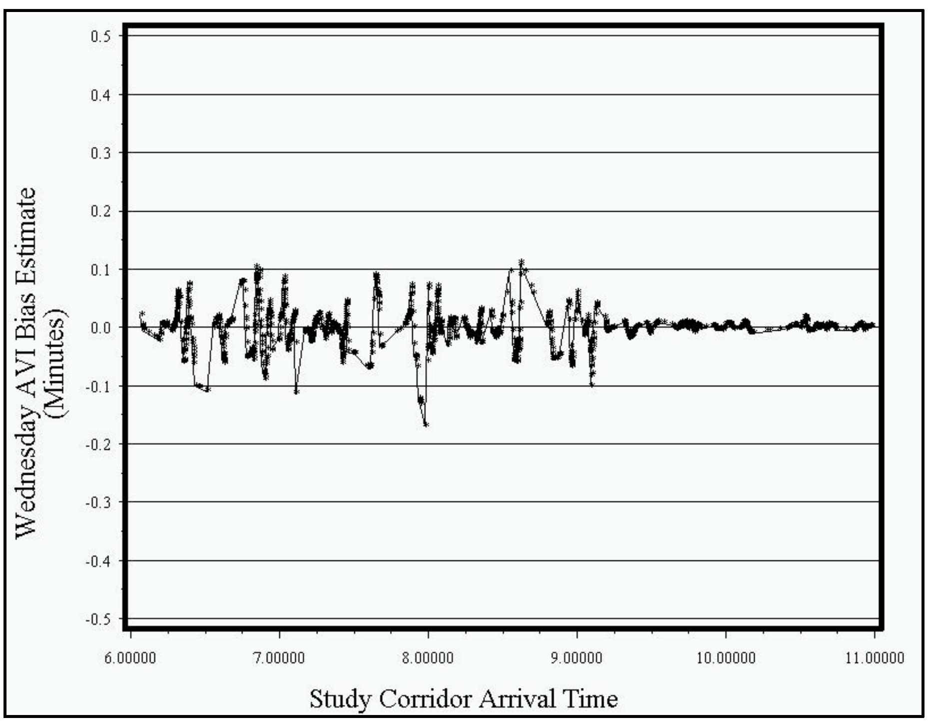

FIGURE B-26 Wednesday Bias Estimate by Time of Arrival for AVI Data

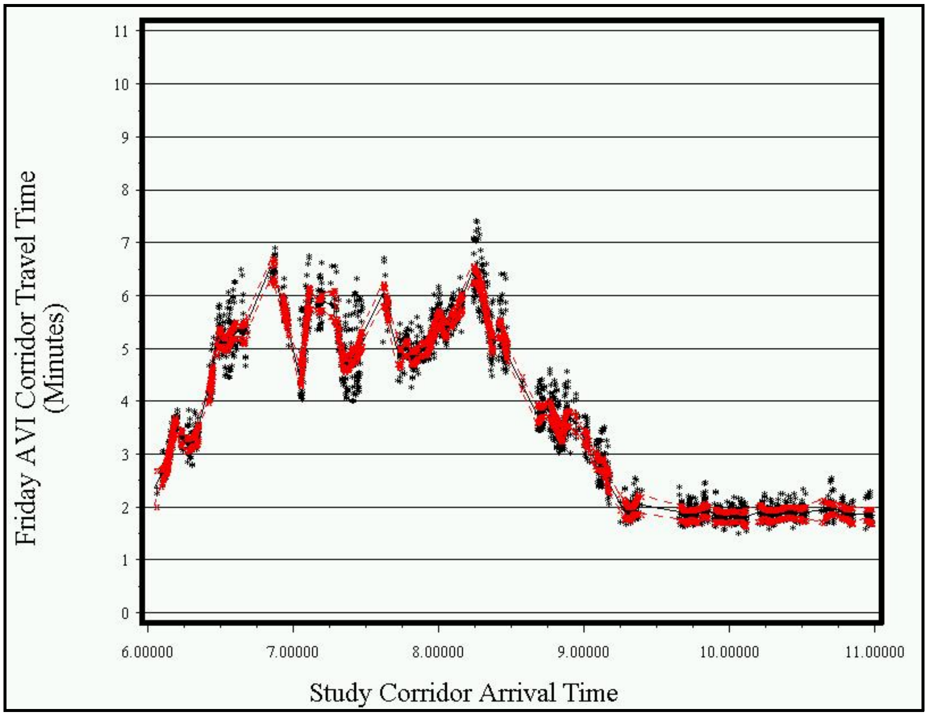

FIGURE B-27 Friday Corridor Travel Time by Time of Arrival for AVI Data Showing Loess Estimation and Confidence Interval

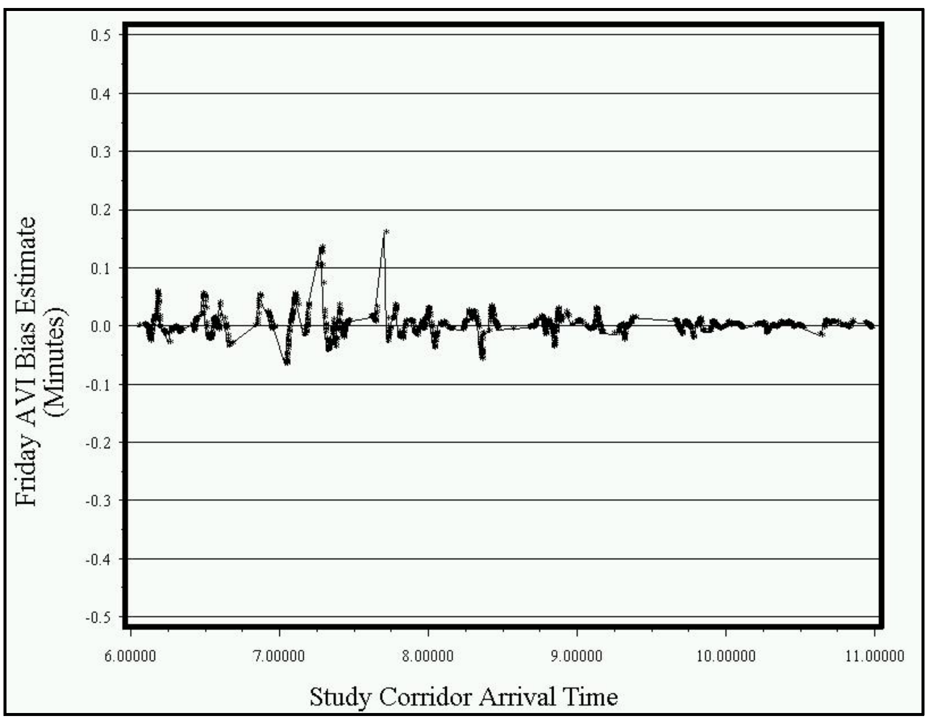

FIGURE B-28 Friday Bias Estimate by Time of Arrival for AVI Data

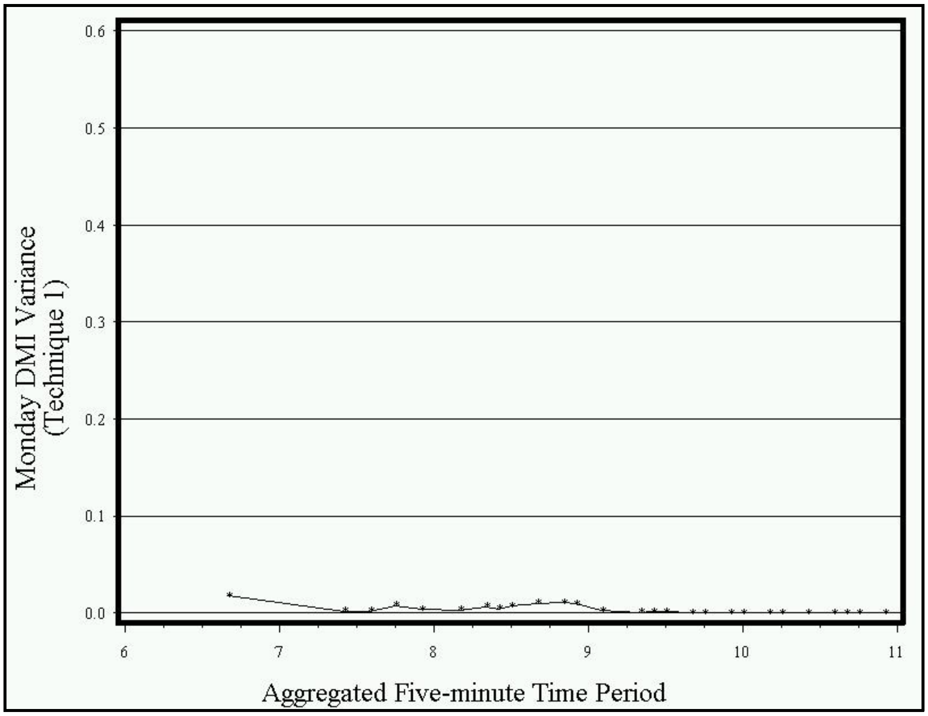

FIGURE B-29 Monday Test Vehicles (DMI) Variance with Technique One

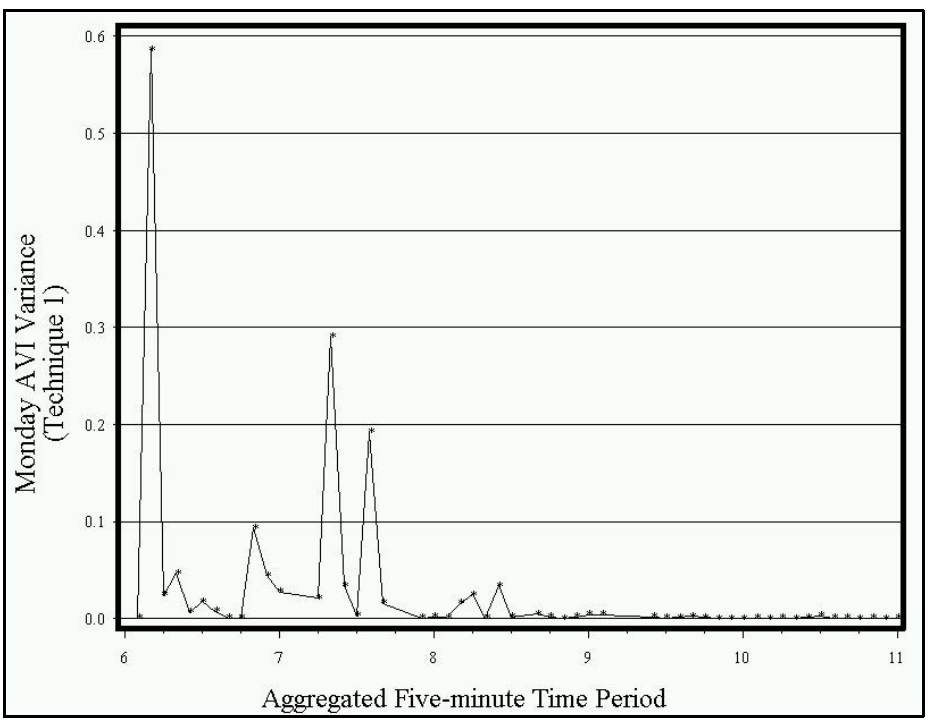

FIGURE B-30 Monday AVI Variance with Technique One

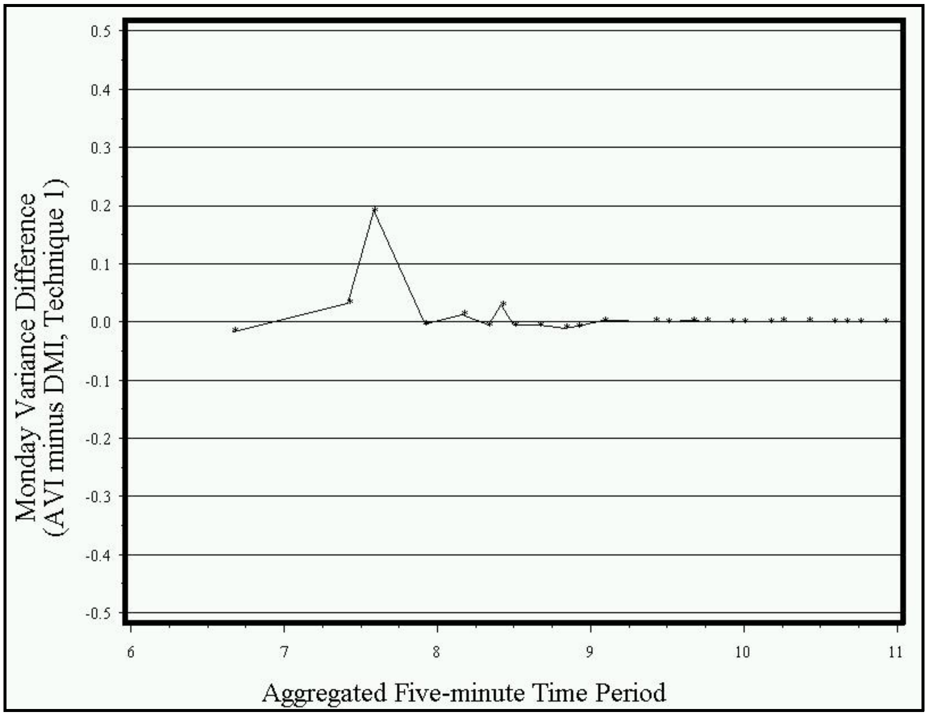

FIGURE B-31 Monday Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

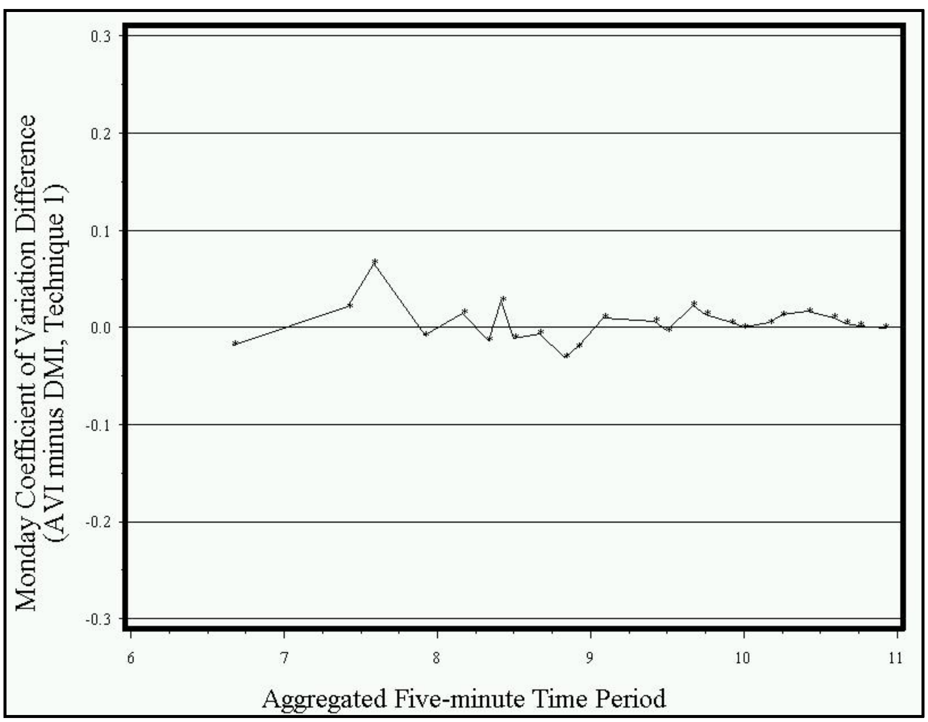

FIGURE B-32 Monday Coefficient of Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

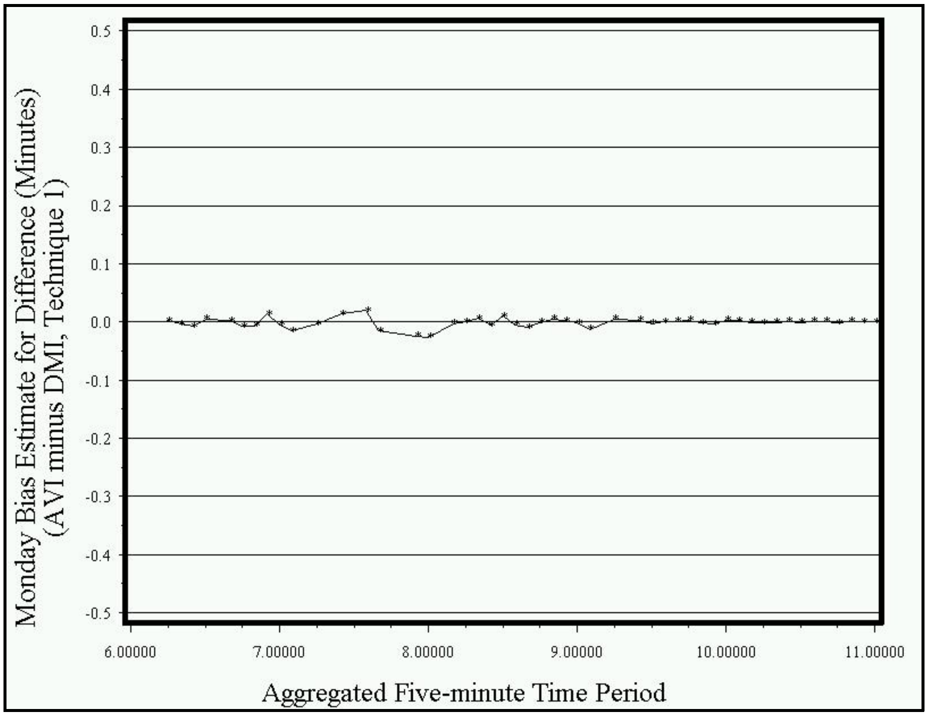

FIGURE B-33 Monday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique One

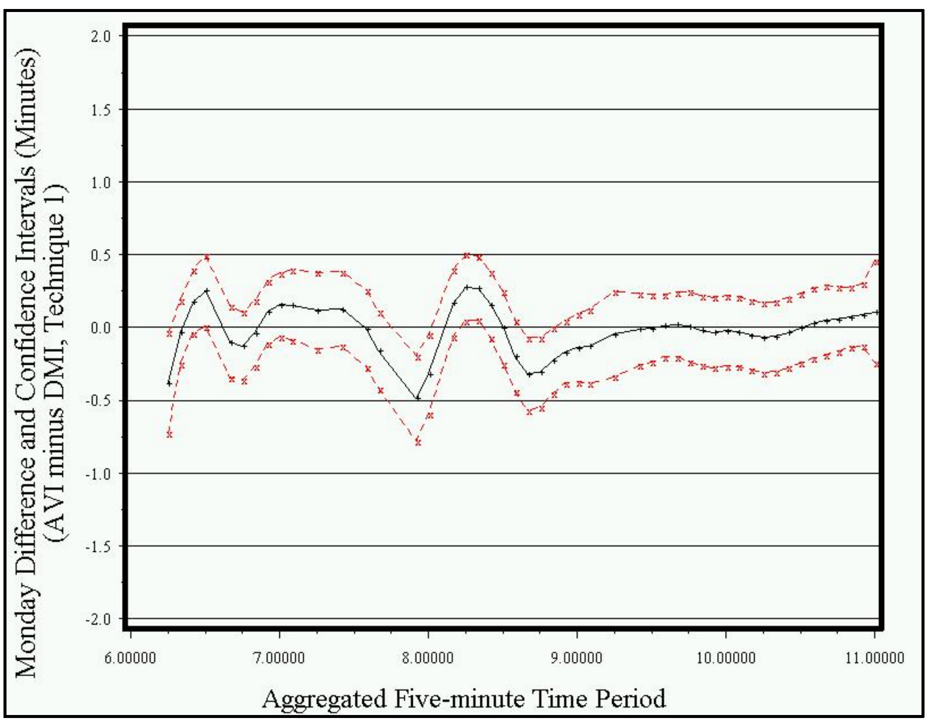

FIGURE B-34 Monday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

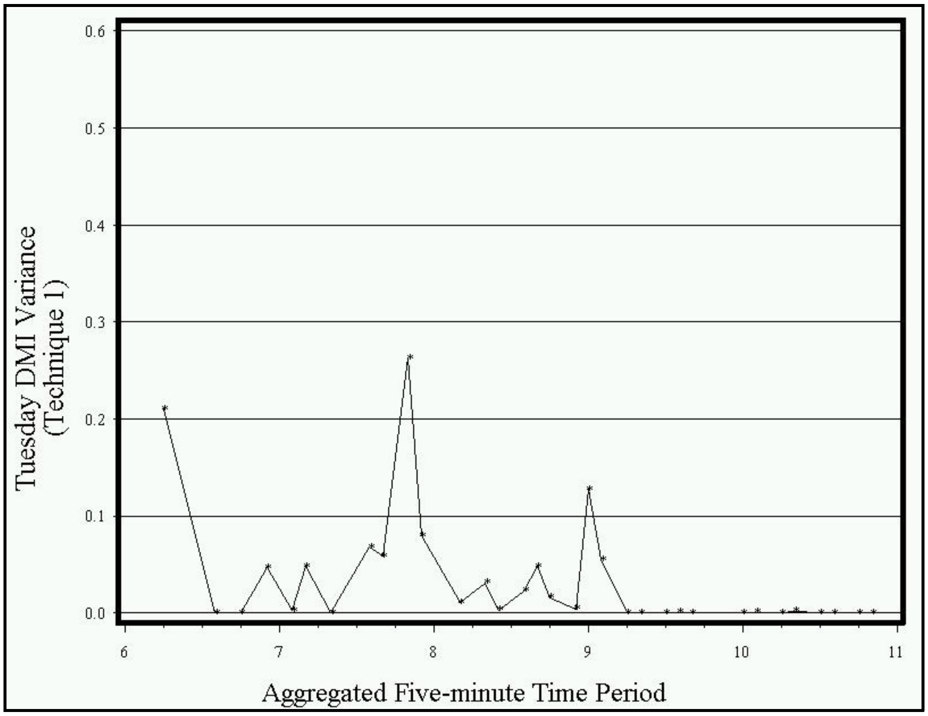

FIGURE B-35 Tuesday Test Vehicles (DMI) Variance with Technique One

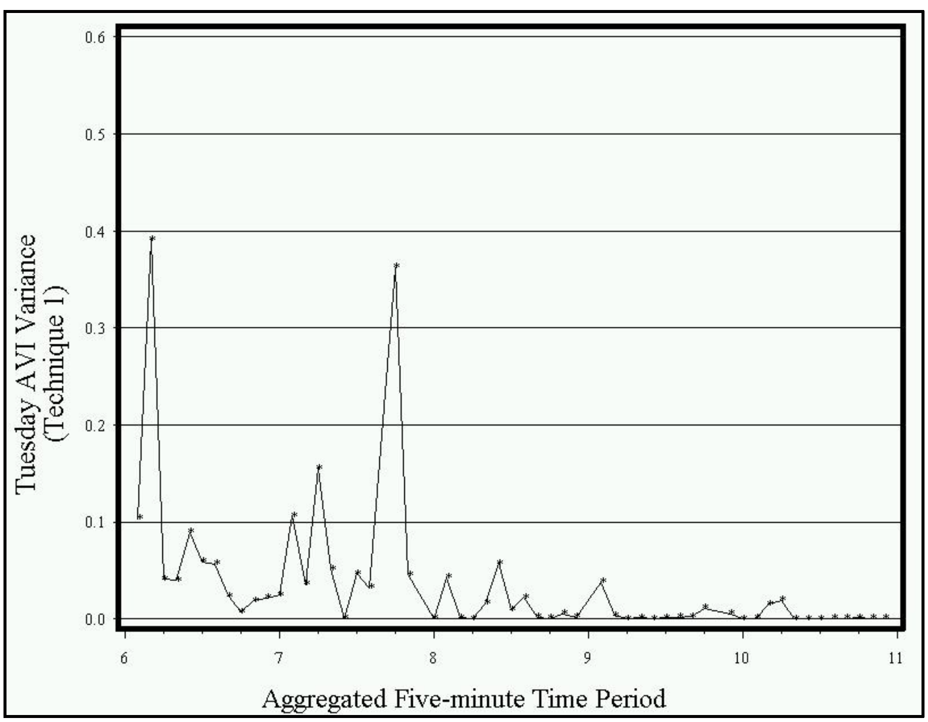

FIGURE B-36 Tuesday AVI Variance with Technique One

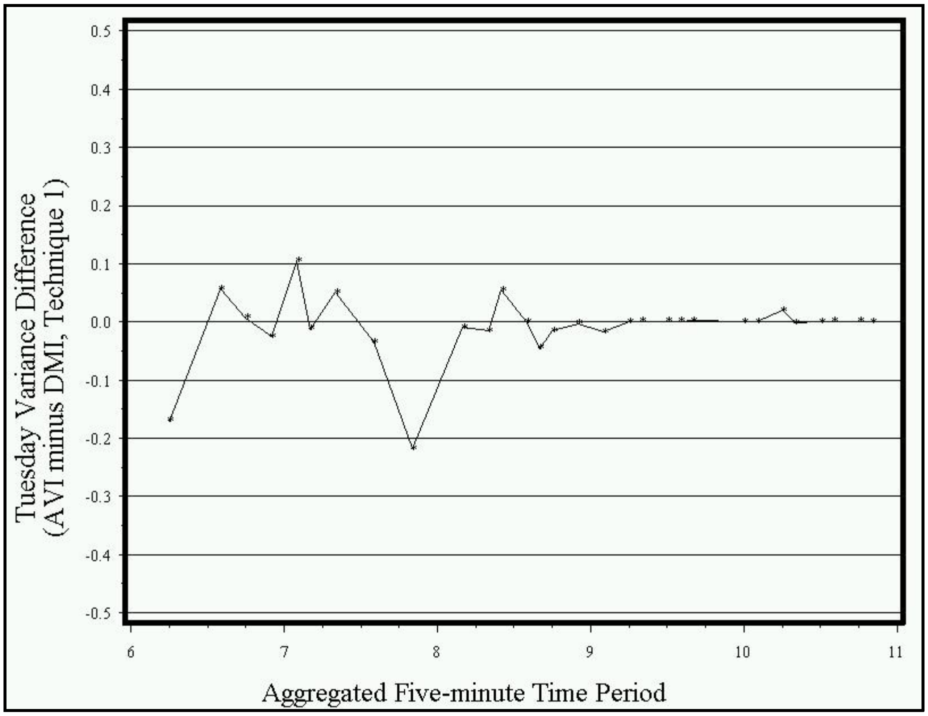

FIGURE B-37 Tuesday Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

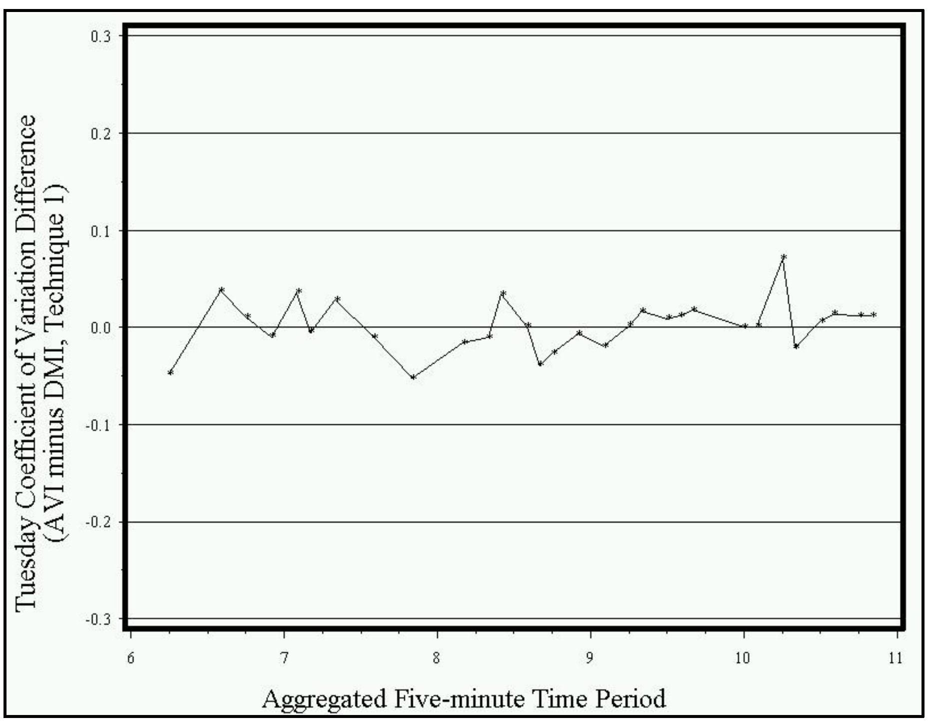

FIGURE B-38 Tuesday Coefficient of Variation Difference Between AVI and Test Vehicles (DMI) with Technique One

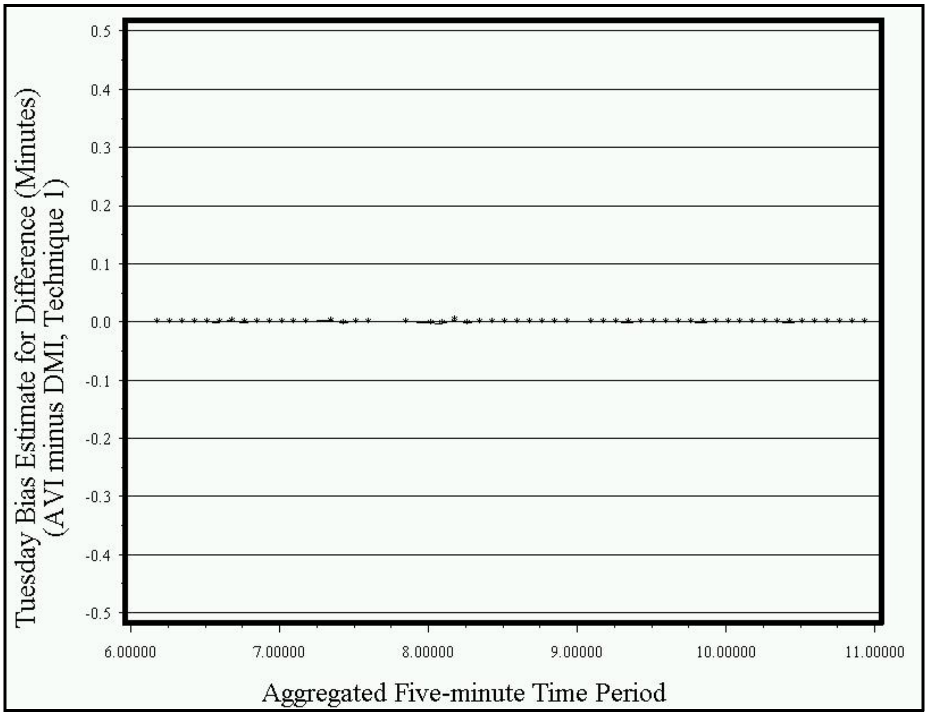

FIGURE B-39 Tuesday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique One

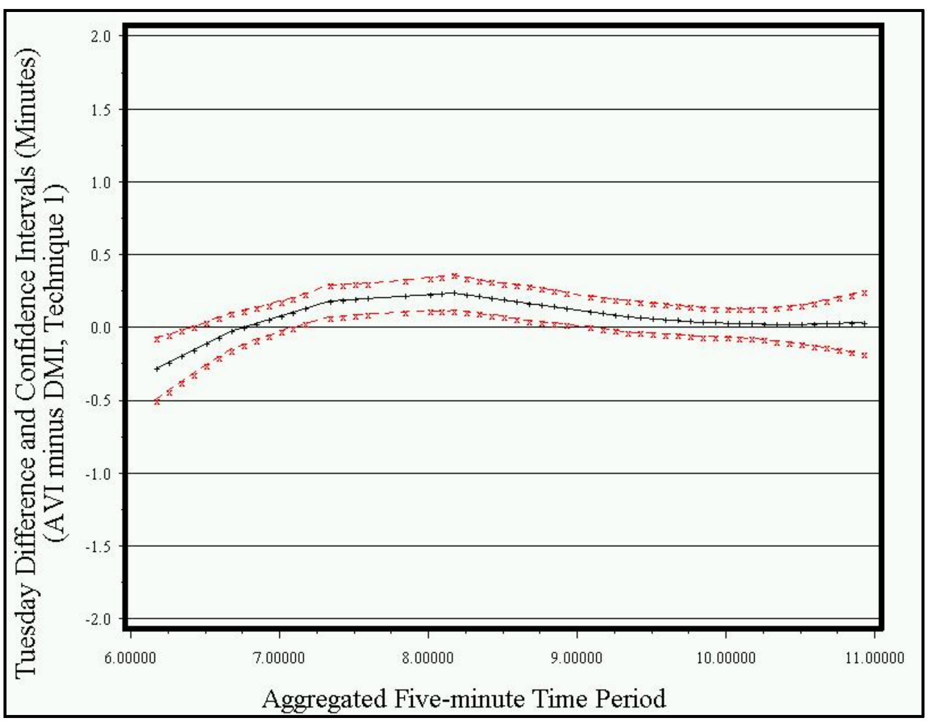

FIGURE B-40 Tuesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

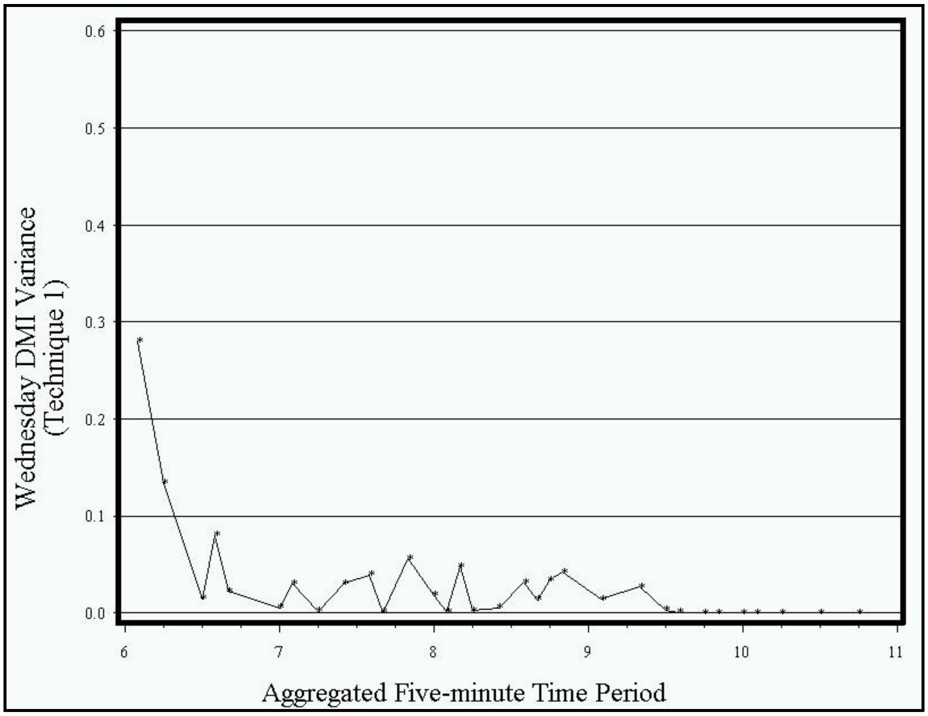

FIGURE B-41 Wednesday Test Vehicles (DMI) Variance with Technique One

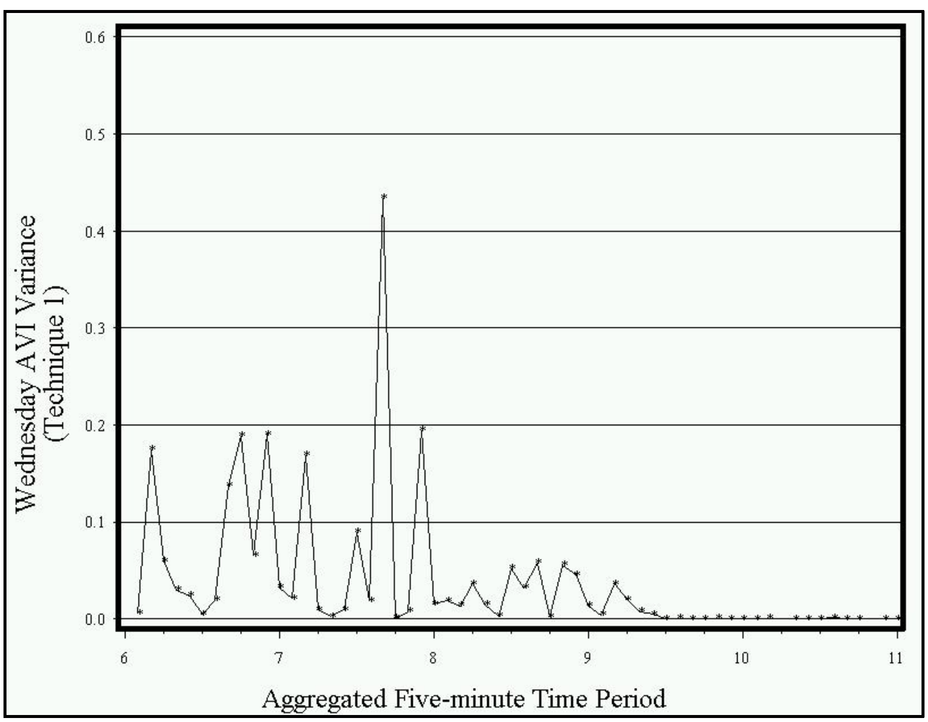

FIGURE B-42 Wednesday AVI Variance with Technique One

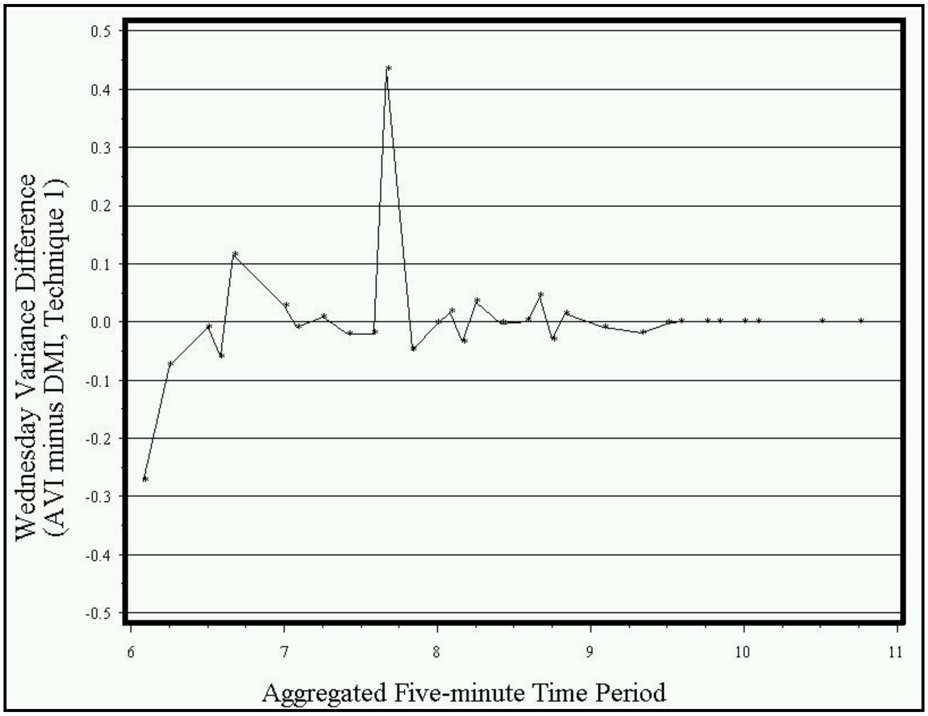

FIGURE B-43 Wednesday Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

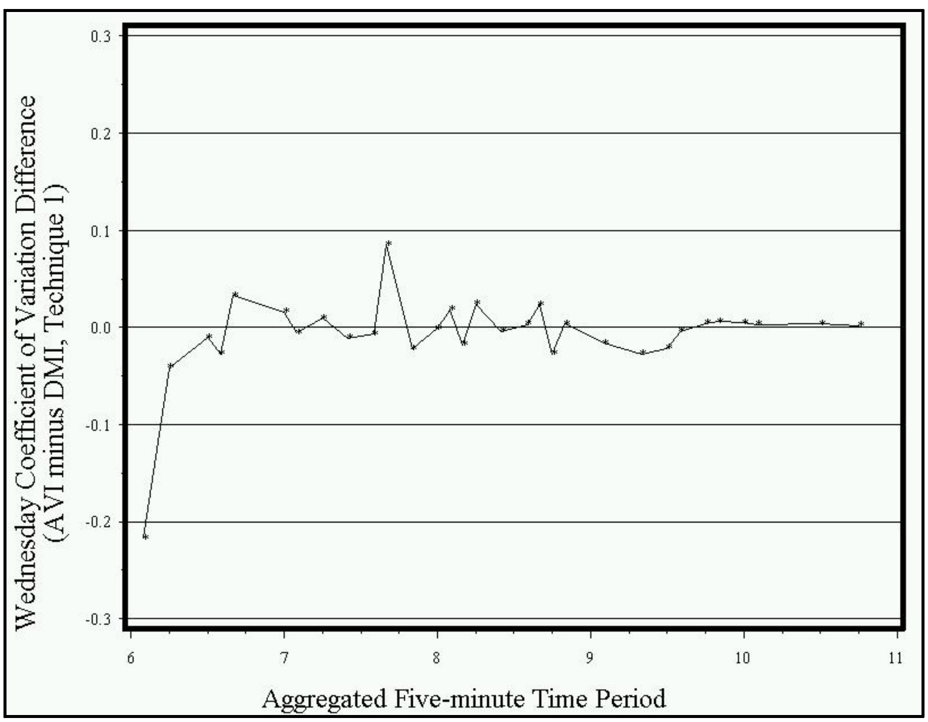

FIGURE B-44 Wednesday Coefficient of Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

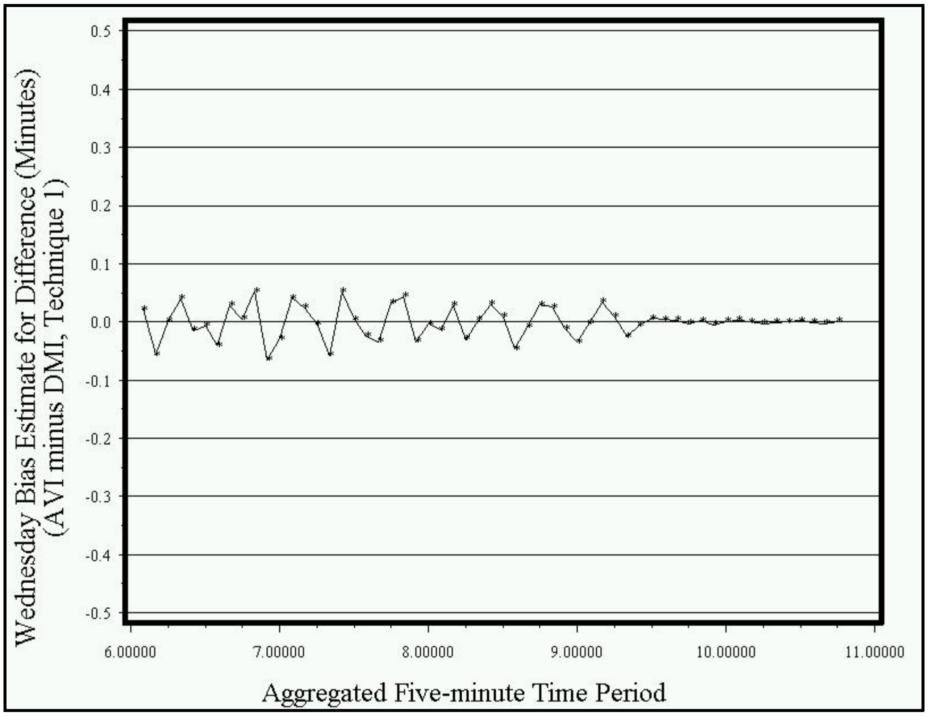

FIGURE B-45 Wednesday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique One

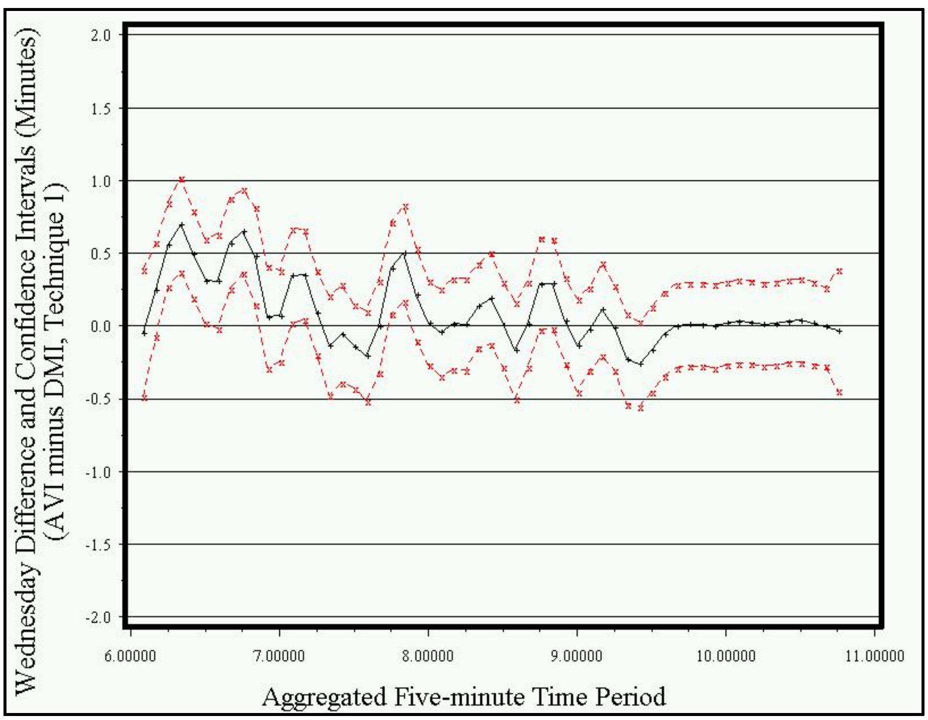

FIGURE B-46 Wednesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

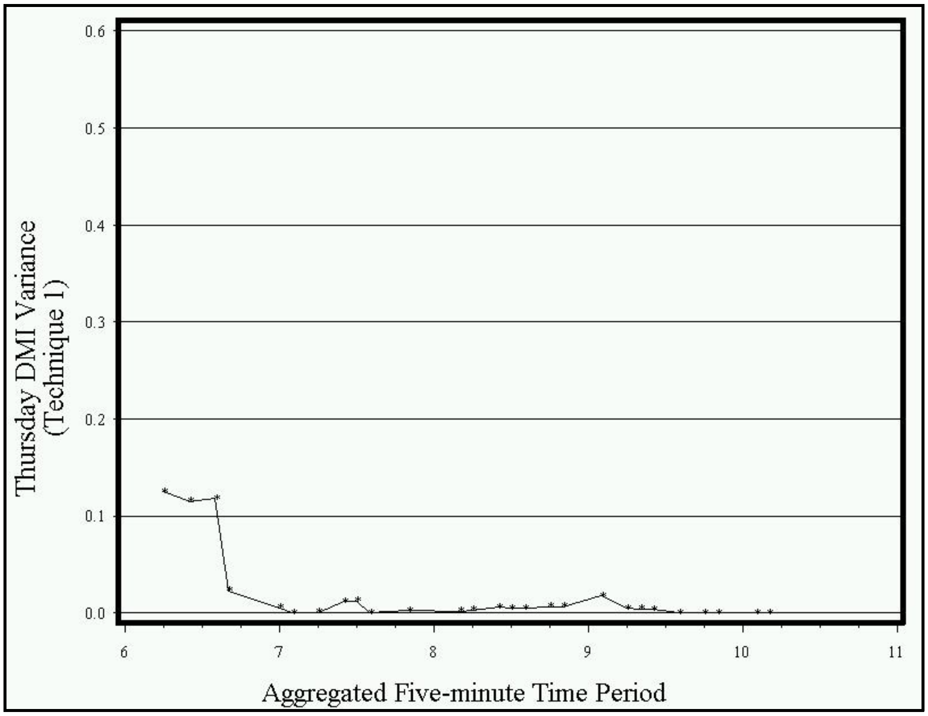

FIGURE B-47 Thursday Test Vehicles (DMI) Variance with Technique One

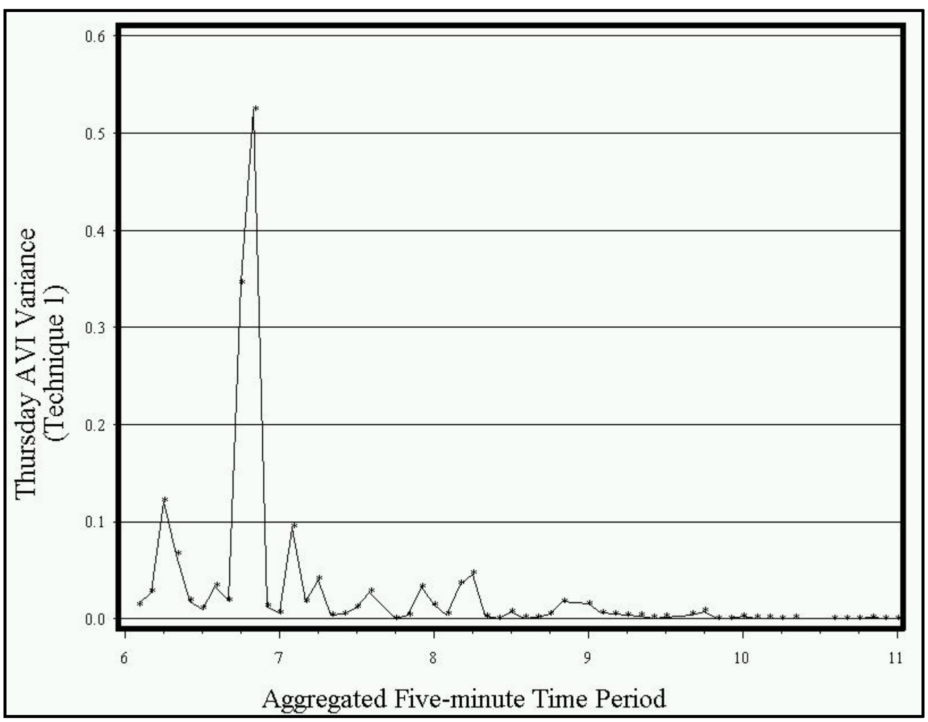

FIGURE B-48 Thursday AVI Variance with Technique One

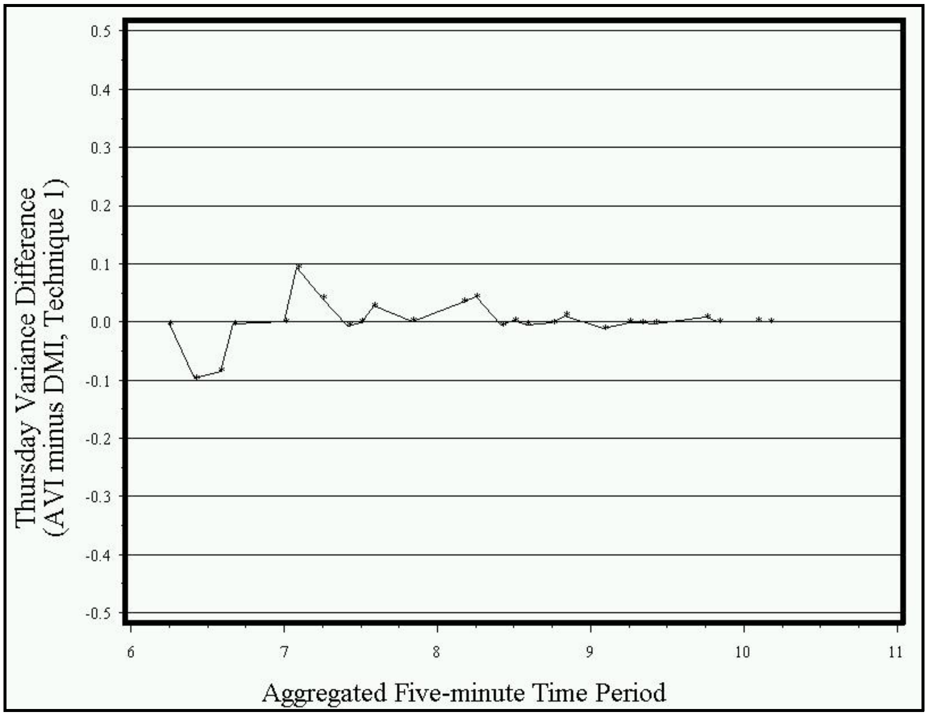

FIGURE B-49 Thursday Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

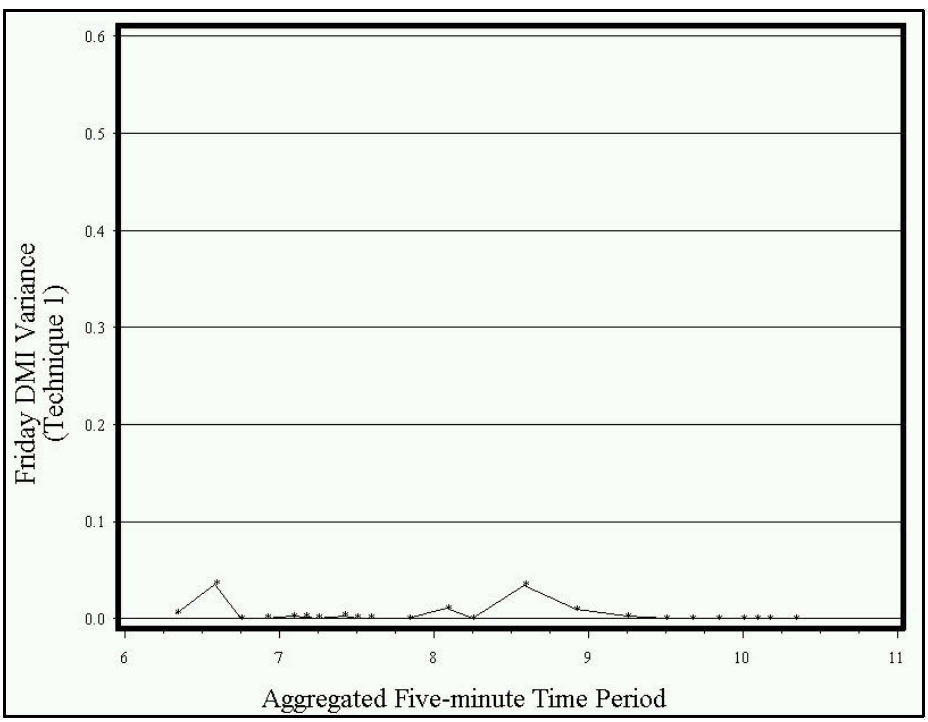

FIGURE B-50 Friday Test Vehicles (DMI) Variance with Technique One

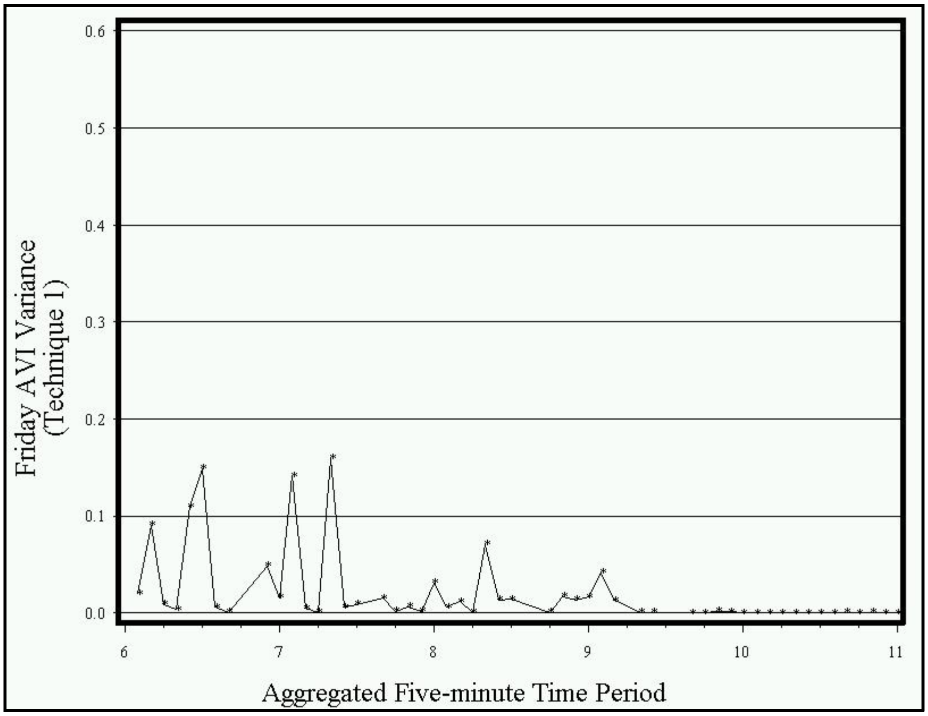

FIGURE B-51 Friday AVI Variance with Technique One

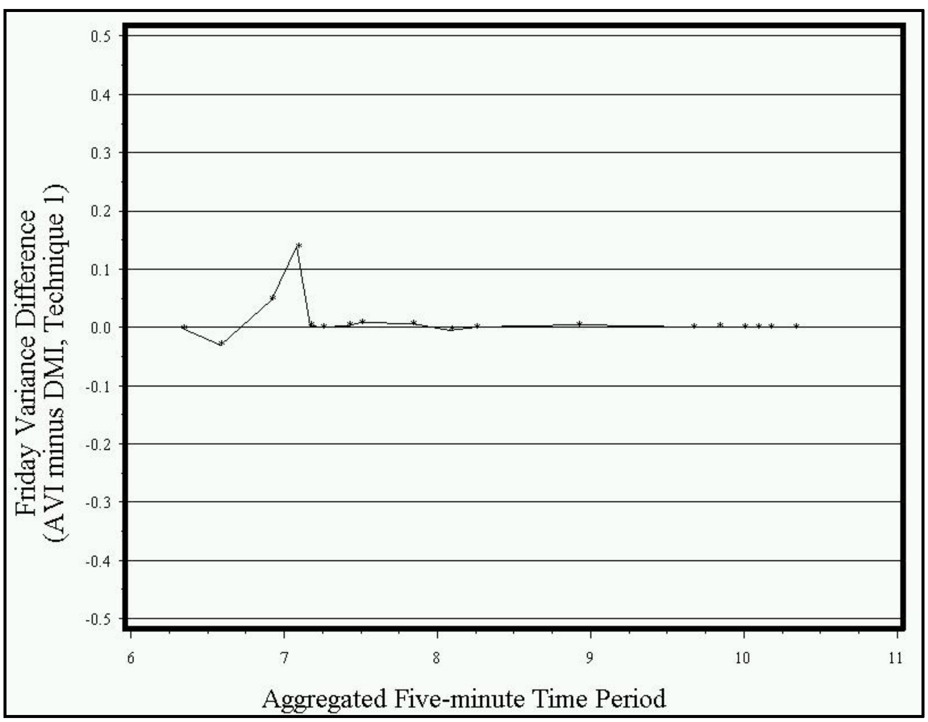

FIGURE B-52 Friday Variance Difference Between AVI and Test Vehicles (DMI) with Technique One

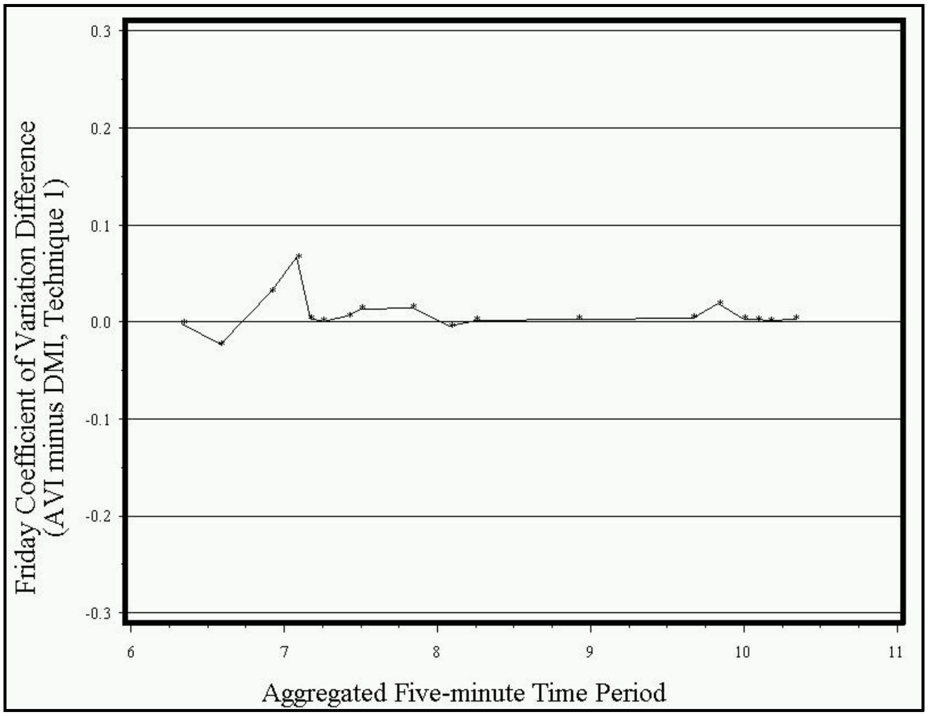

FIGURE B-53 Friday Coefficient of Variation Difference Between AVI and Test Vehicles (DMI) with Technique One

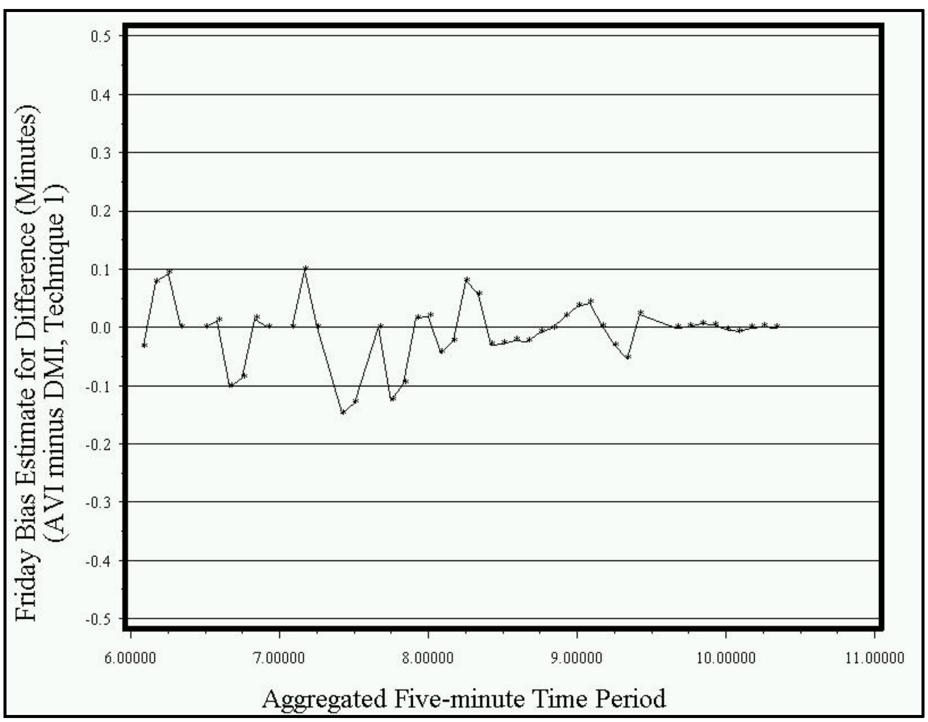

FIGURE B-54 Friday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique One

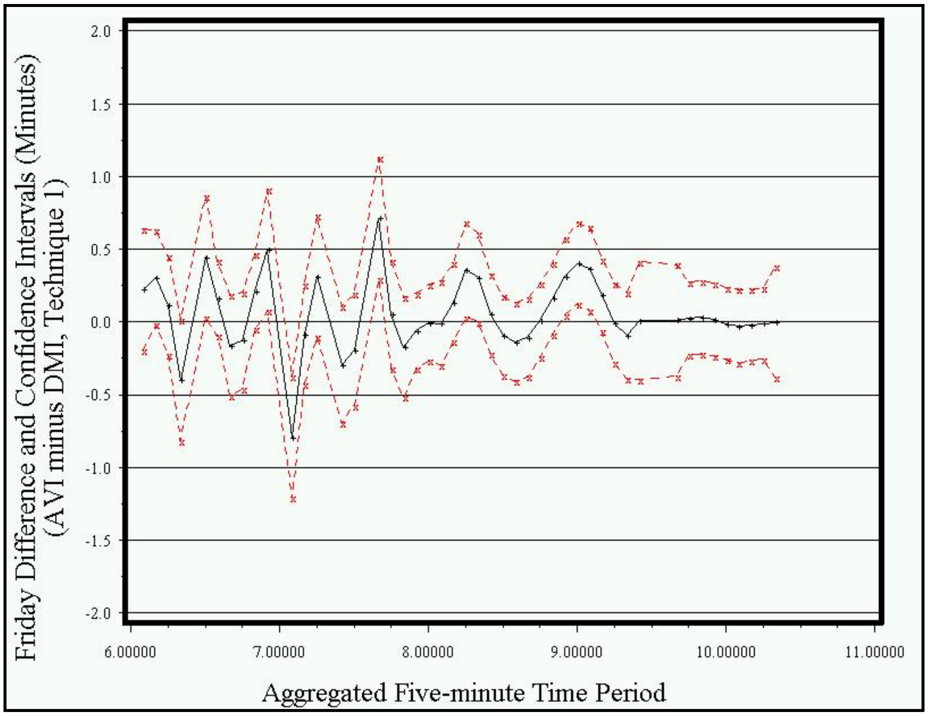

FIGURE B-55 Friday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

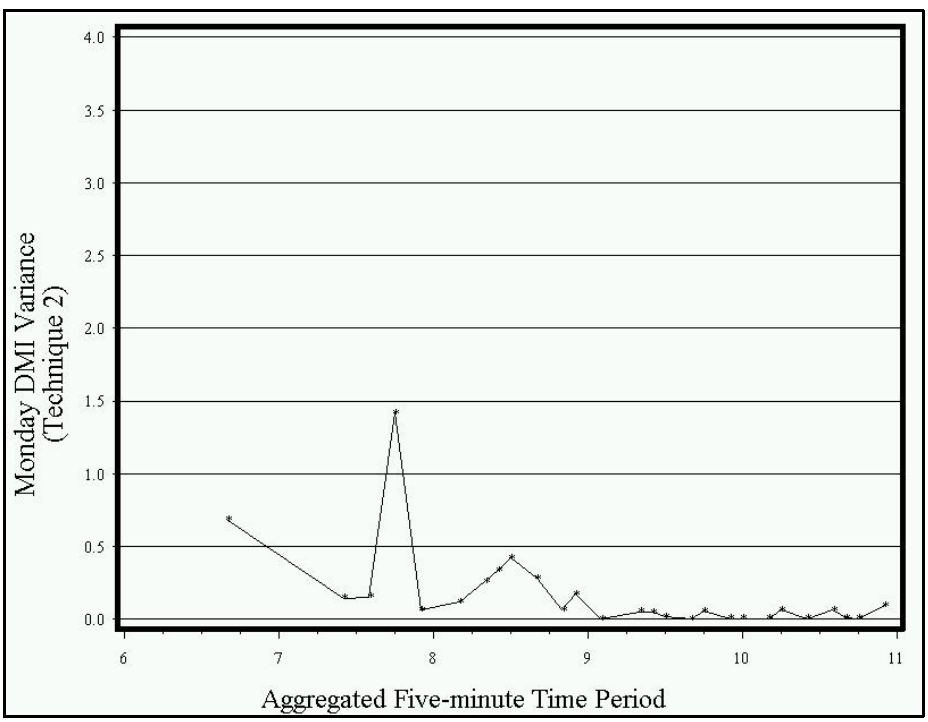

FIGURE B-56 Monday Test Vehicles (DMI) Variance with Technique Two

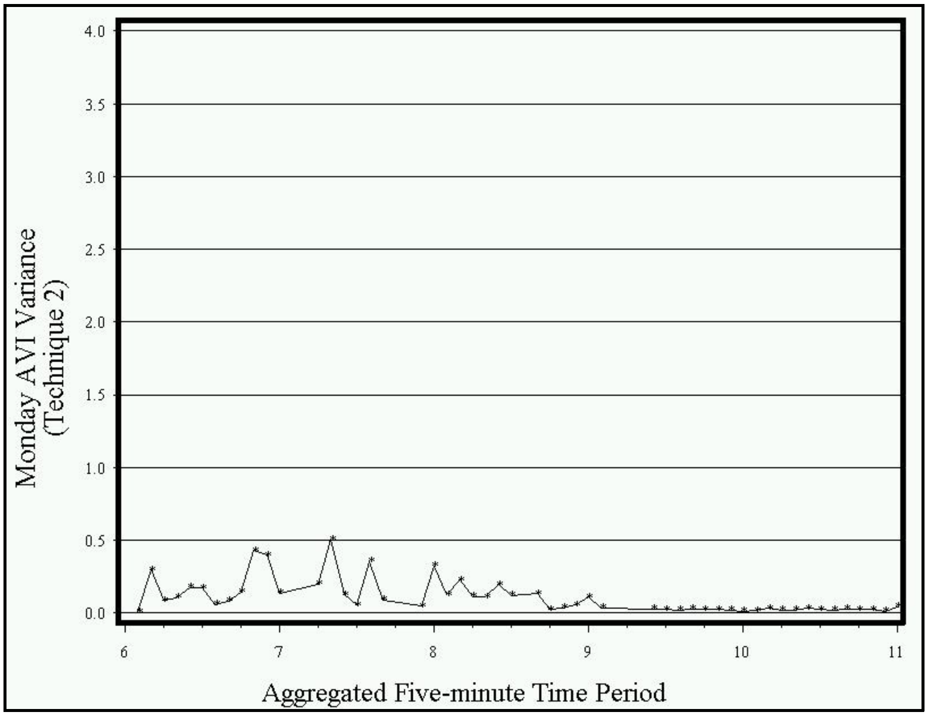

FIGURE B-57 Monday AVI Variance with Technique Two

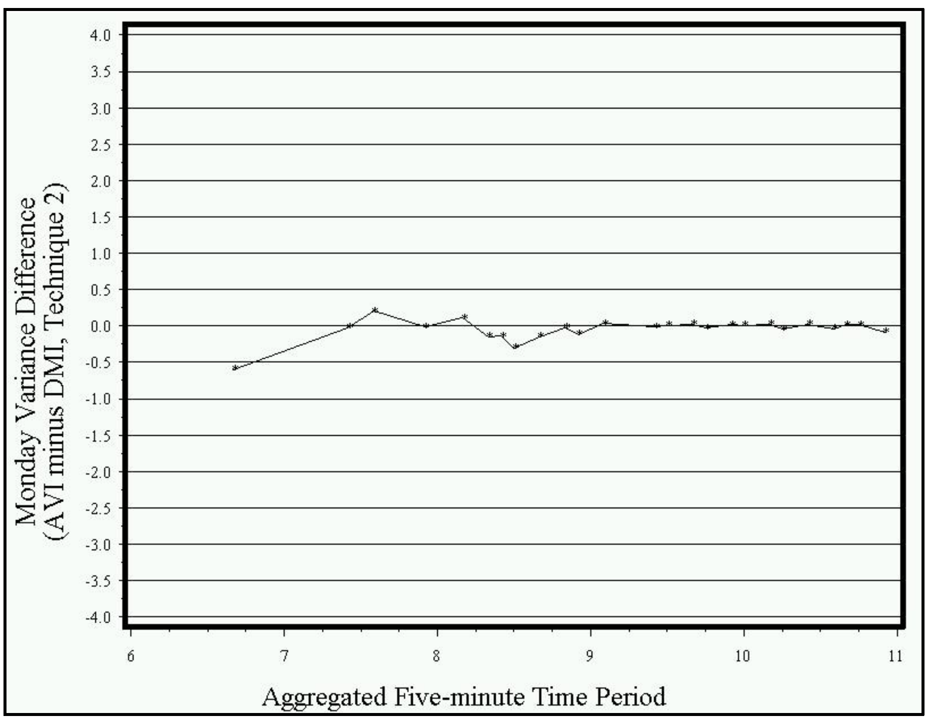

FIGURE B-58 Monday Variance Difference Between AVI and Test Vehicles (DMI) with Technique Two

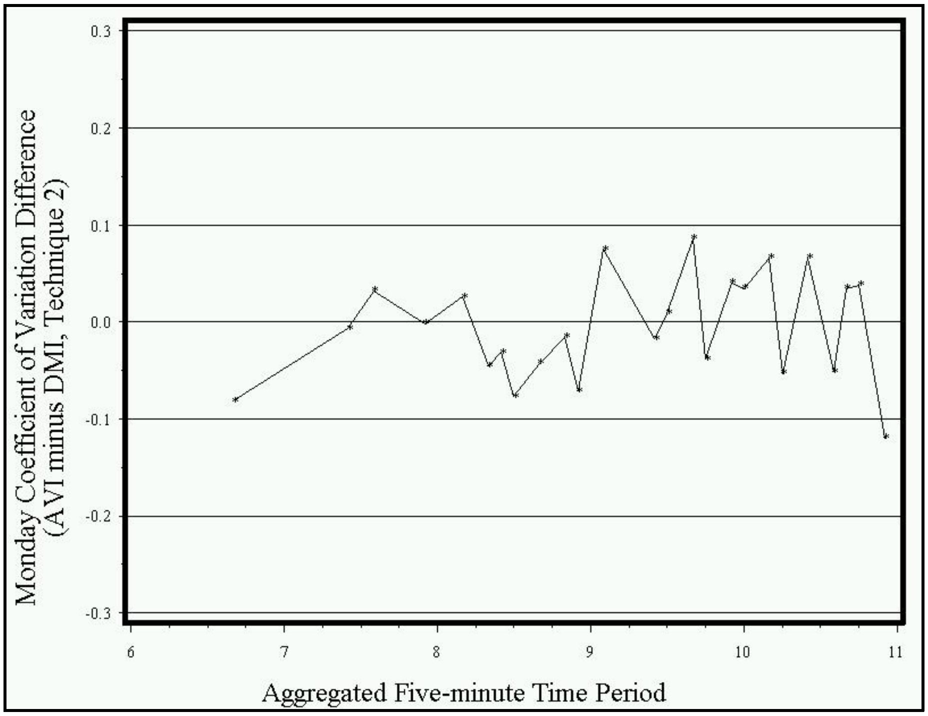

FIGURE B-59 Monday Coefficient of Variation Difference Between AVI and Test Vehicles (DMI) with Technique Two

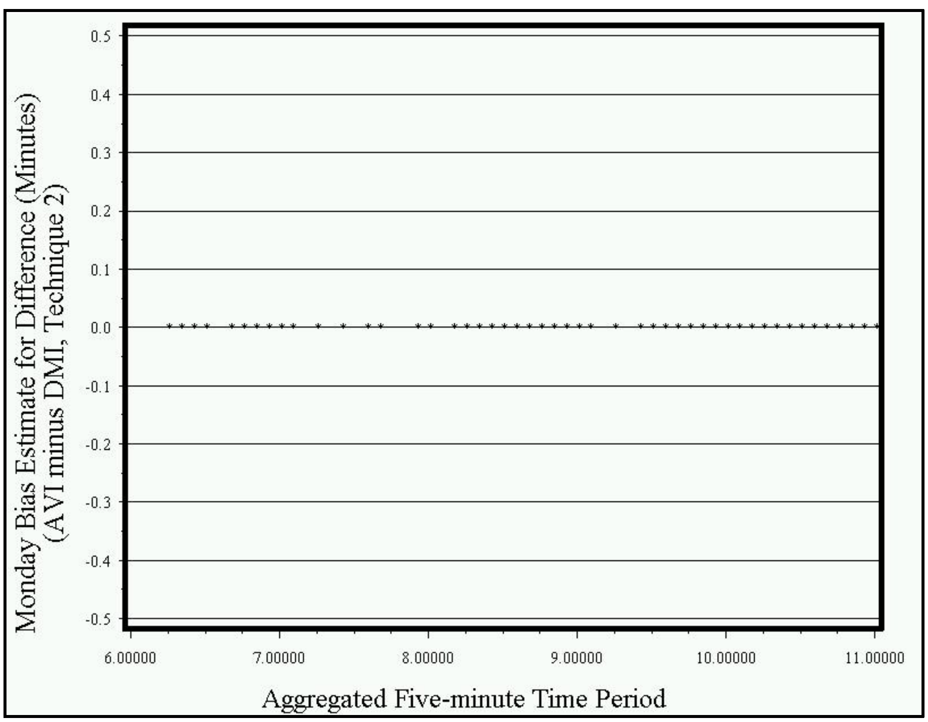

FIGURE B-60 Monday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique Two

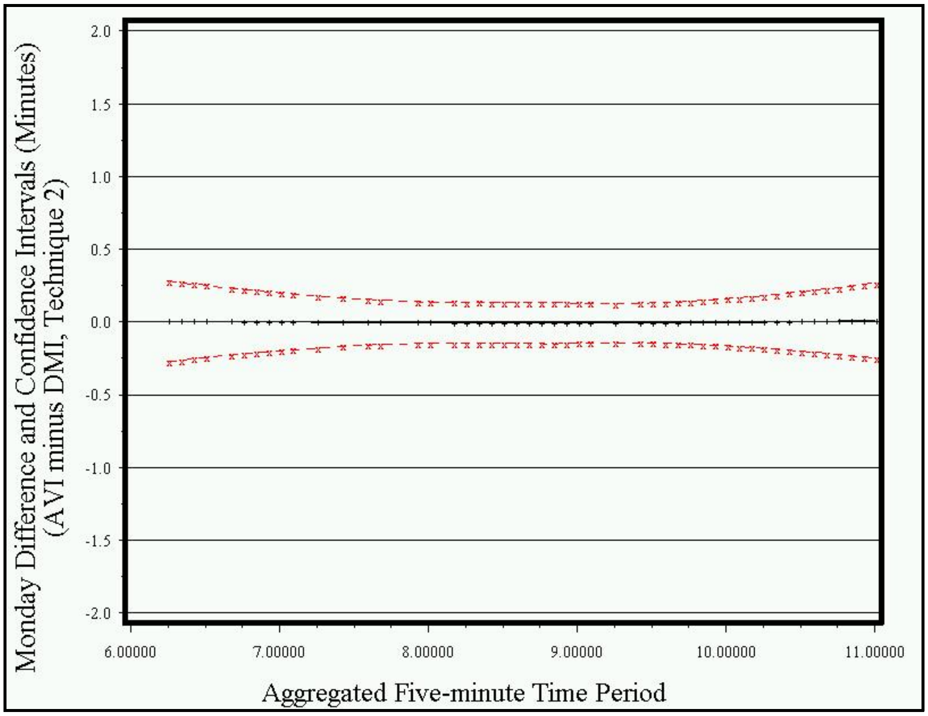

FIGURE B-61 Monday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

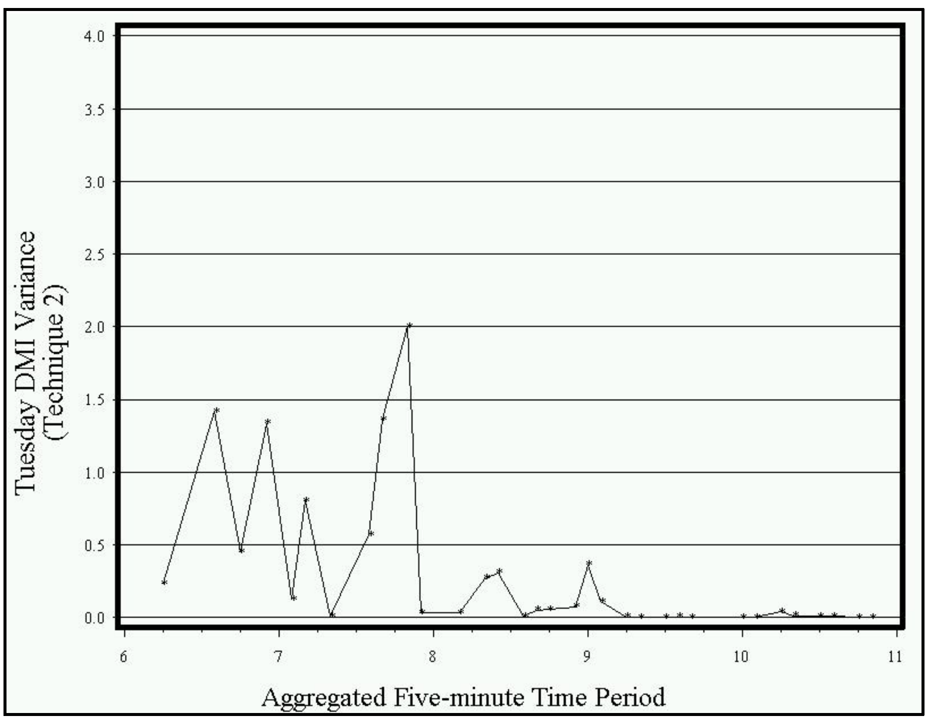

FIGURE B-62 Tuesday Test Vehicles (DMI) Variance with Technique Two

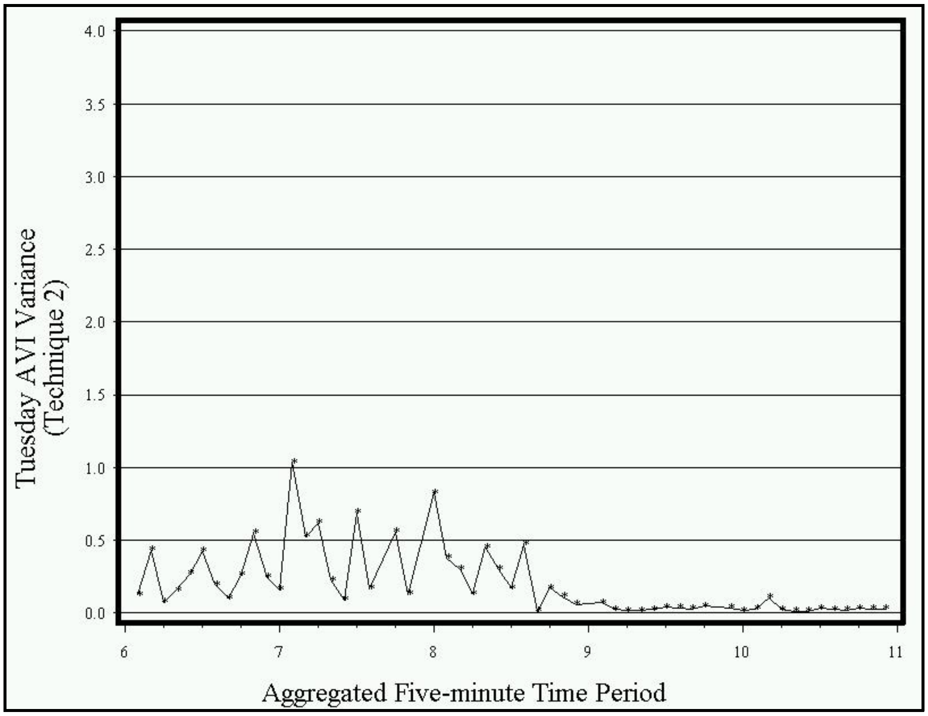

FIGURE B-63 Tuesday AVI Variance with Technique Two

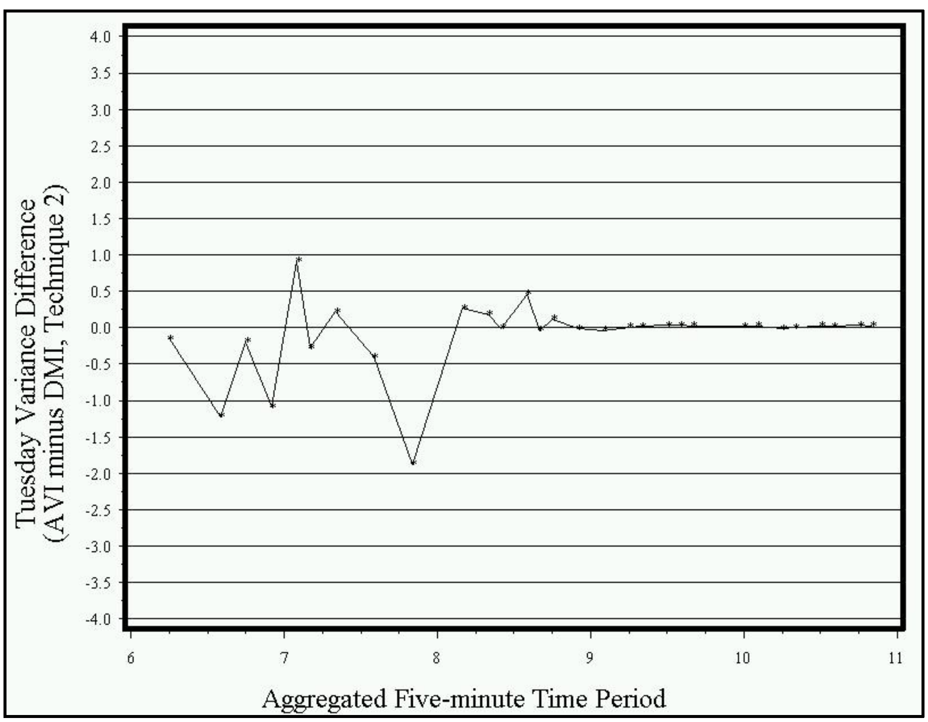

FIGURE B-64 Tuesday Variance Difference Between AVI and Test Vehicles (DMI) with Technique Two

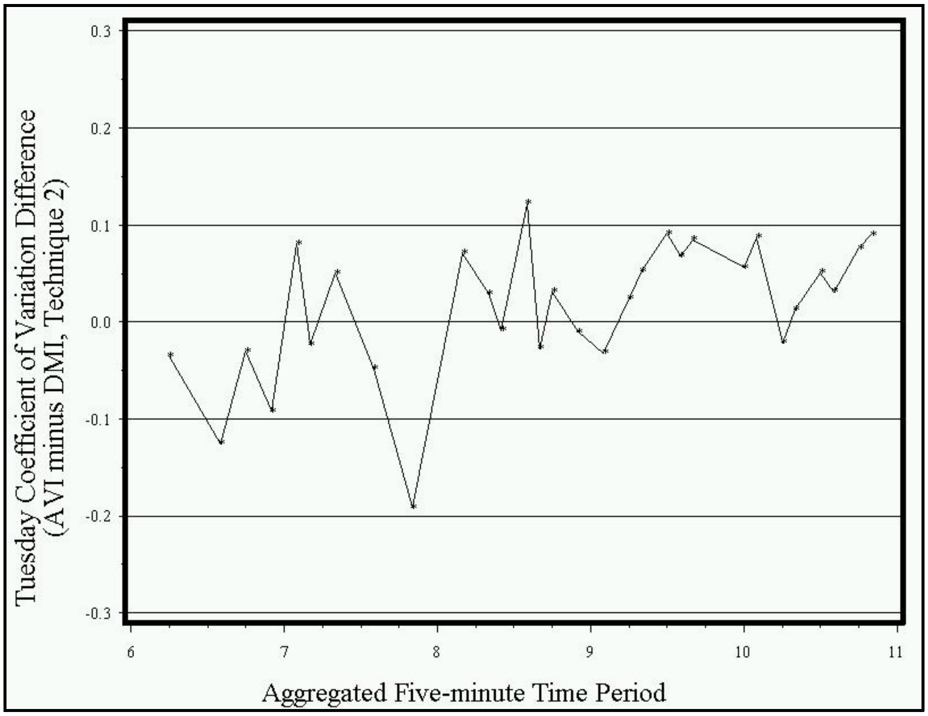

FIGURE B-65 Tuesday Coefficient of Variation Difference Between AVI and Test Vehicles (DMI) with Technique Two

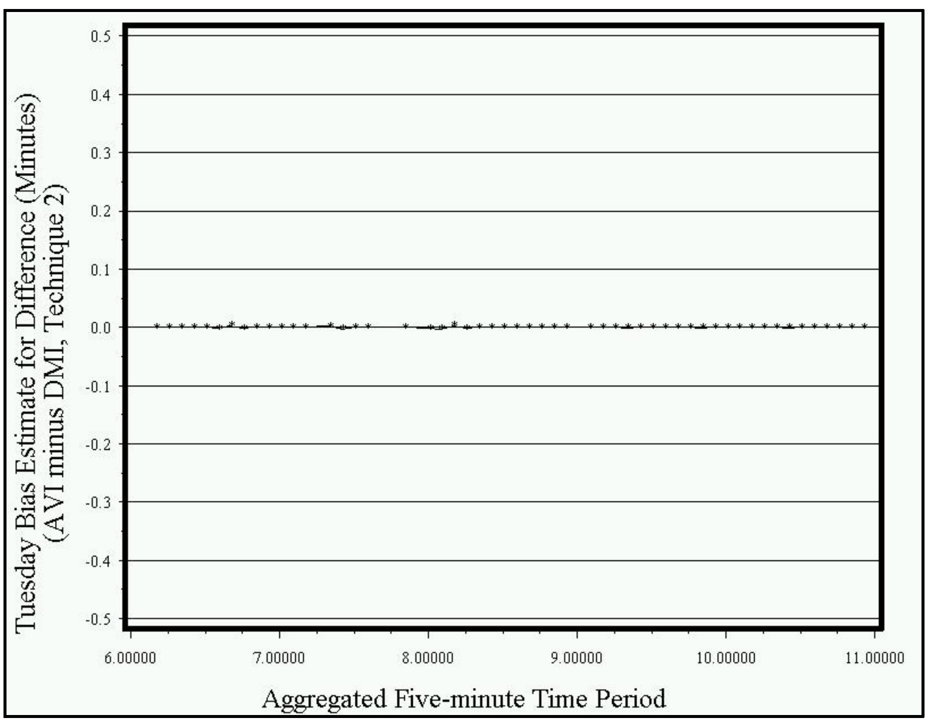

FIGURE B-66 Tuesday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique Two

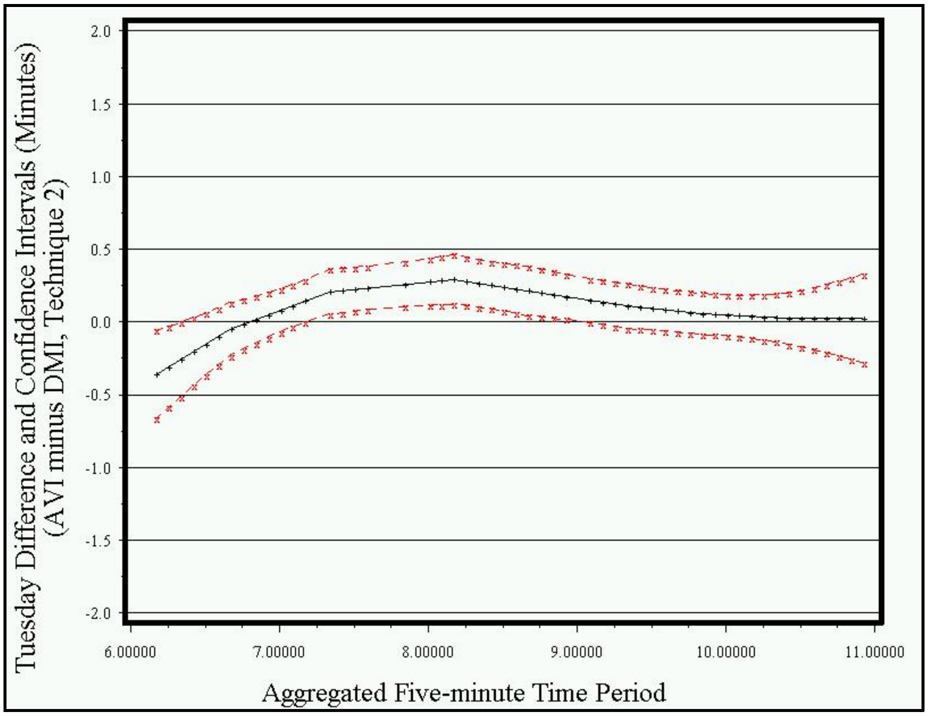

FIGURE B-67 Tuesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

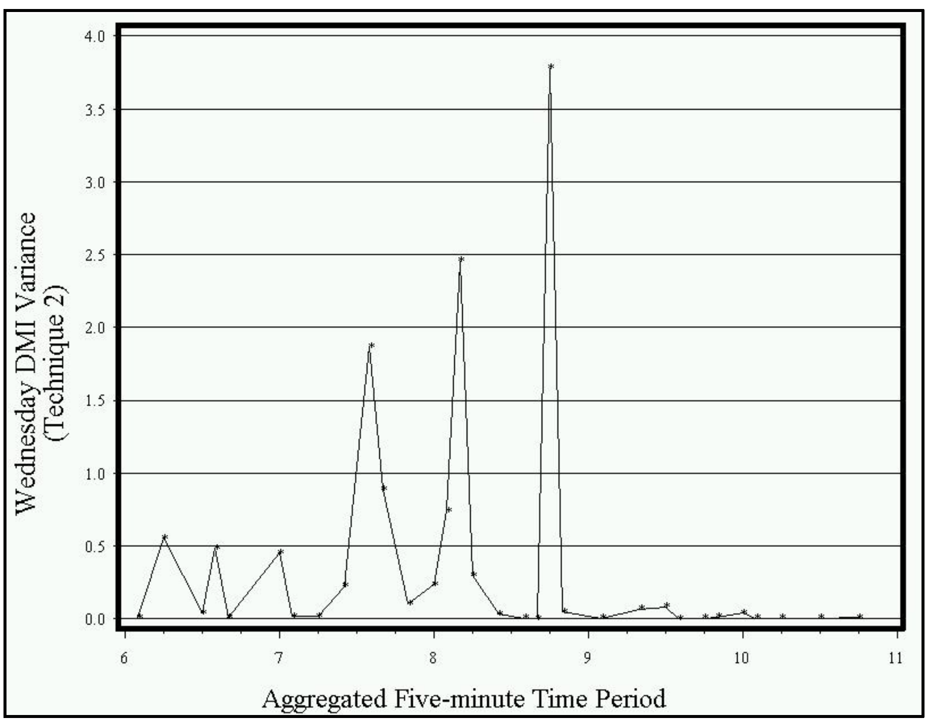

FIGURE B-68 Wednesday Test Vehicles (DMI) Variance with Technique Two

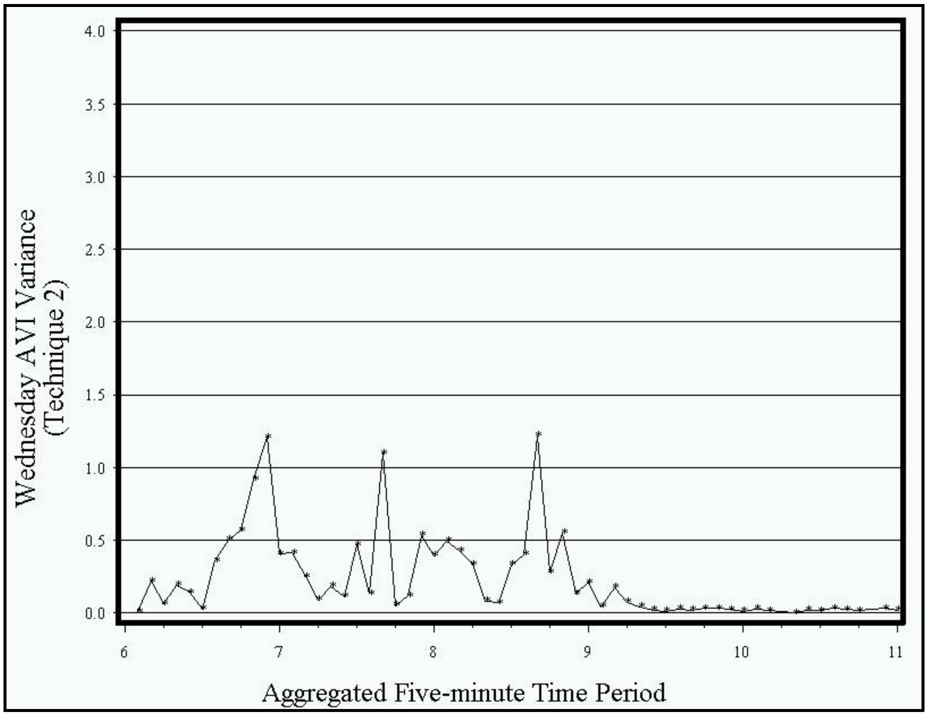

FIGURE B-69 Wednesday AVI Variance with Technique Two

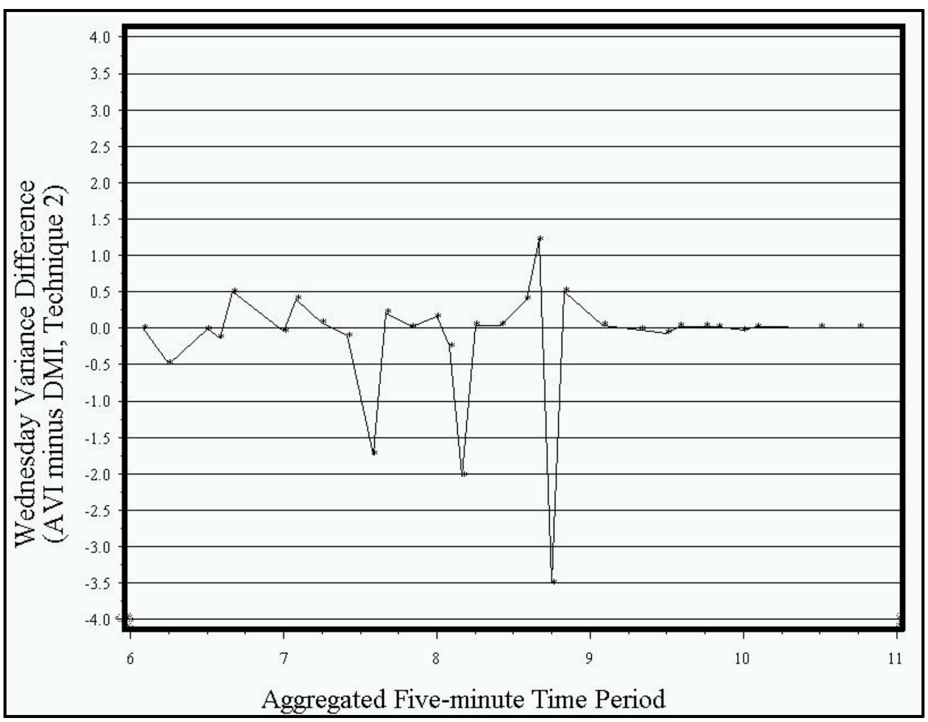

FIGURE B-70 Wednesday Variance Difference Between AVI and Test Vehicles (DMI) with Technique Two

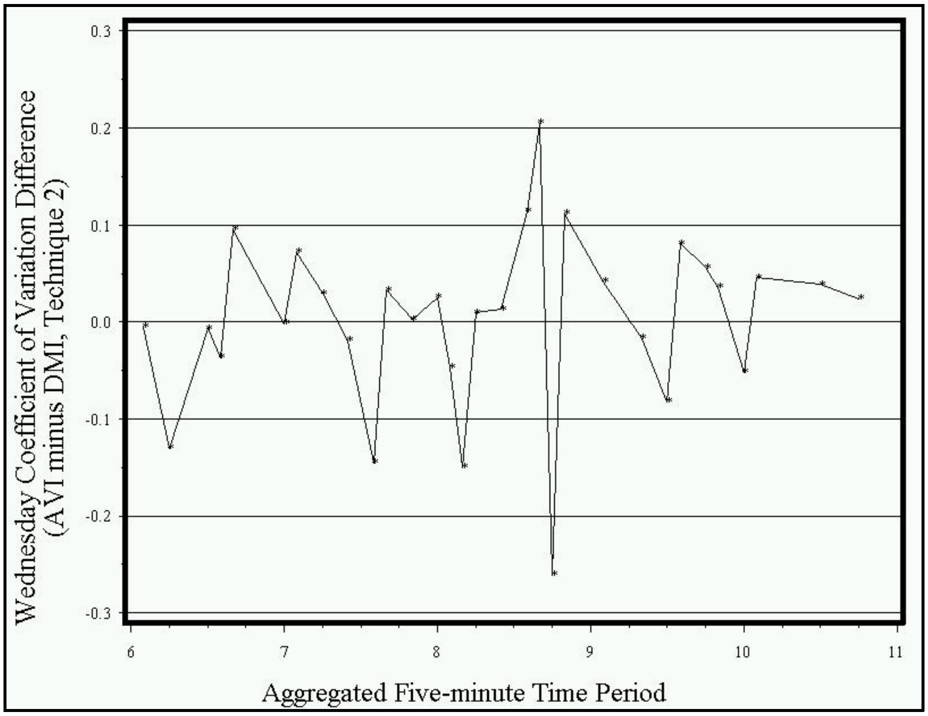

FIGURE B-71 Wednesday Coefficient of Variation Difference Between AVI and Test Vehicles (DMI) with Technique Two

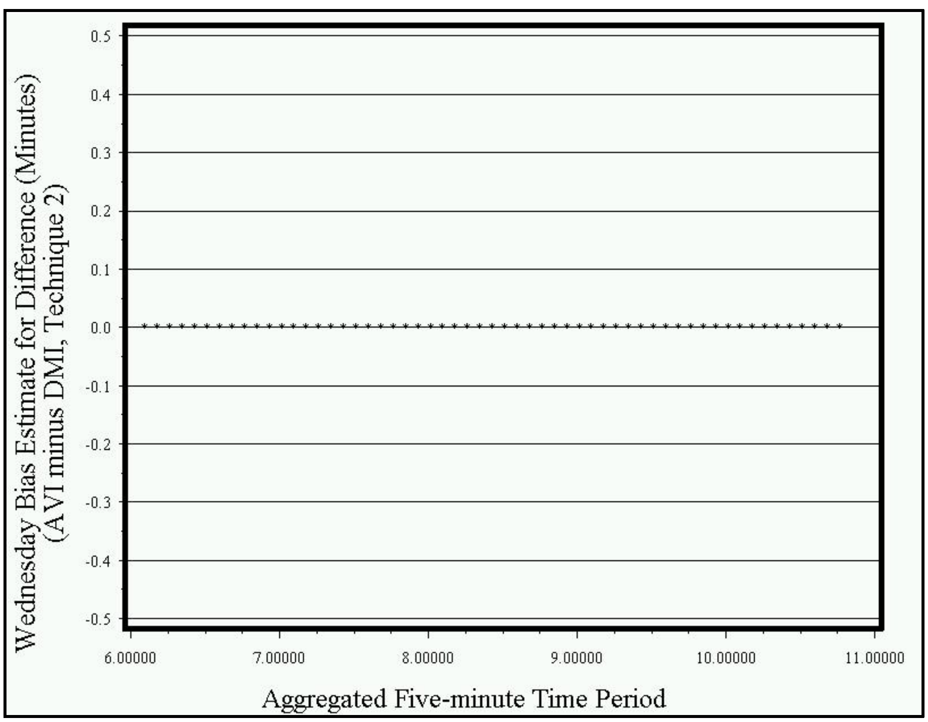

FIGURE B-72 Wednesday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique Two

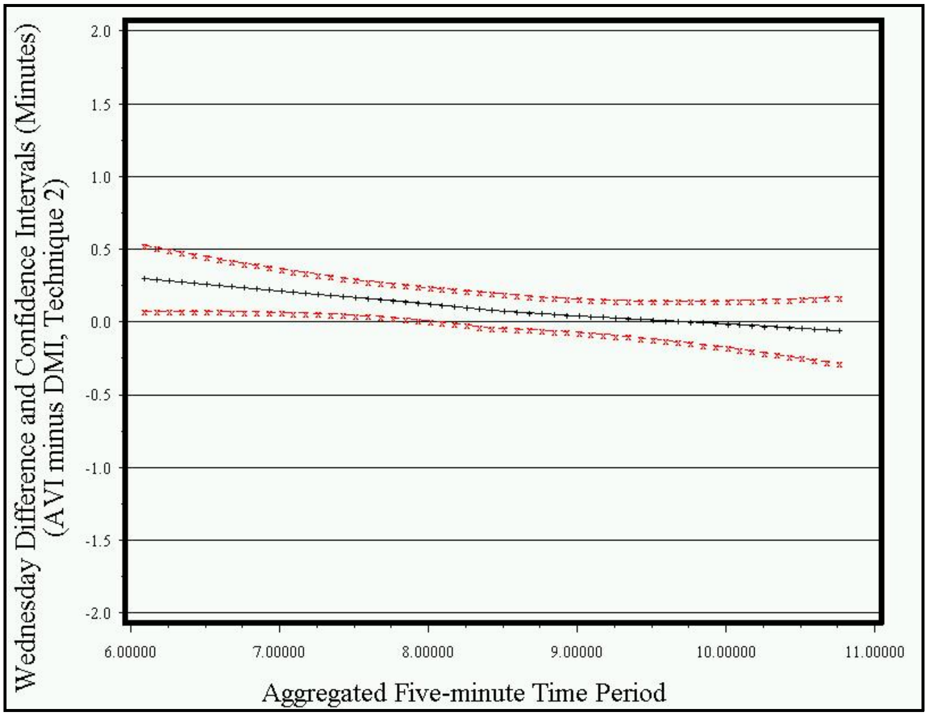

FIGURE B-73 Wednesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

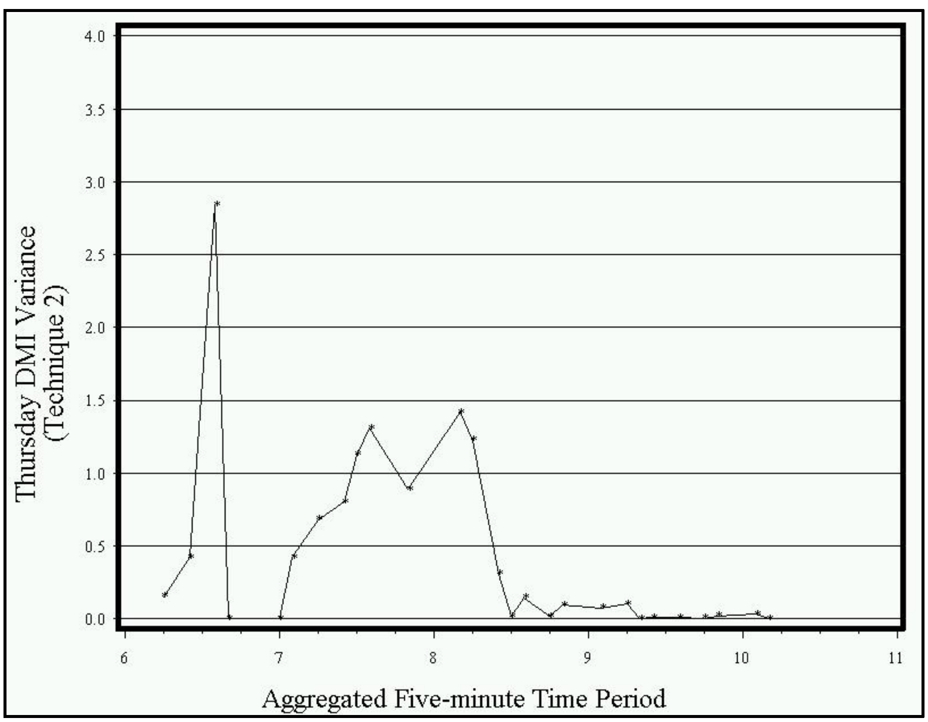

FIGURE B-74 Thursday Test Vehicles (DMI) Variance with Technique Two

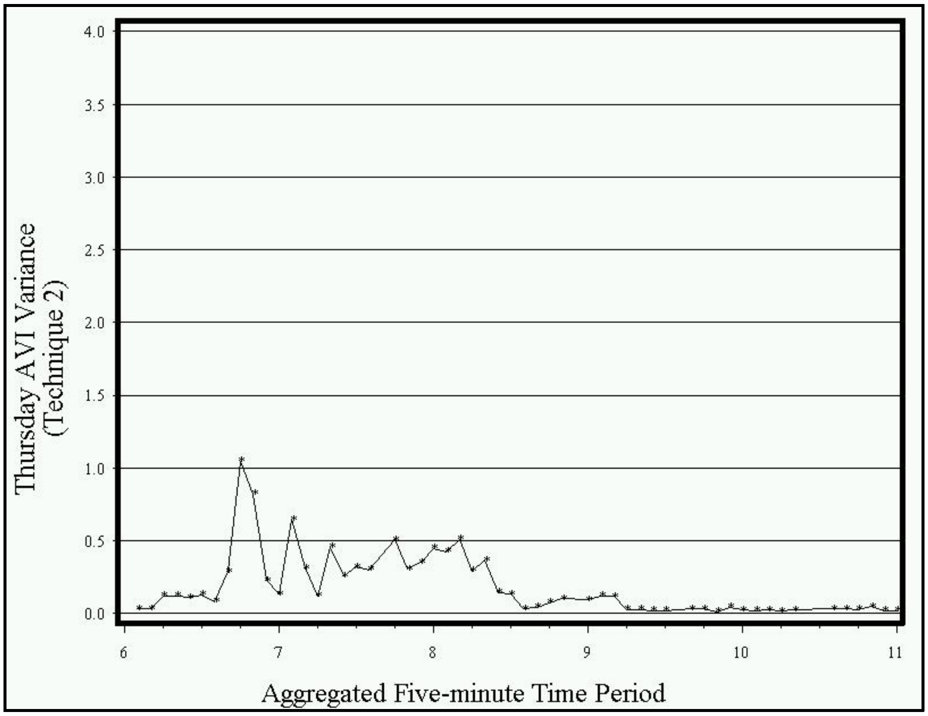

FIGURE B-75 Thursday AVI Variance with Technique Two

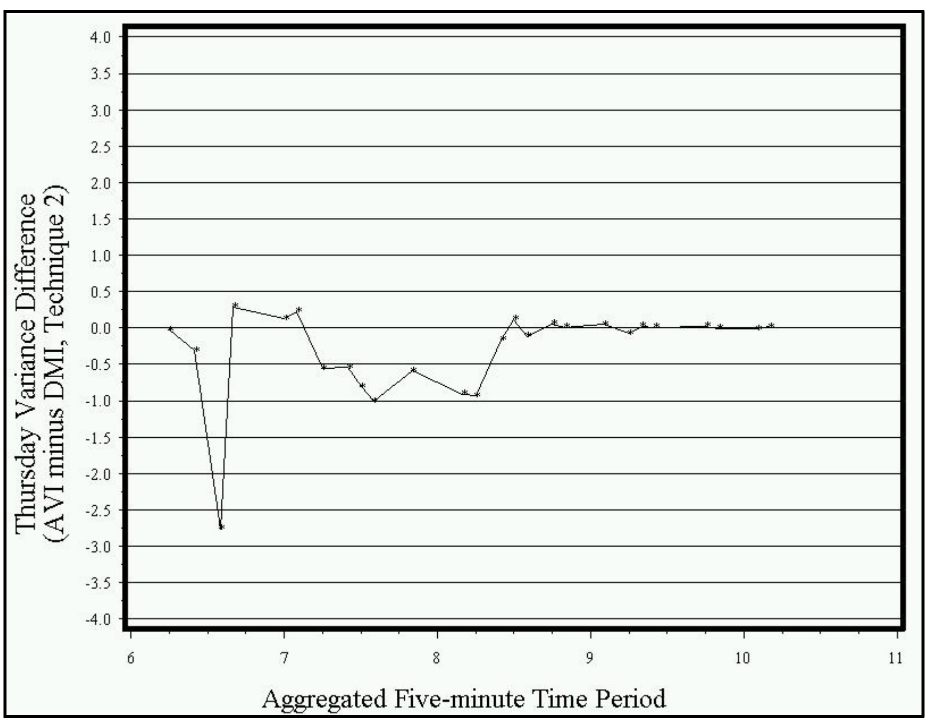

FIGURE B-76 Thursday Variance Difference Between AVI and Test Vehicles (DMI) with Technique Two

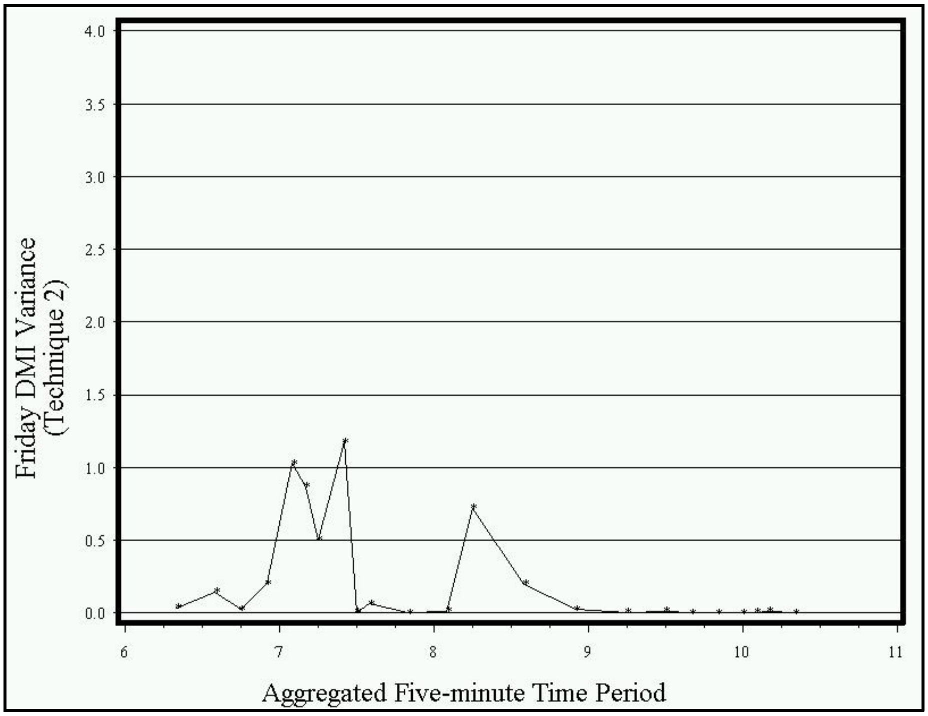

FIGURE B-77 Friday Test Vehicles (DMI) Variance with Technique Two

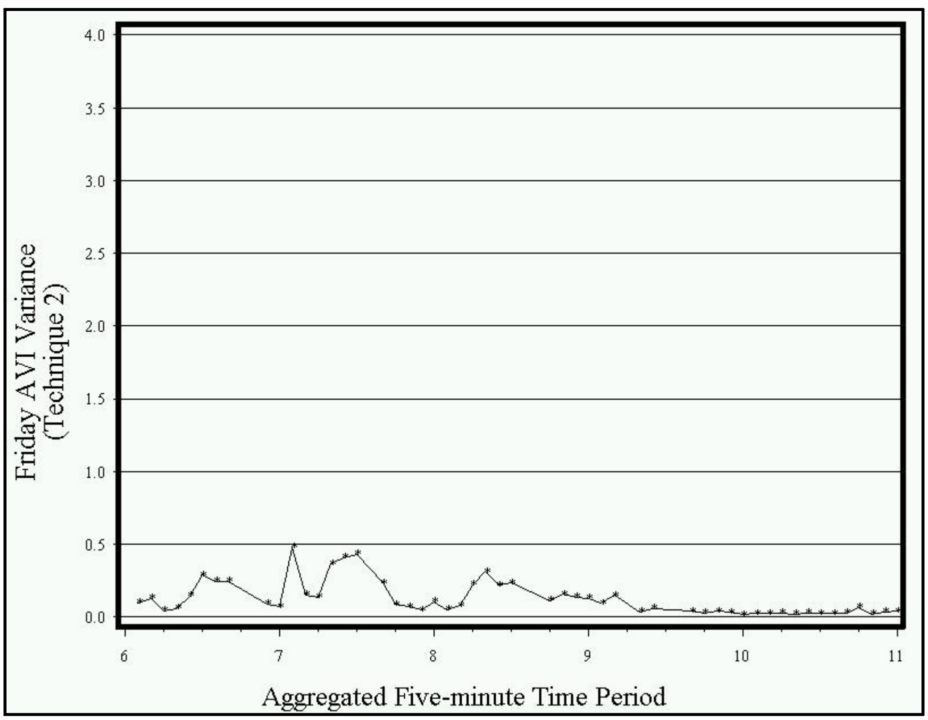

FIGURE B-78 Friday AVI Variance with Technique Two

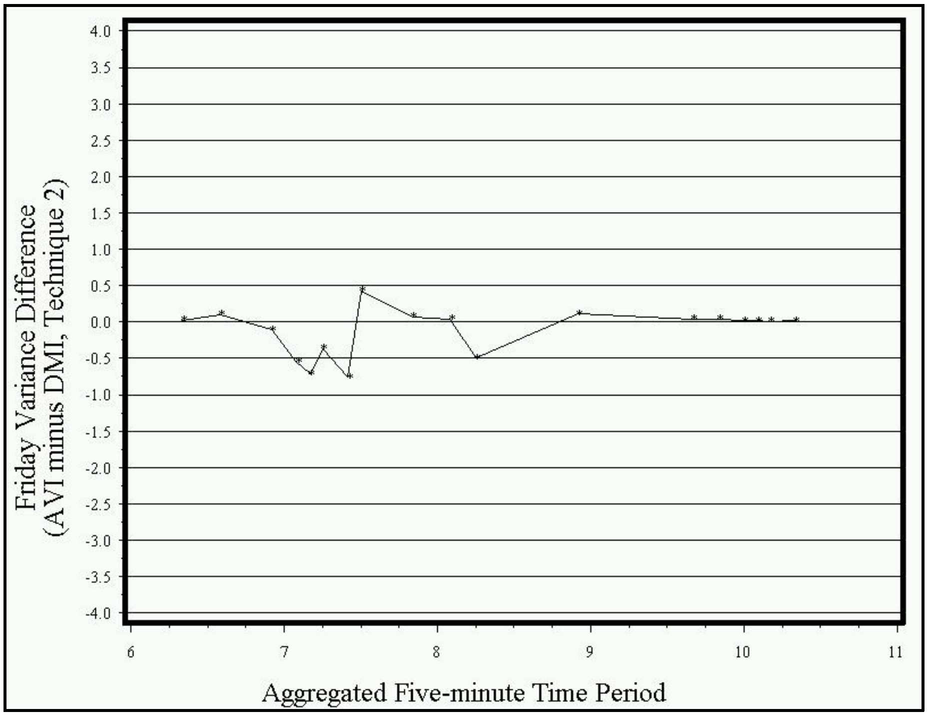

FIGURE B-79 Friday Variance Difference Between AVI and Test Vehicles (DMI) with Technique Two

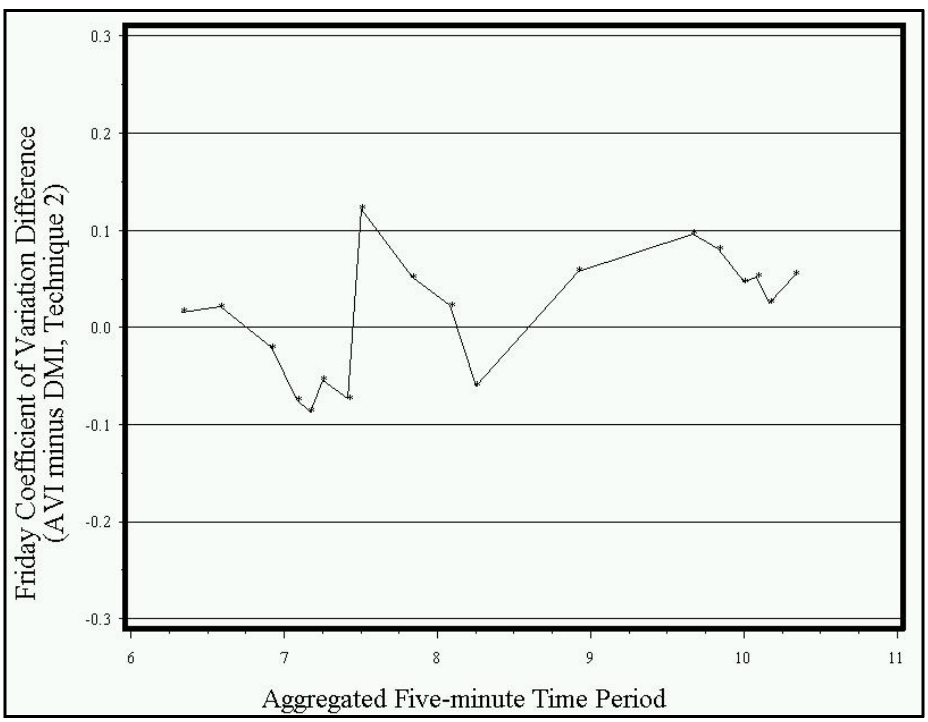

FIGURE B-80 Friday Coefficient of Variation Difference Between AVI and Test Vehicles (DMI) with Technique Two

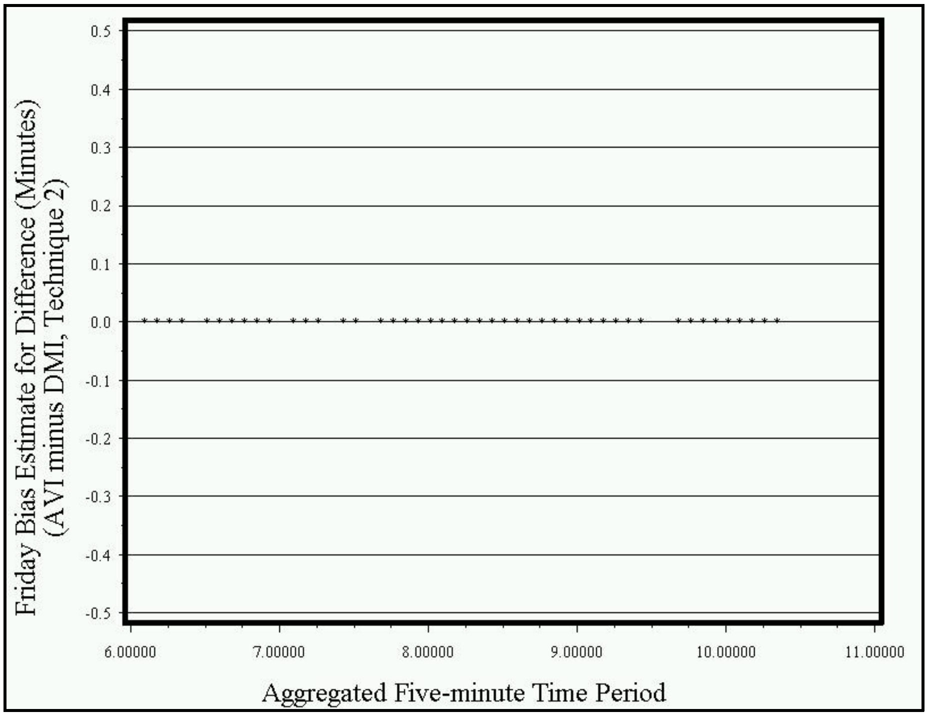

FIGURE B-81 Friday Bias Estimate for Difference Between AVI and Test Vehicles (DMI) with Technique Two

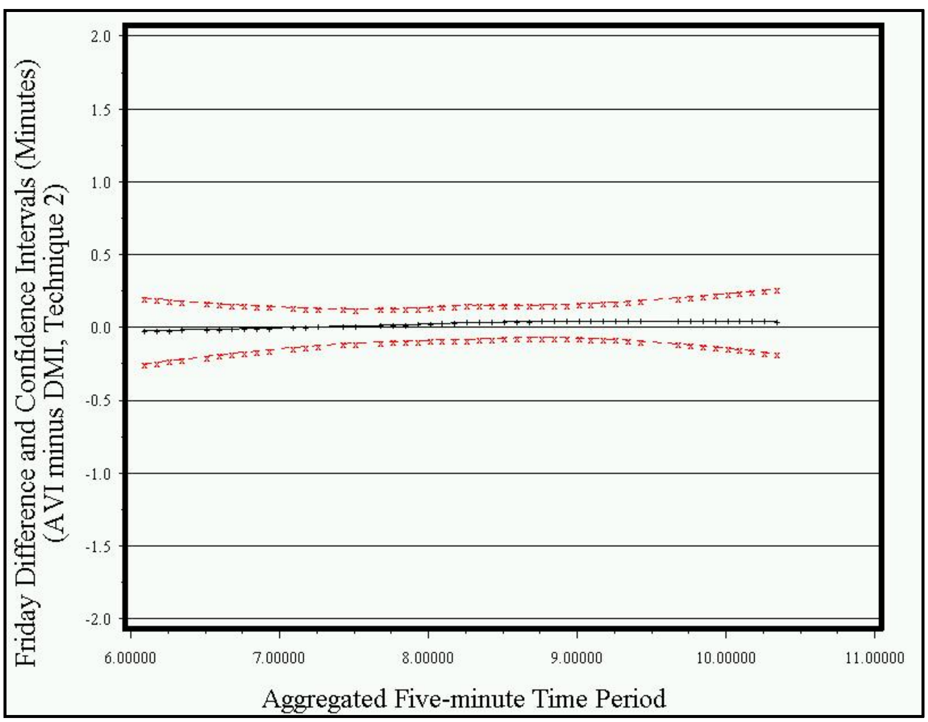

FIGURE B-82 Friday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

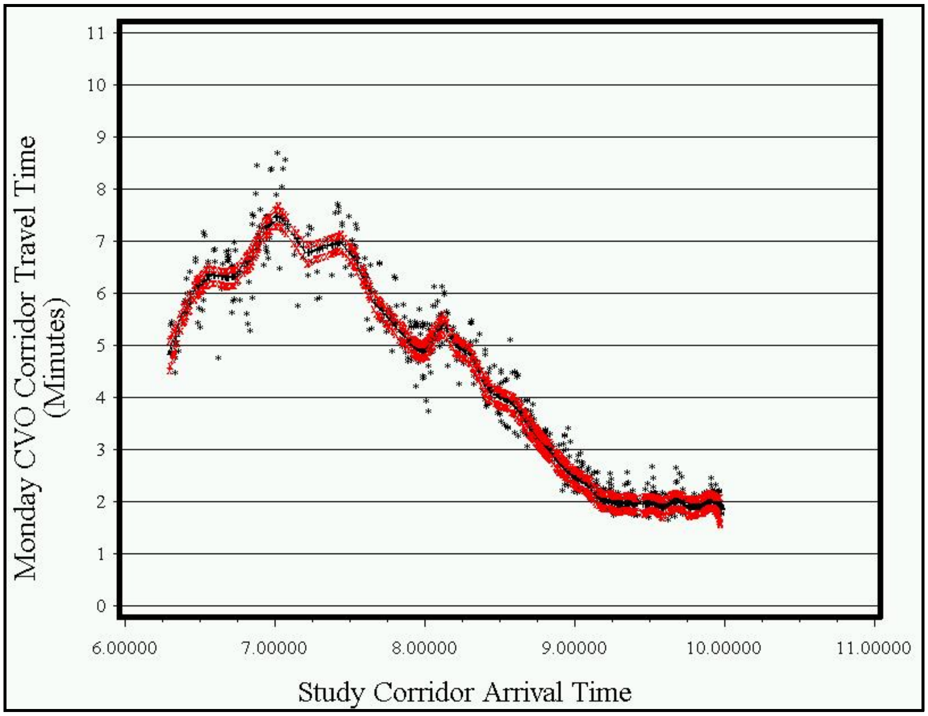

FIGURE B-83 Monday Corridor Travel Time by Time of Arrival for CVO Data Showing Loess Estimation and Confidence Interval

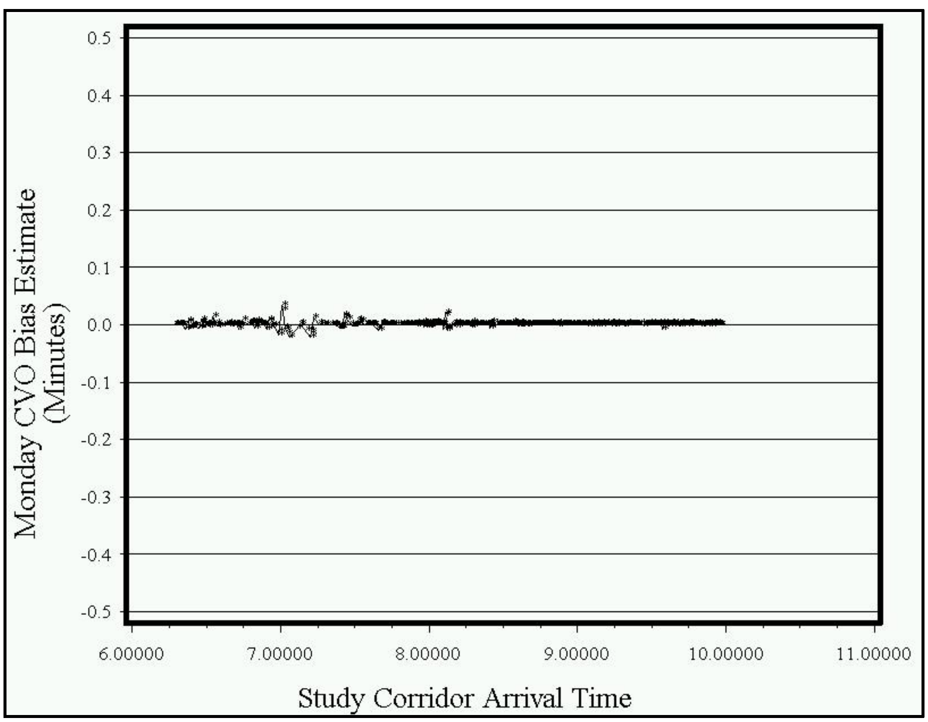

FIGURE B-84 Monday Bias Estimate by Time of Arrival for CVO Data

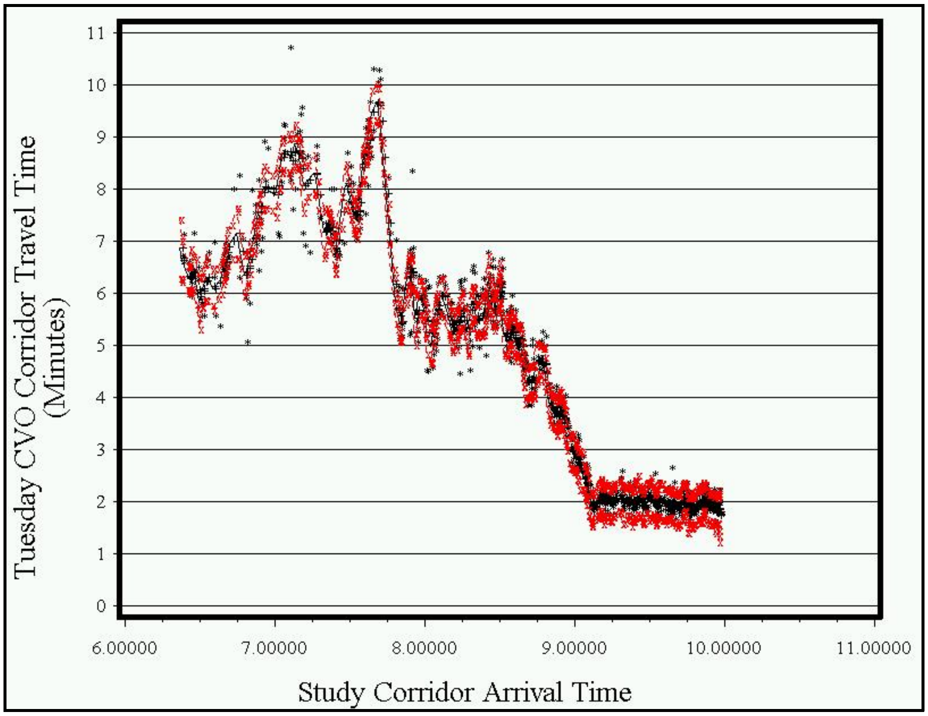

FIGURE B-85 Tuesday Corridor Travel Time by Time of Arrival for CVO Data Showing Loess Estimation and Confidence Interval

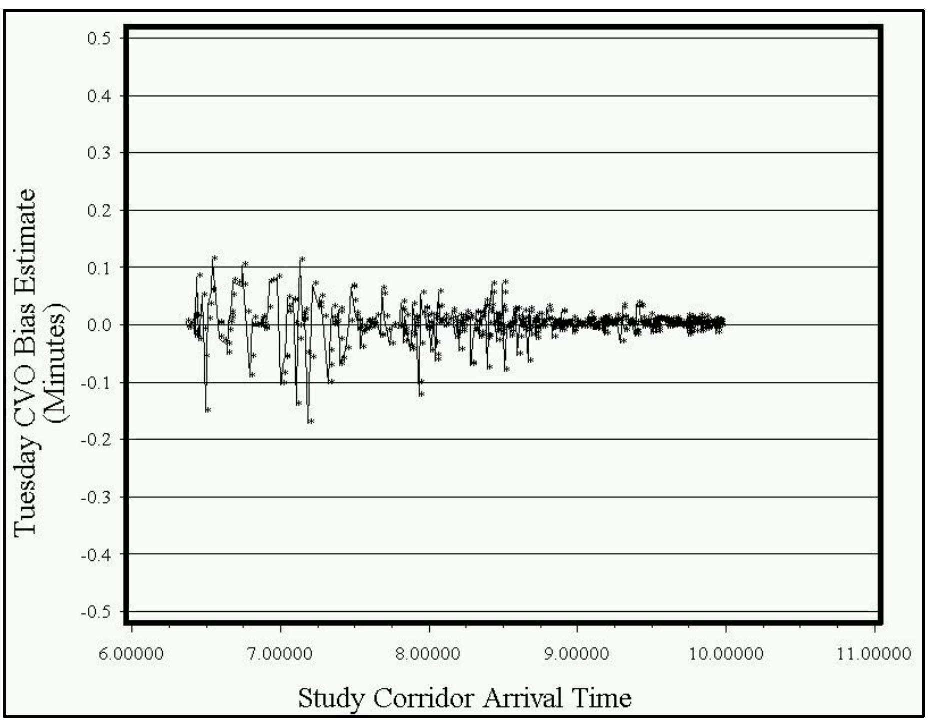

FIGURE B-86 Tuesday Bias Estimate by Time of Arrival for CVO Data

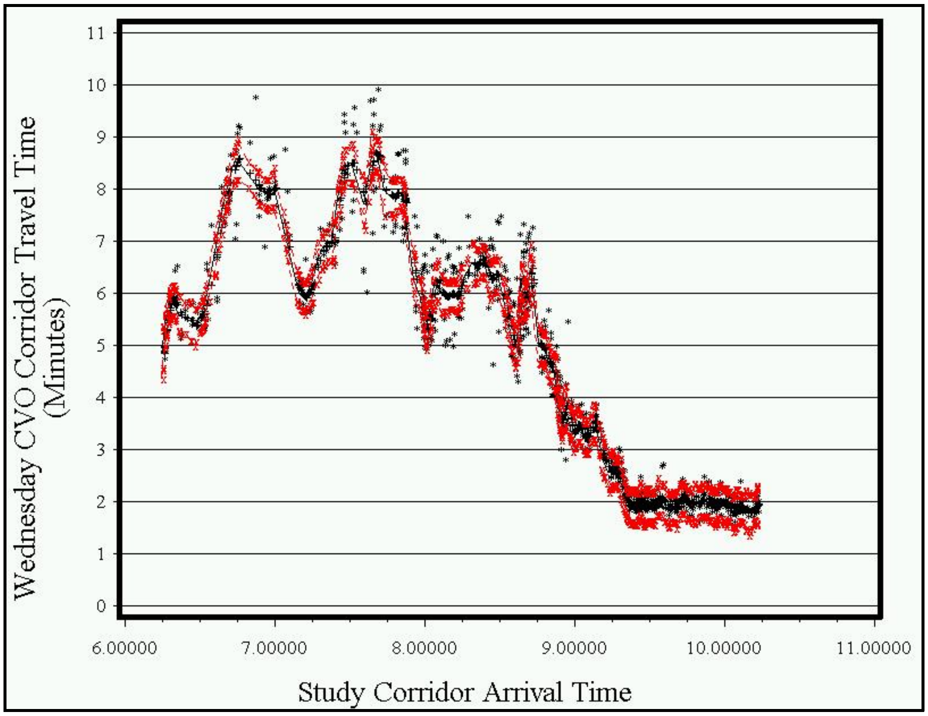

FIGURE B-87 Wednesday Corridor Travel Time by Time of Arrival for CVO Data Showing Loess Estimation and Confidence Interval

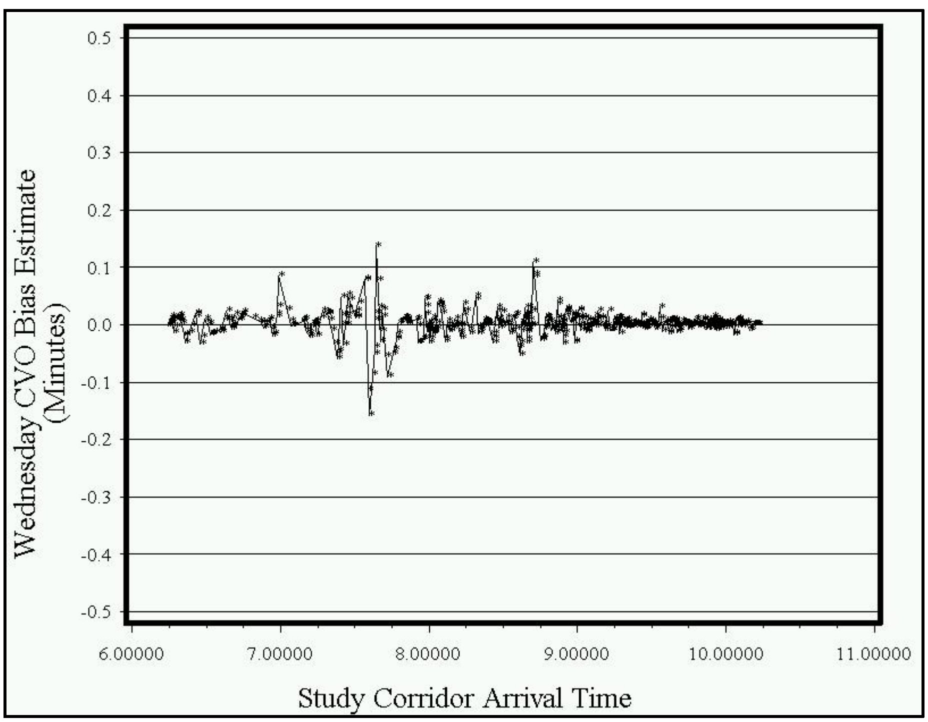

FIGURE B-88 Wednesday Bias Estimate by Time of Arrival for CVO Data

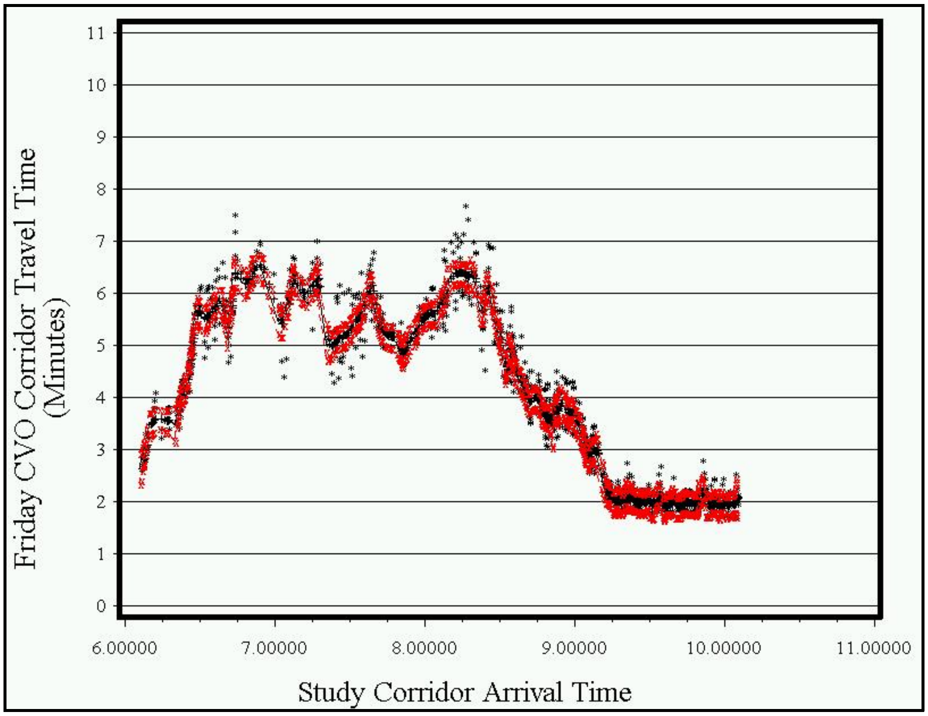

FIGURE B-89 Friday Corridor Travel Time by Time of Arrival for CVO Data Showing Loess Estimation and Confidence Interval

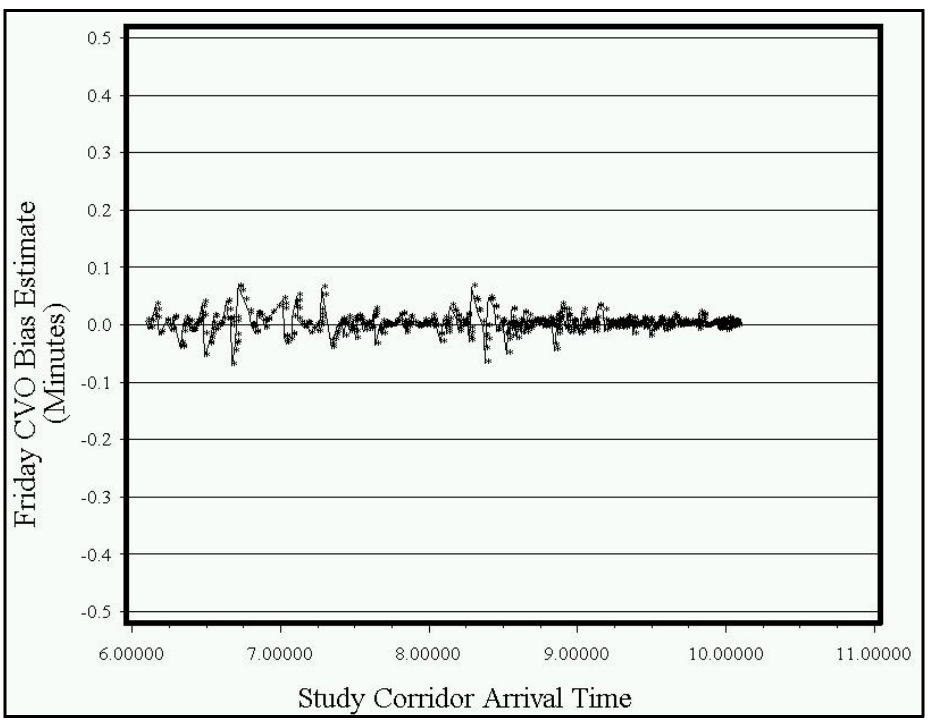

FIGURE B-90 Friday Bias Estimate by Time of Arrival for CVO Data

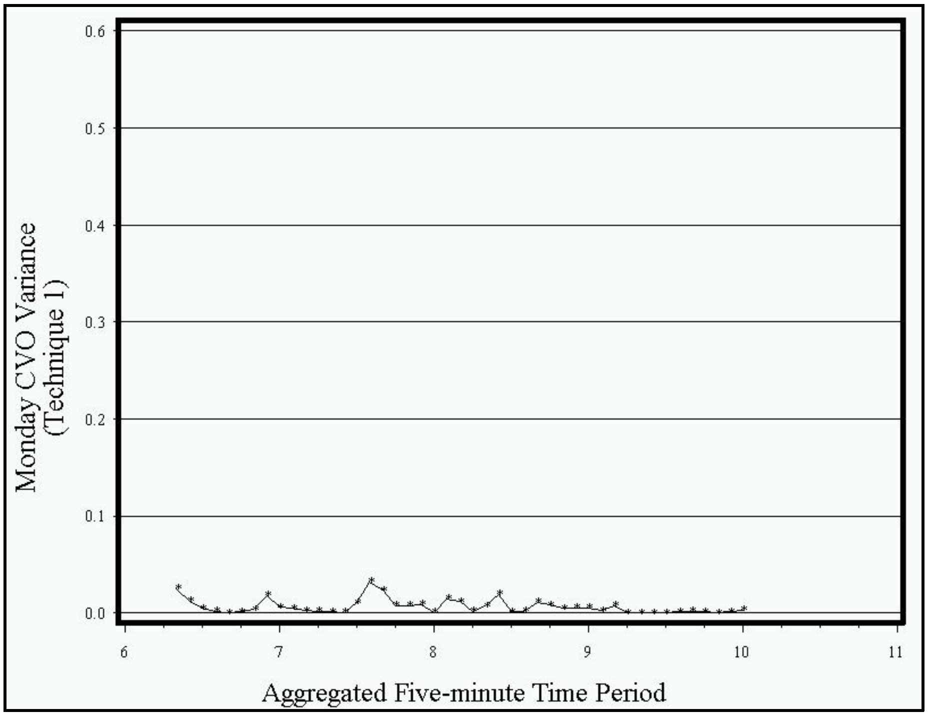

FIGURE B-91 Monday CVO Variance with Technique One

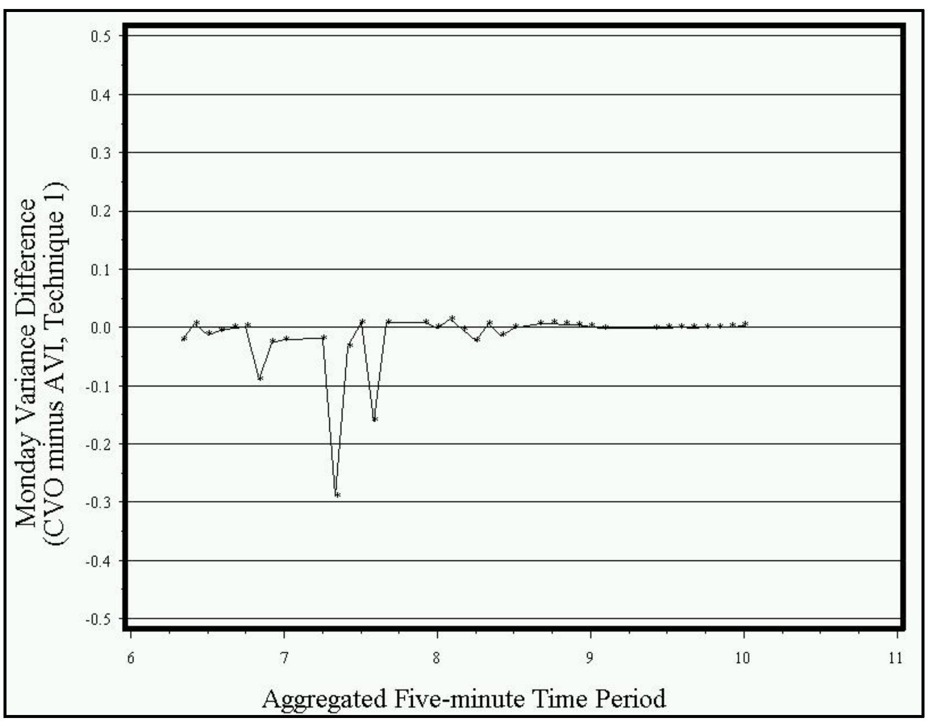

FIGURE B-92 Monday Variance Difference Between CVO and AVI with Technique One

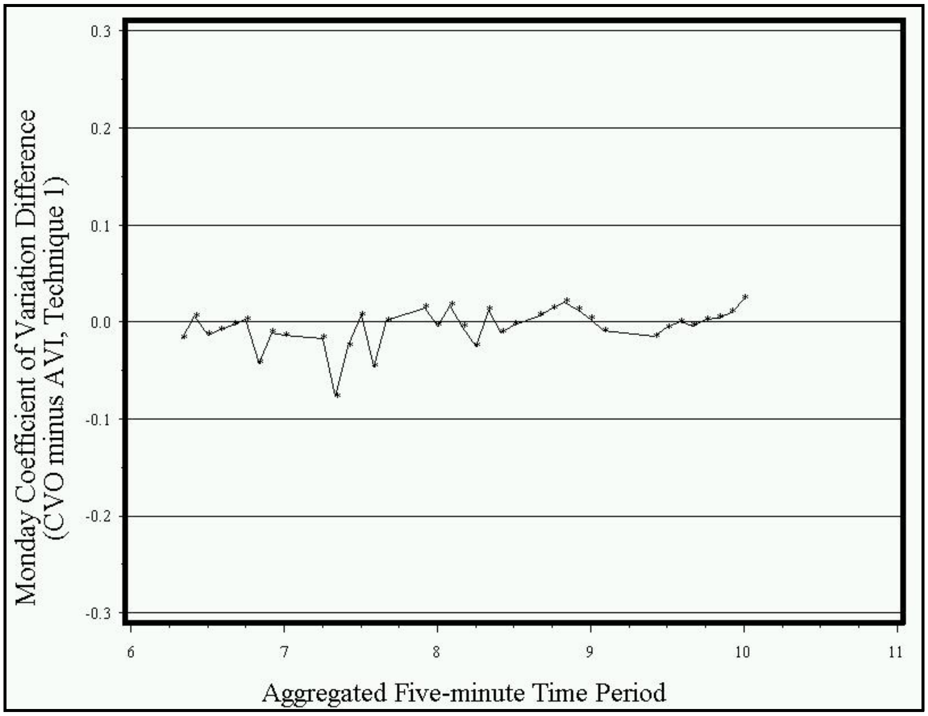

FIGURE B-93 Monday Coefficient of Variation Difference Between CVO and AVI with Technique One

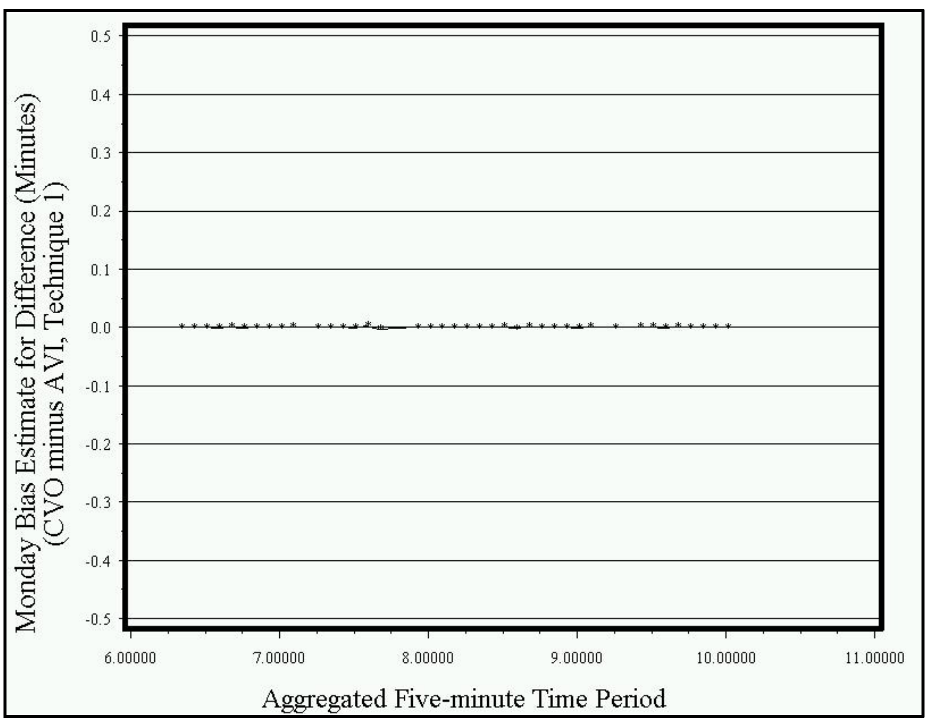

FIGURE B-94 Monday Bias Estimate for Difference Between CVO and AVI with Technique One

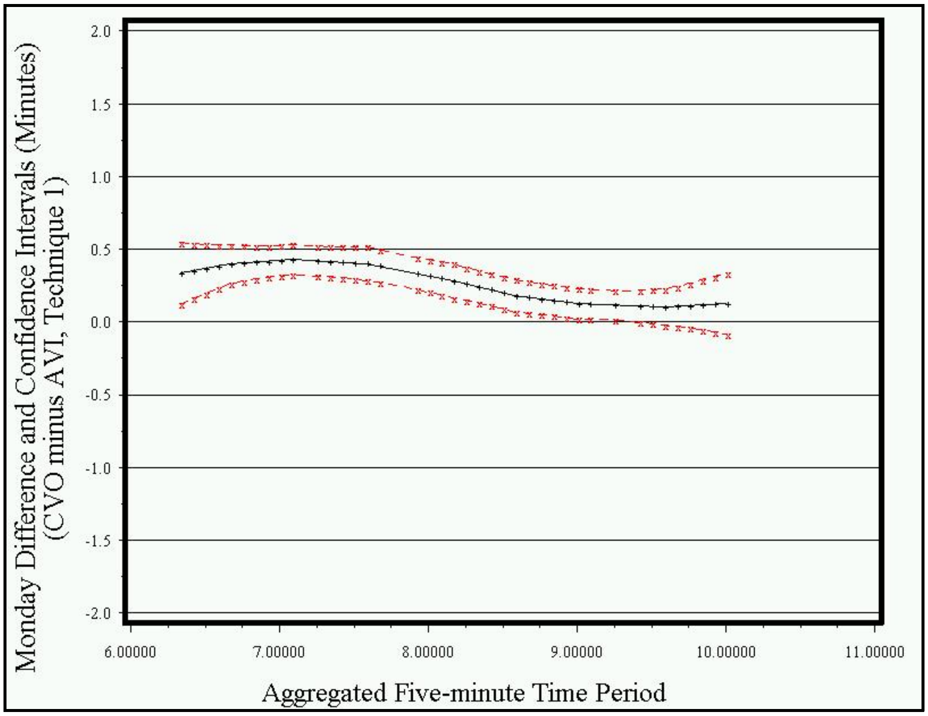

FIGURE B-95 Monday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

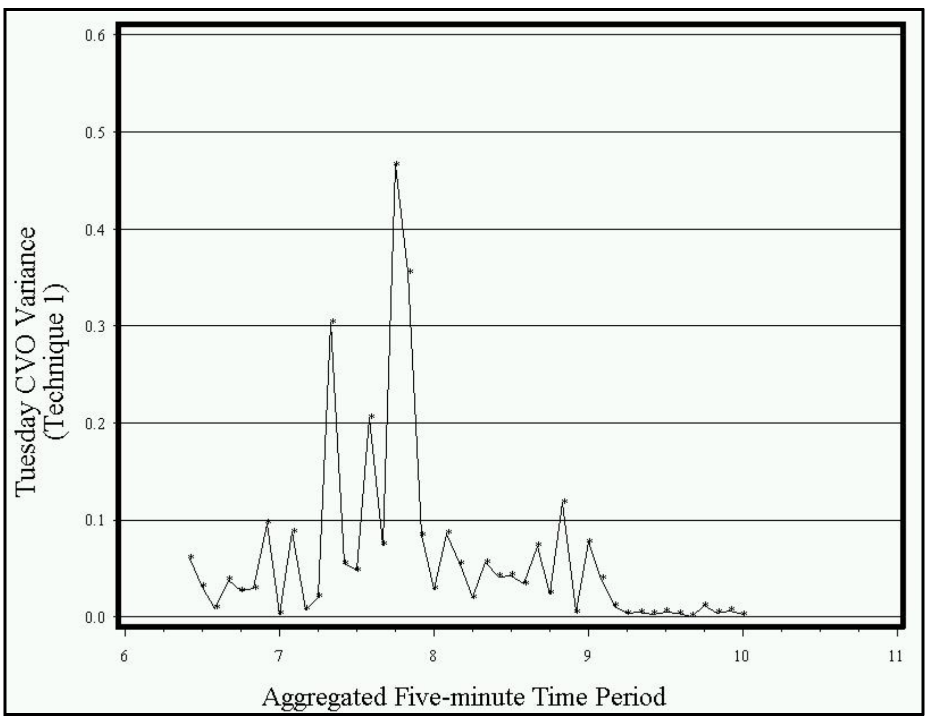

FIGURE B-96 Tuesday CVO Variance with Technique One

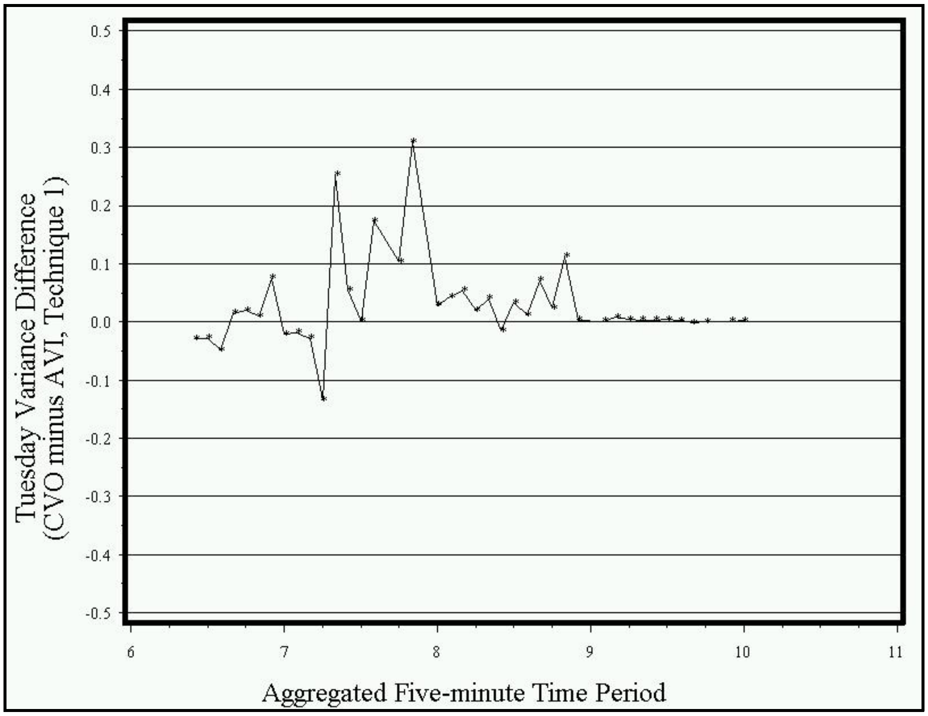

FIGURE B-97 Tuesday Variance Difference Between CVO and AVI with Technique One

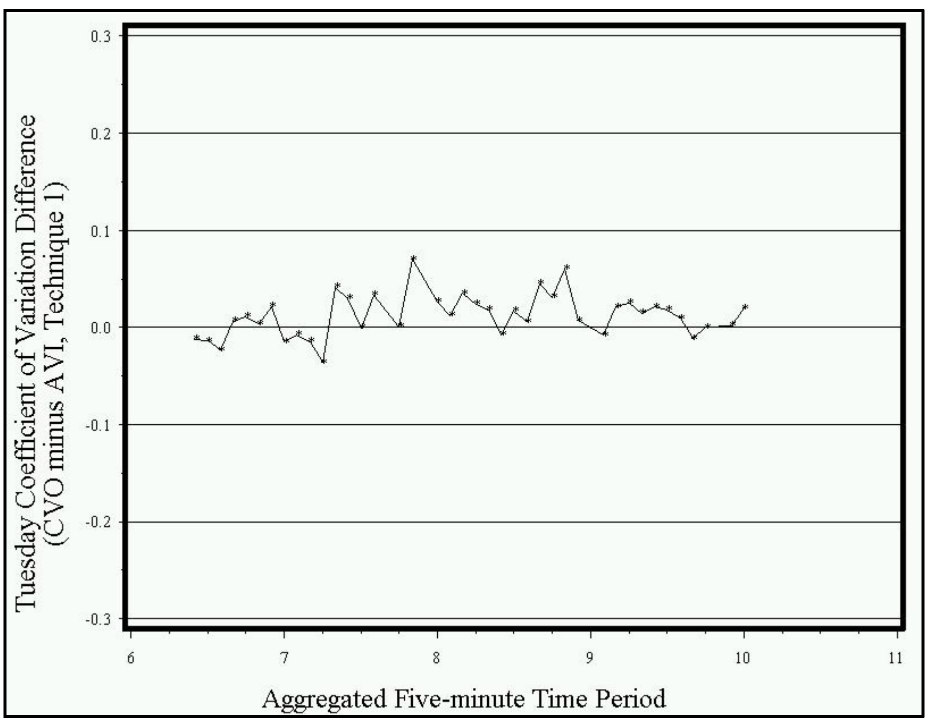

FIGURE B-98 Tuesday Coefficient of Variation Difference Between CVO and AVI with Technique One

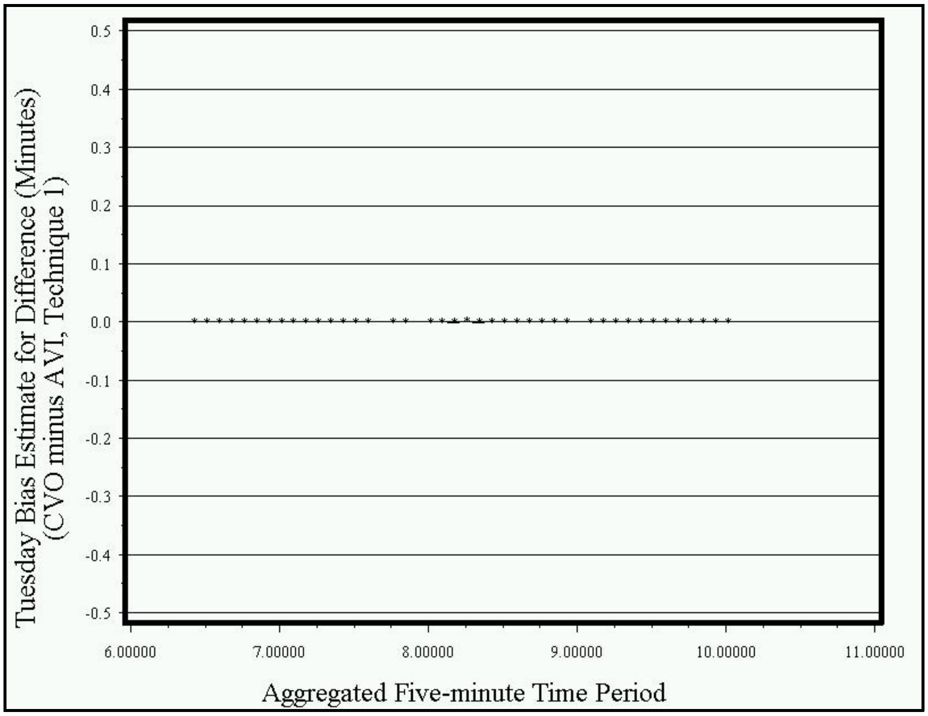

FIGURE B-99 Tuesday Bias Estimate for Difference Between CVO and AVI with Technique One

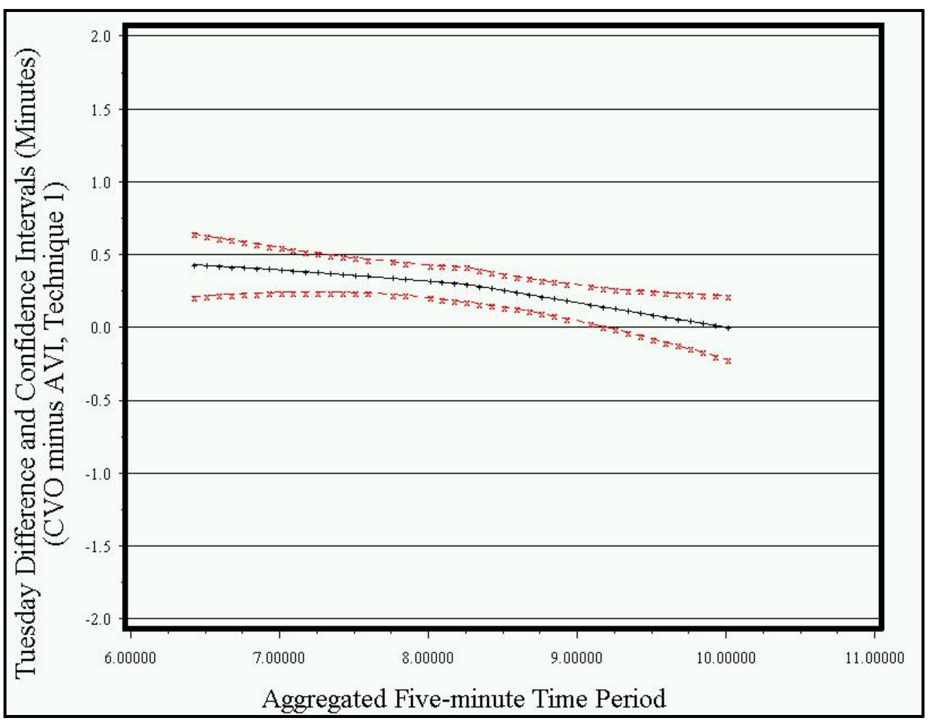

FIGURE B-100 Tuesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

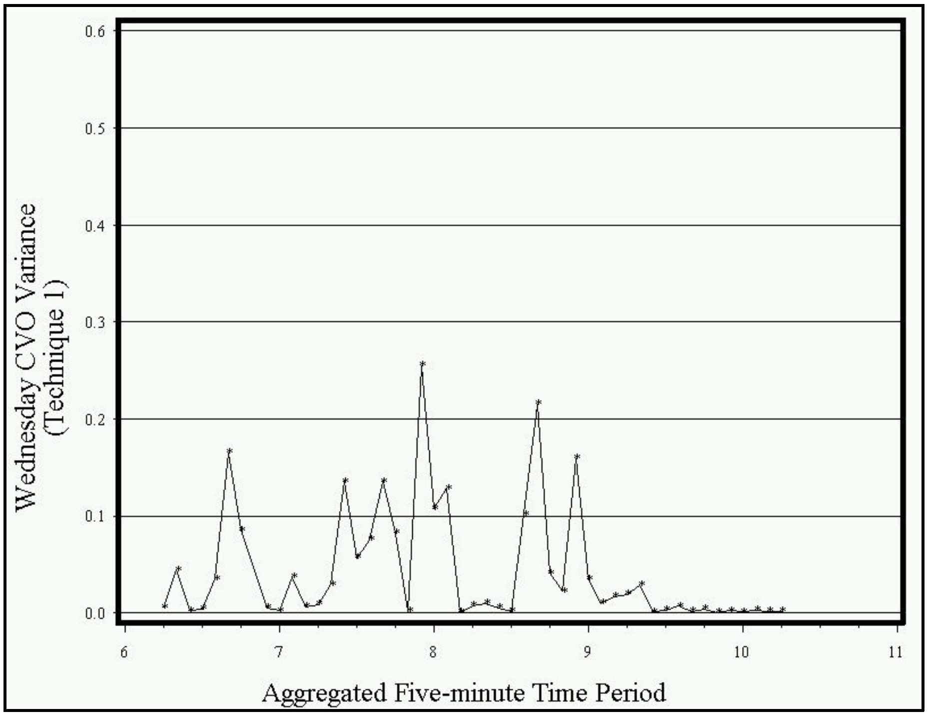

FIGURE B-101 Wednesday CVO Variance with Technique One

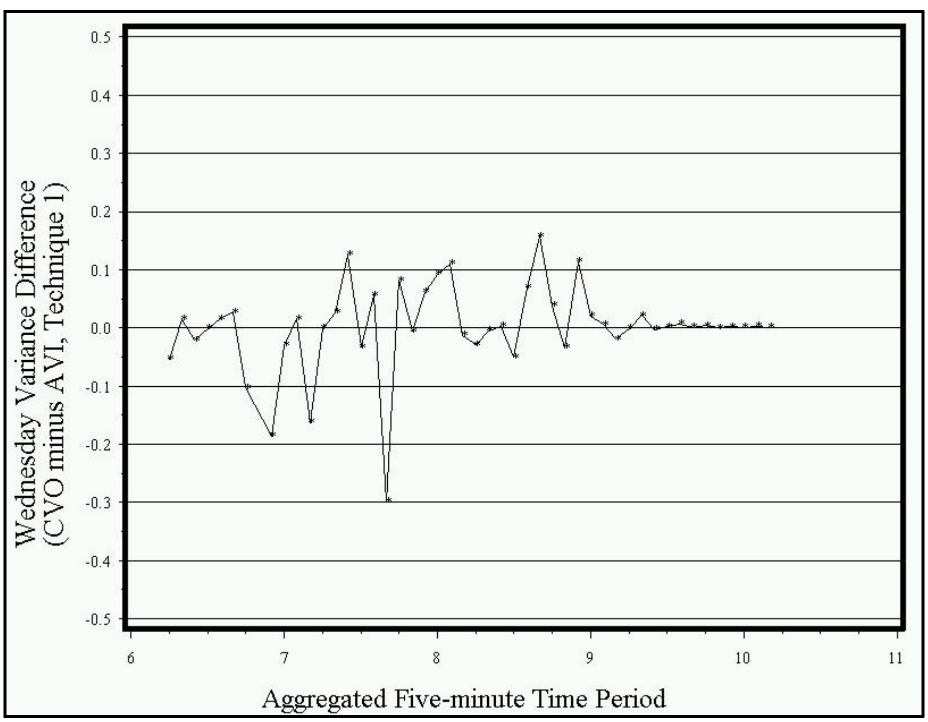

FIGURE B-102 Wednesday Variance Difference Between CVO and AVI with Technique One

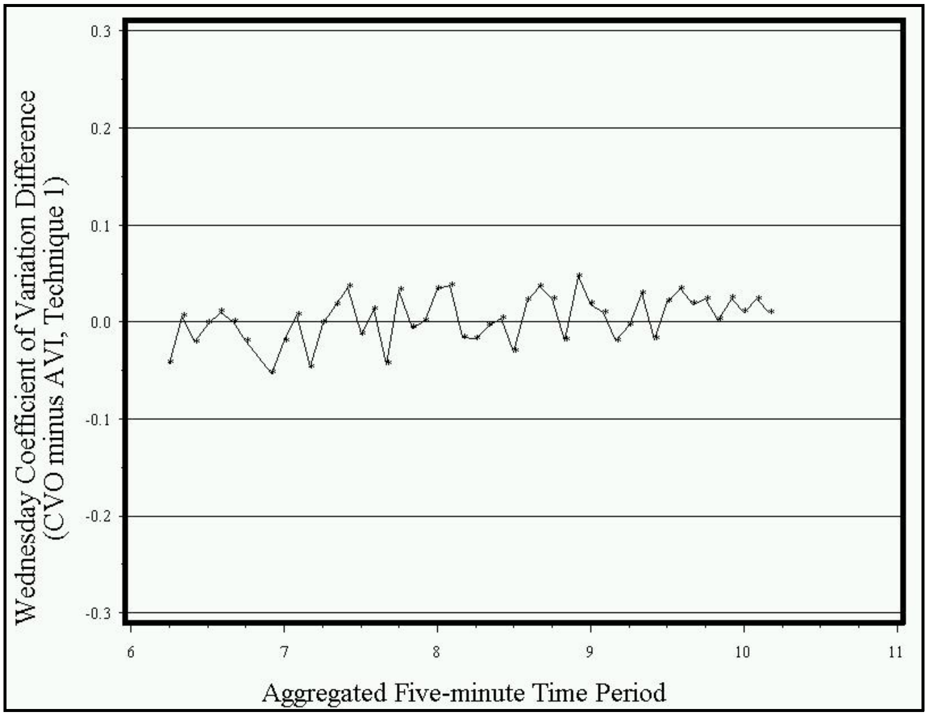

FIGURE B-103 Wednesday Coefficient of Variation Difference Between CVO and AVI with Technique One

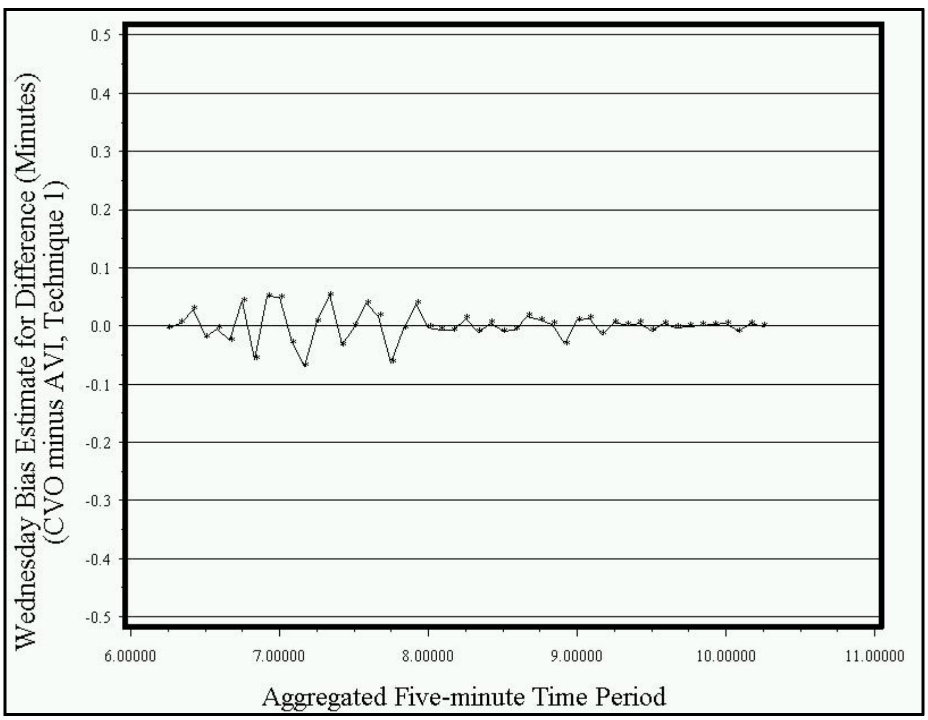

FIGURE B-104 Wednesday Bias Estimate for Difference Between CVO and AVI with Technique One

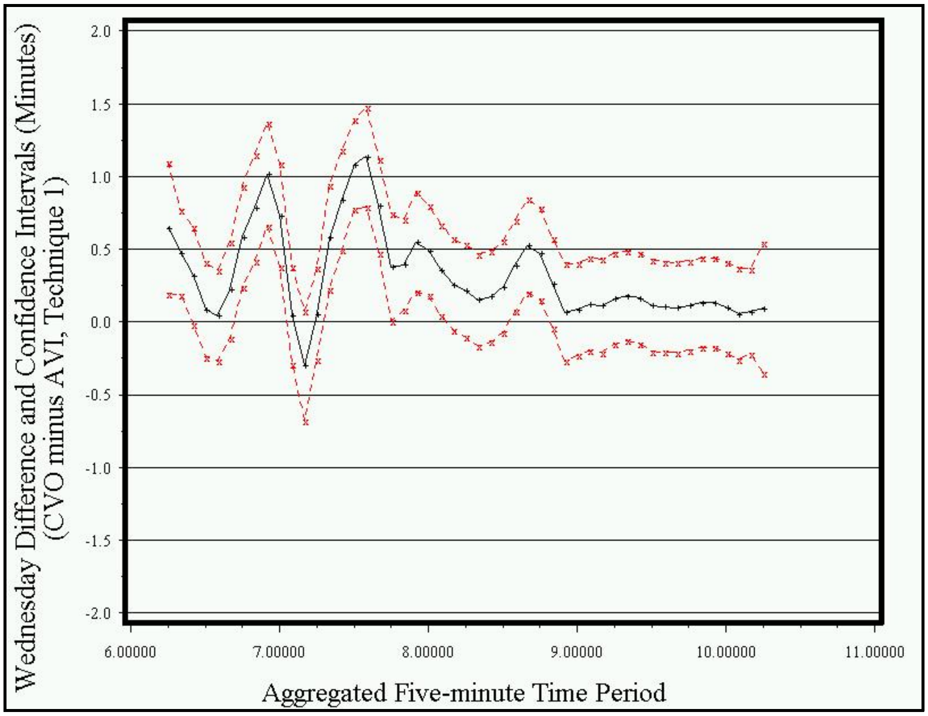

FIGURE B-105 Wednesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique One

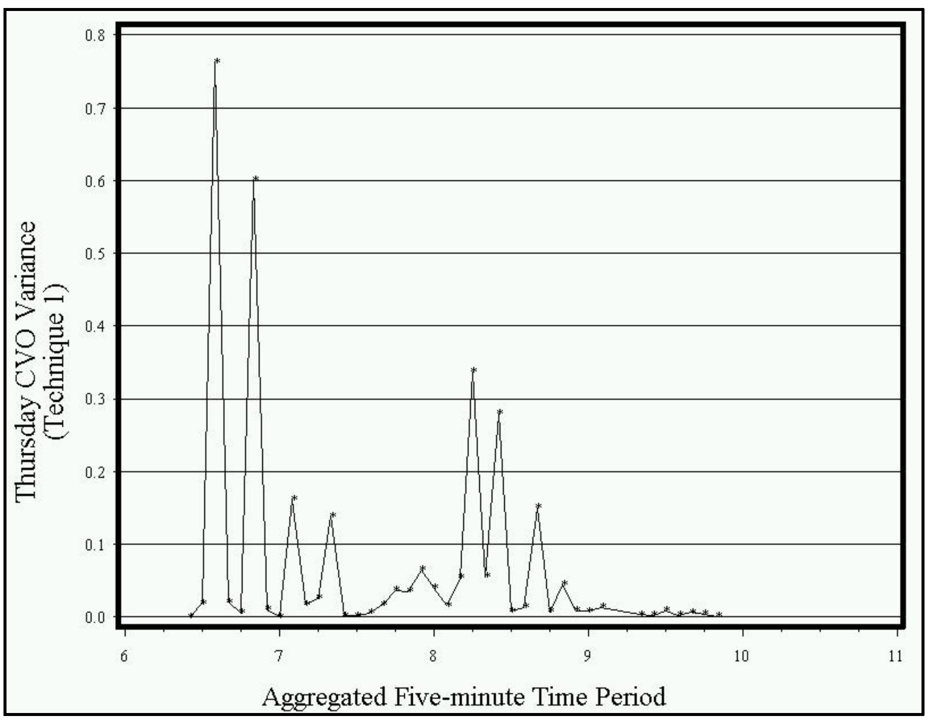

FIGURE B-106 Thursday CVO Variance with Technique One

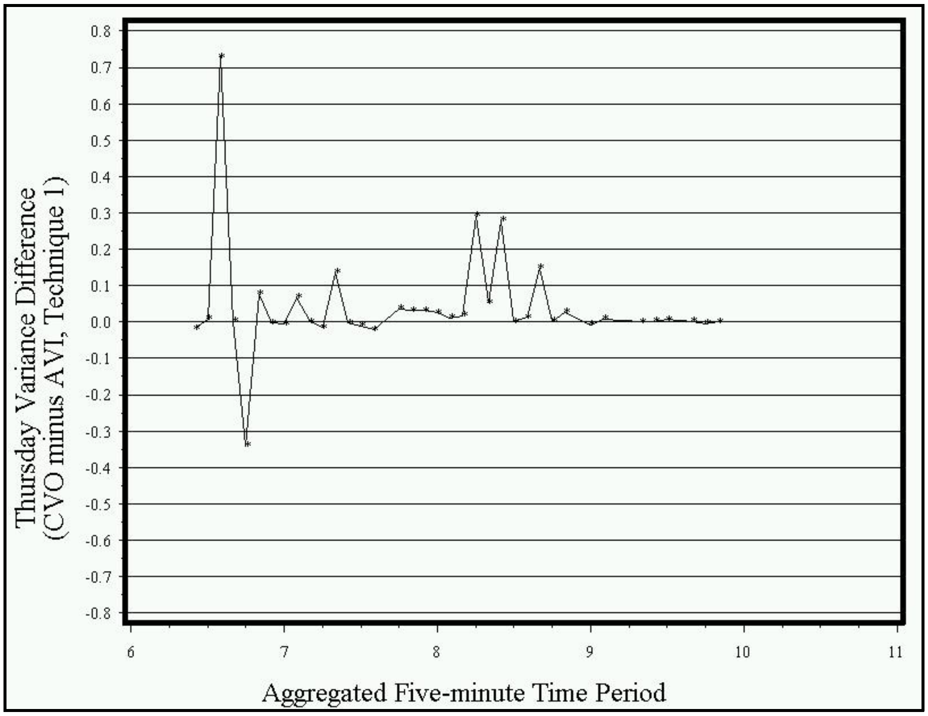

FIGURE B-107 Thursday Variance Difference Between CVO and AVI with Technique One

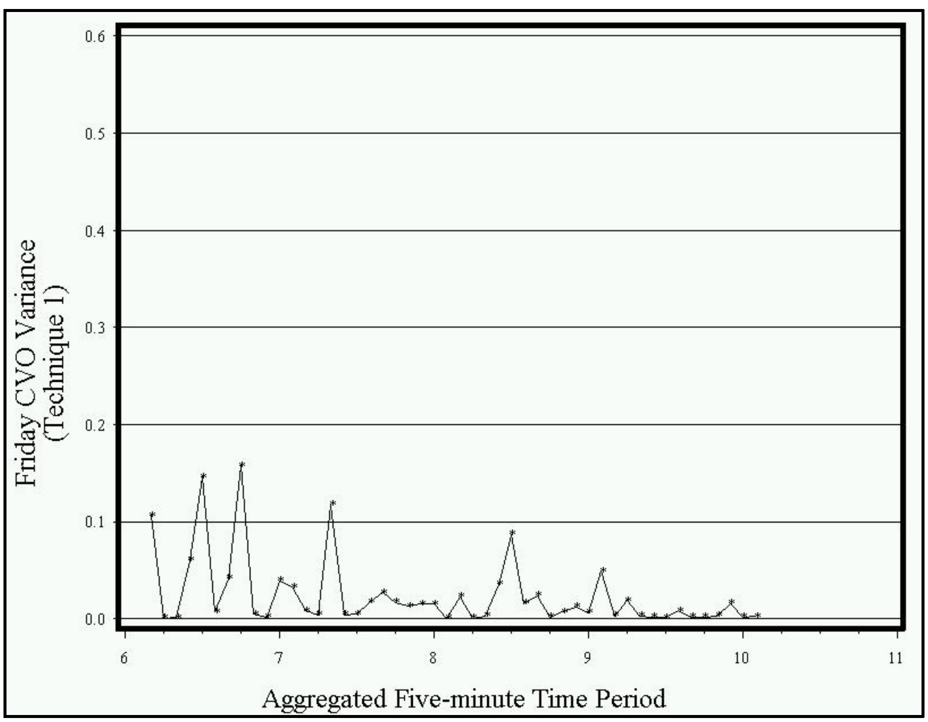

FIGURE B-108 Friday CVO Variance with Technique One

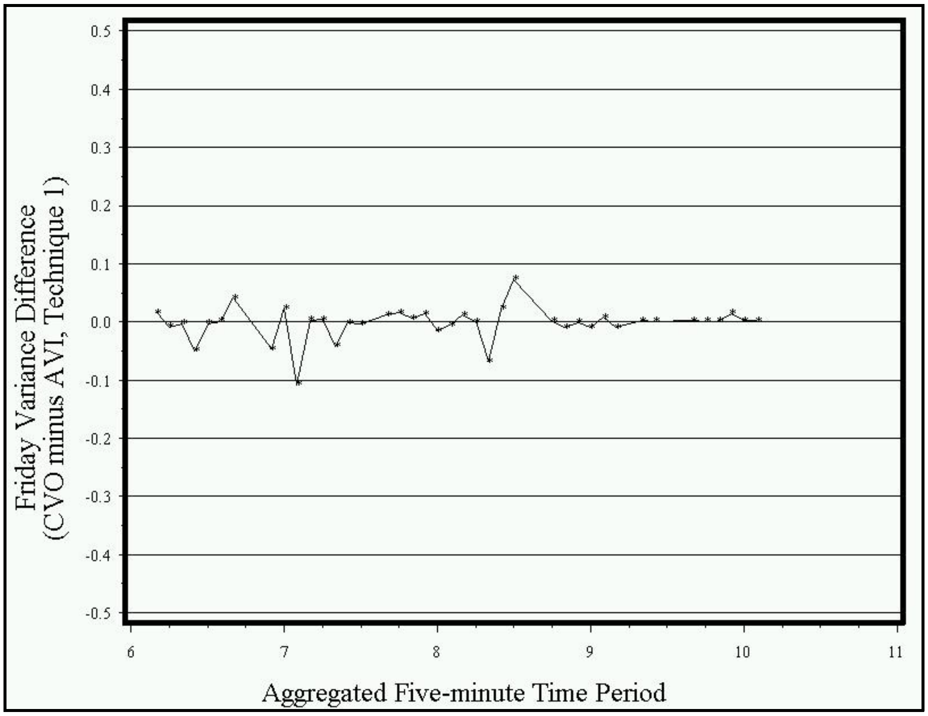

FIGURE B-109 Friday Variance Difference Between CVO and AVI with Technique One

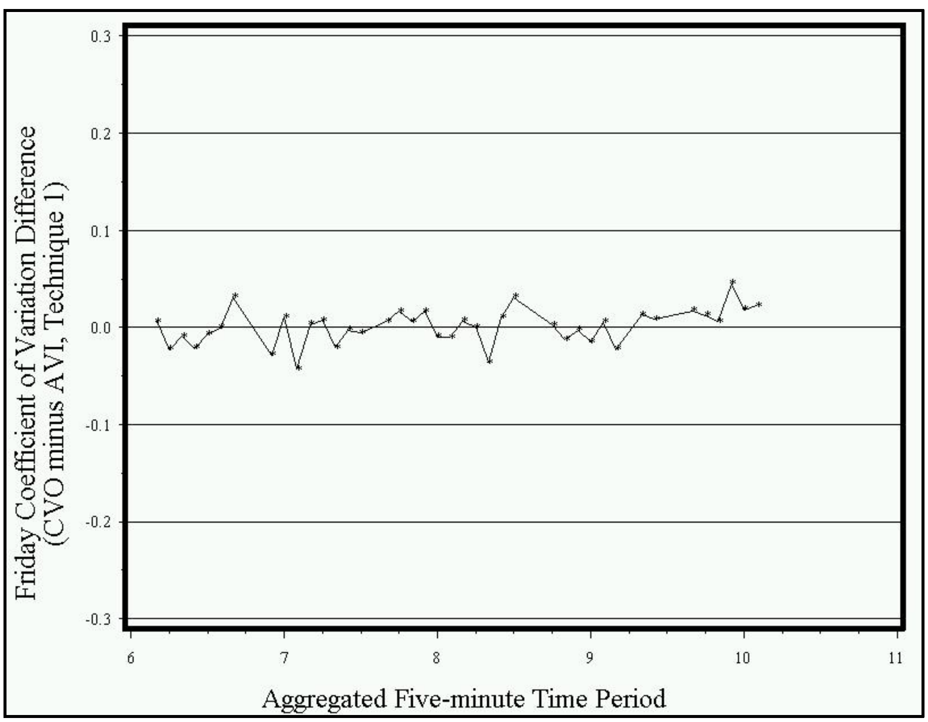

FIGURE B-110 Friday Coefficient of Variation Difference Between CVO and AVI with Technique One

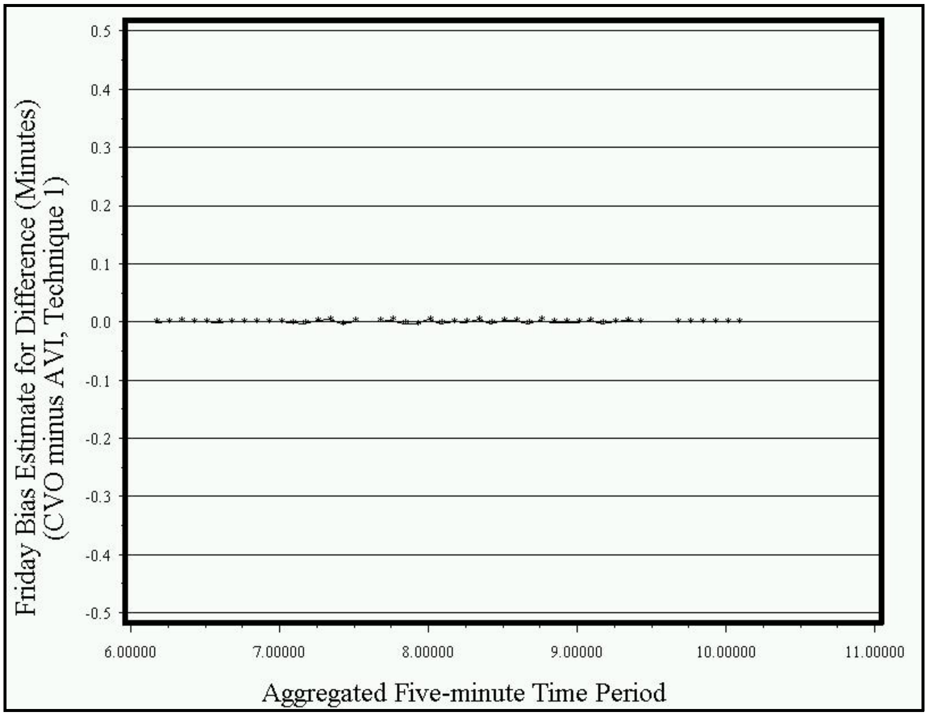

FIGURE B-111 Friday Bias Estimate for Difference Between CVO and AVI with Technique One

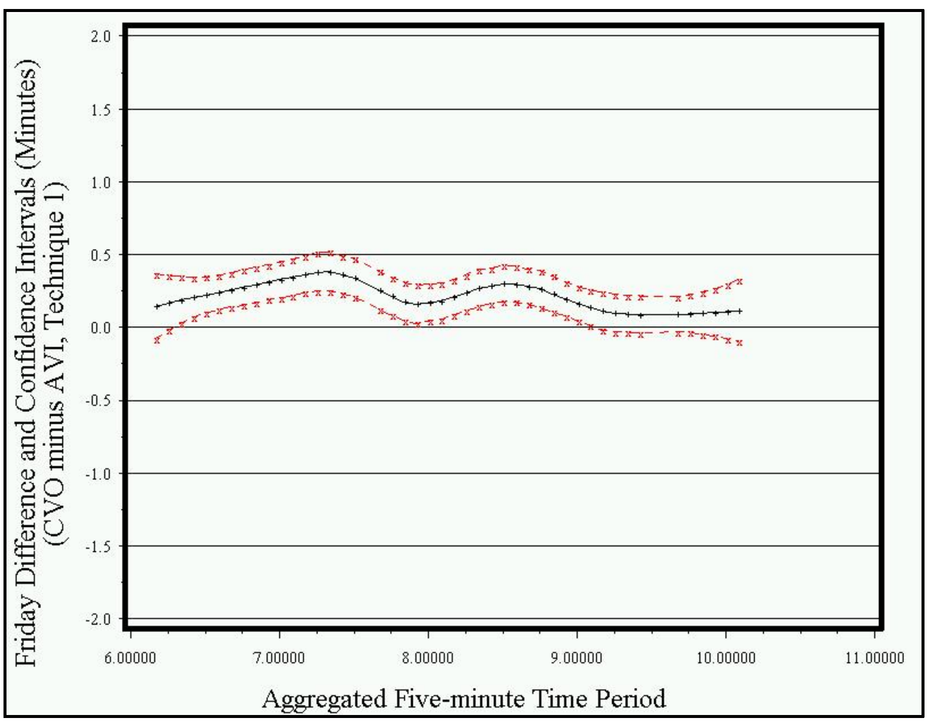

FIGURE B-112 Friday Difference and Confidence Intervals Including Correction for Estimated Boas for Technique One

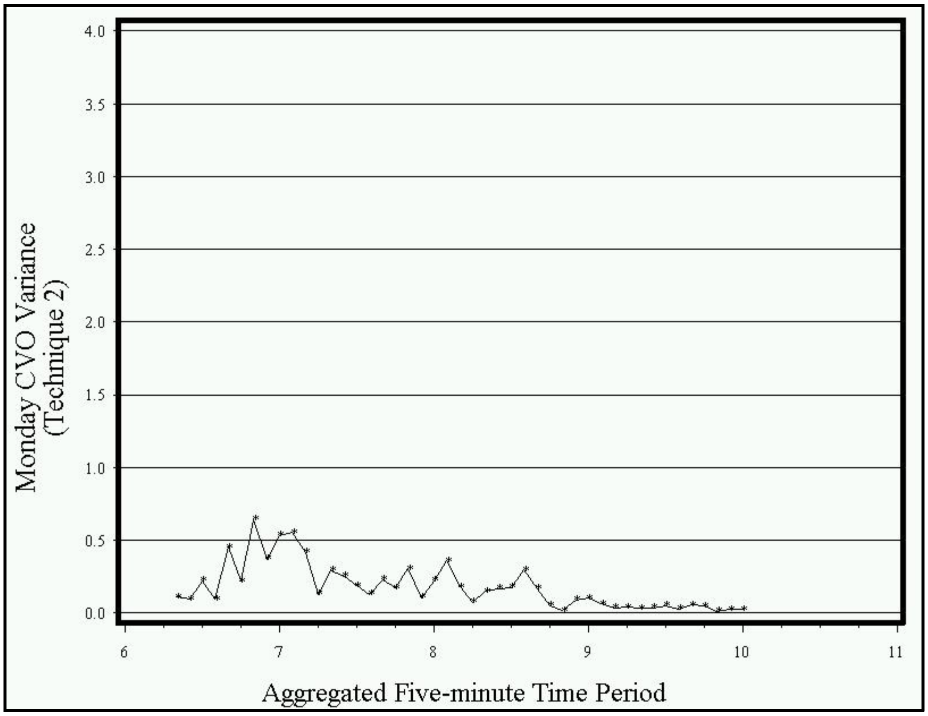

FIGURE B-113 Monday CVO Variance with Technique Two

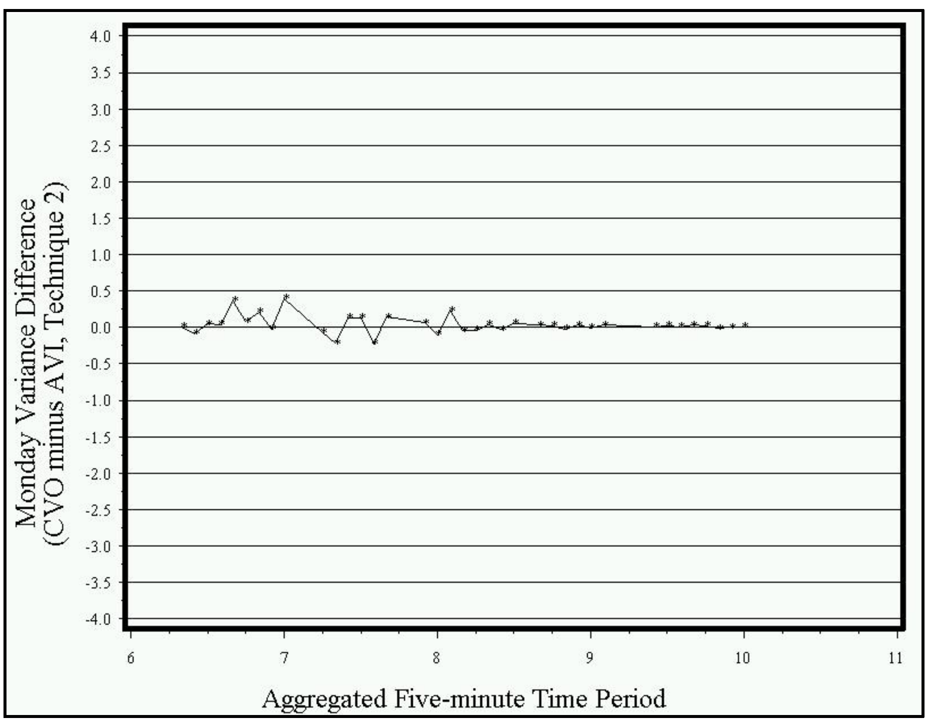

FIGURE B-114 Monday Variance Difference Between CVO and AVI with Technique Two

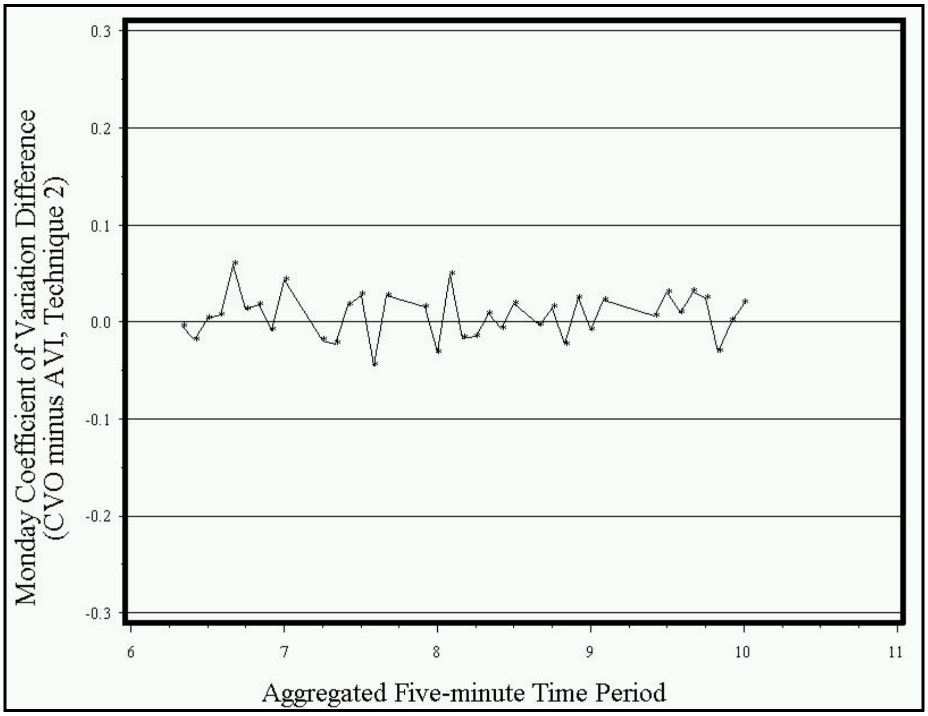

FIGURE B-115 Monday Coefficient of Variation Difference Between CVO and AVI with Technique Two

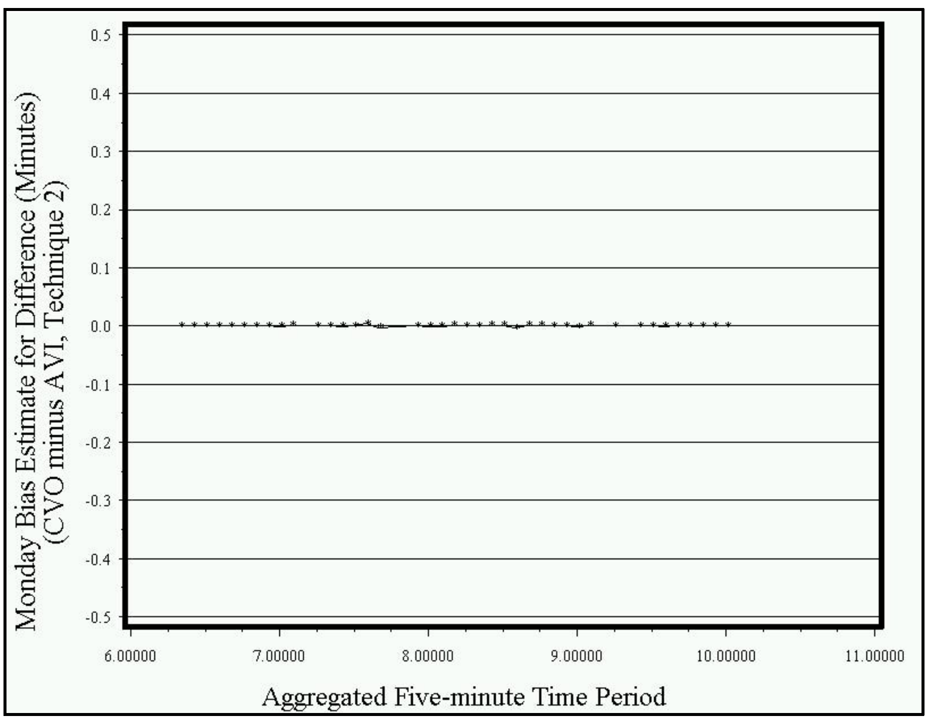

FIGURE B-116 Monday Bias Estimate for Difference Between CVO and AVI with Technique Two

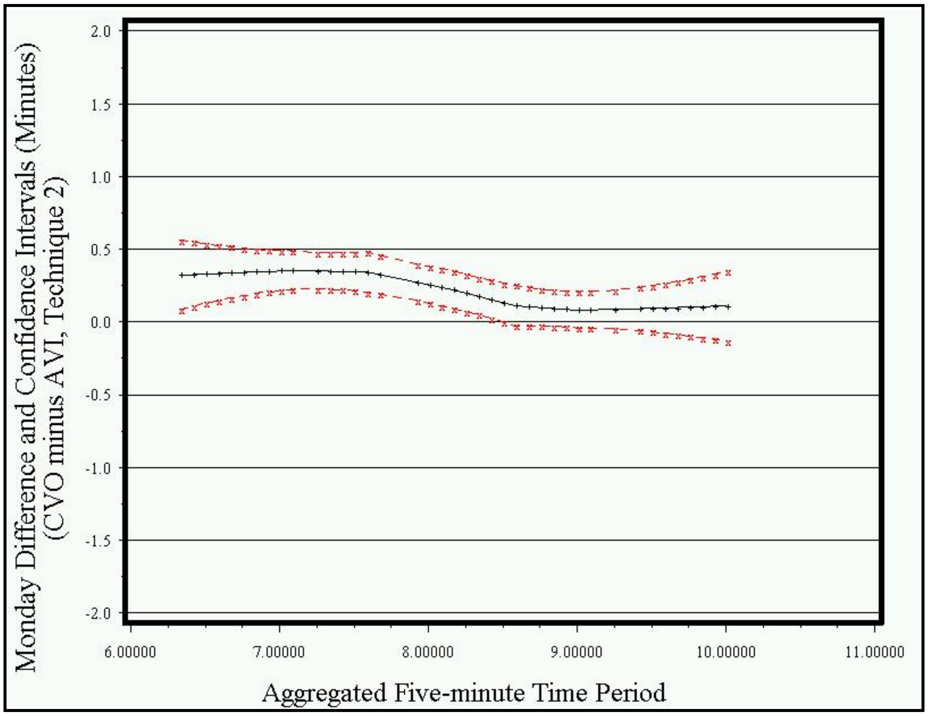

FIGURE B-117 Monday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

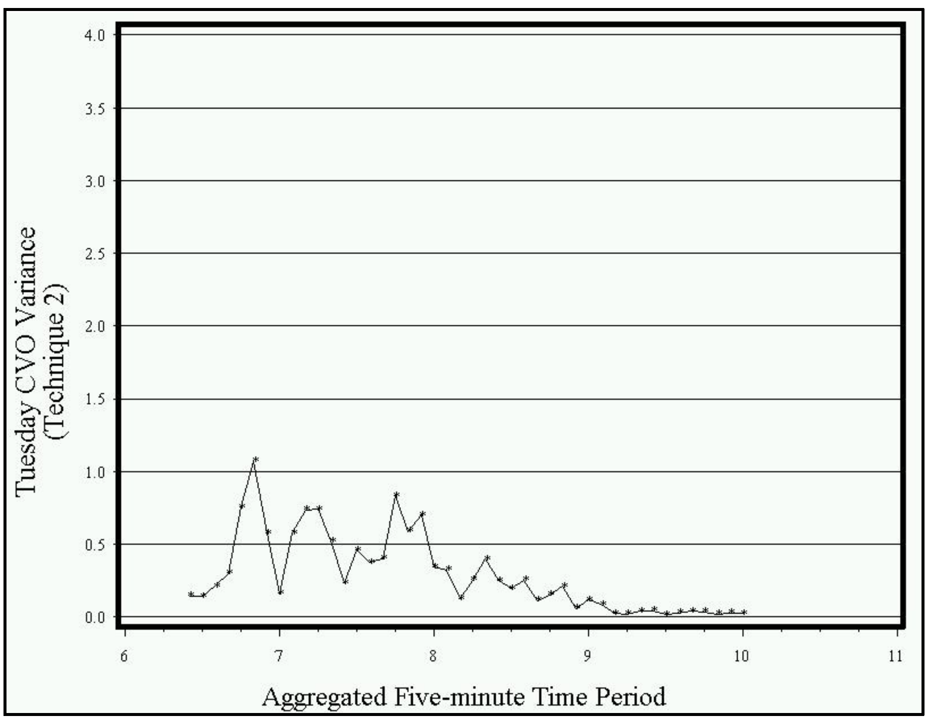

FIGURE B-118 Tuesday CVO Variance with Technique Two

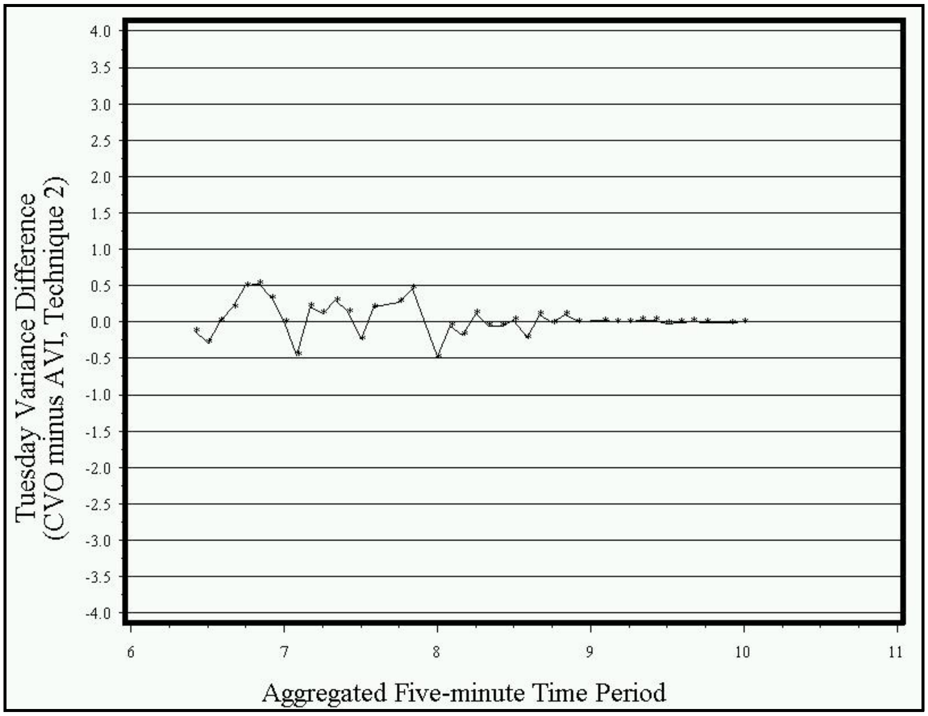

FIGURE B-119 Tuesday Variance Difference Between CVO and AVI with Technique Two

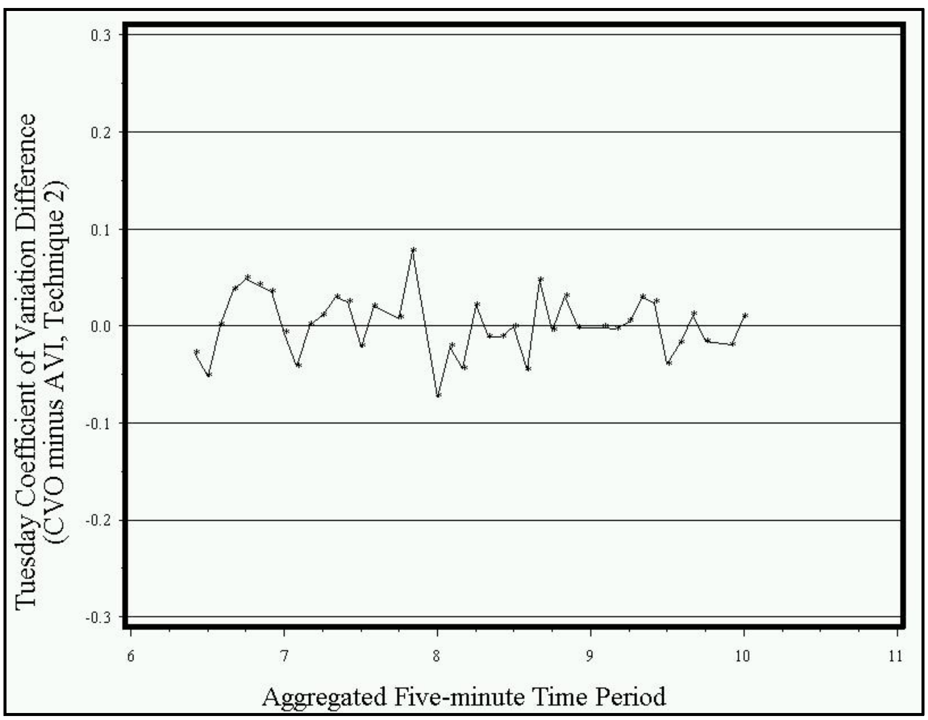

FIGURE B-120 Tuesday Coefficient of Variation Difference Between CVO and AVI with Technique Two

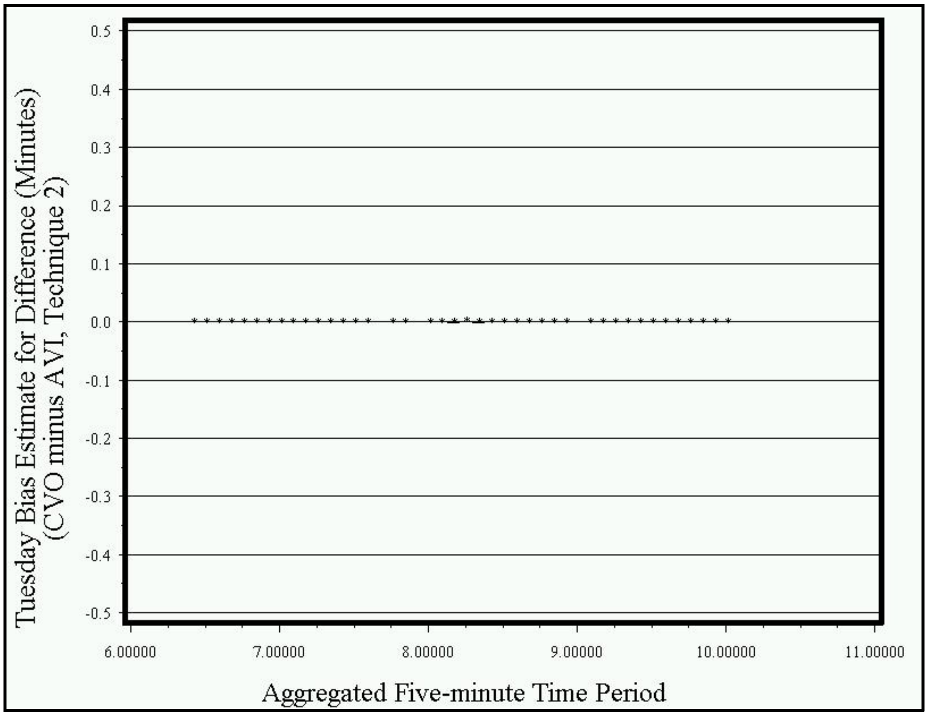

FIGURE B-121 Tuesday Bias Estimate for Difference Between CVO and AVI with Technique Two

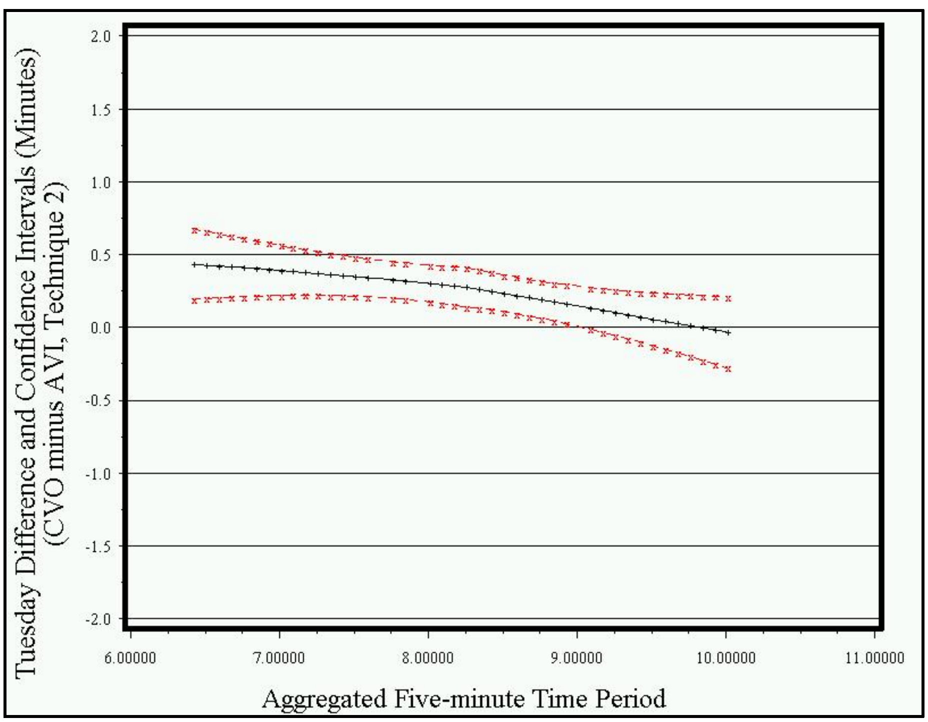

FIGURE B-122 Tuesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

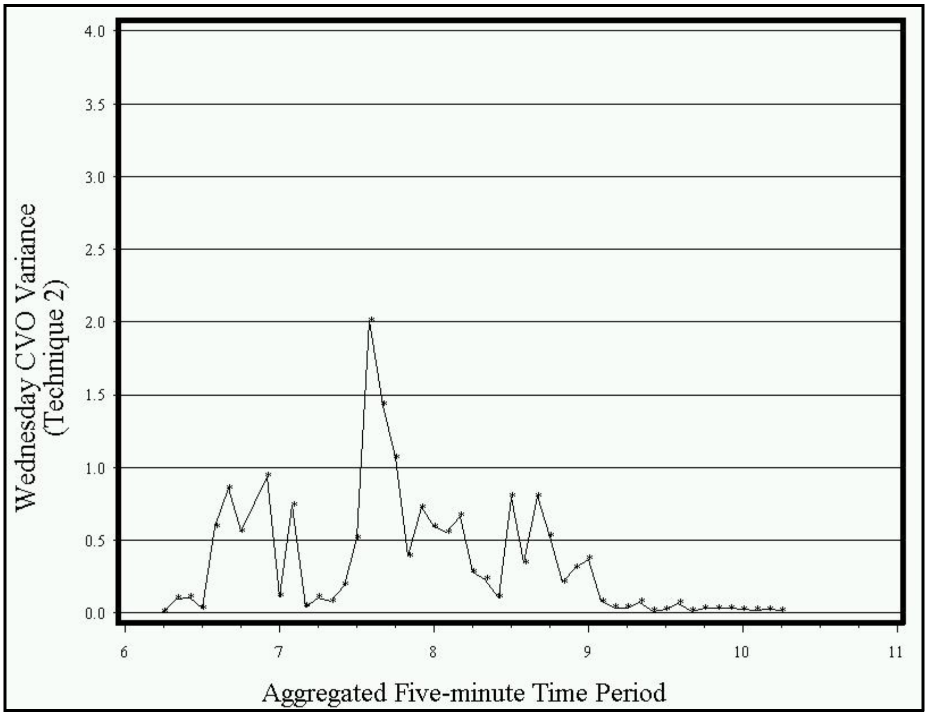

FIGURE B-123 Wednesday CVO Variance with Technique Two

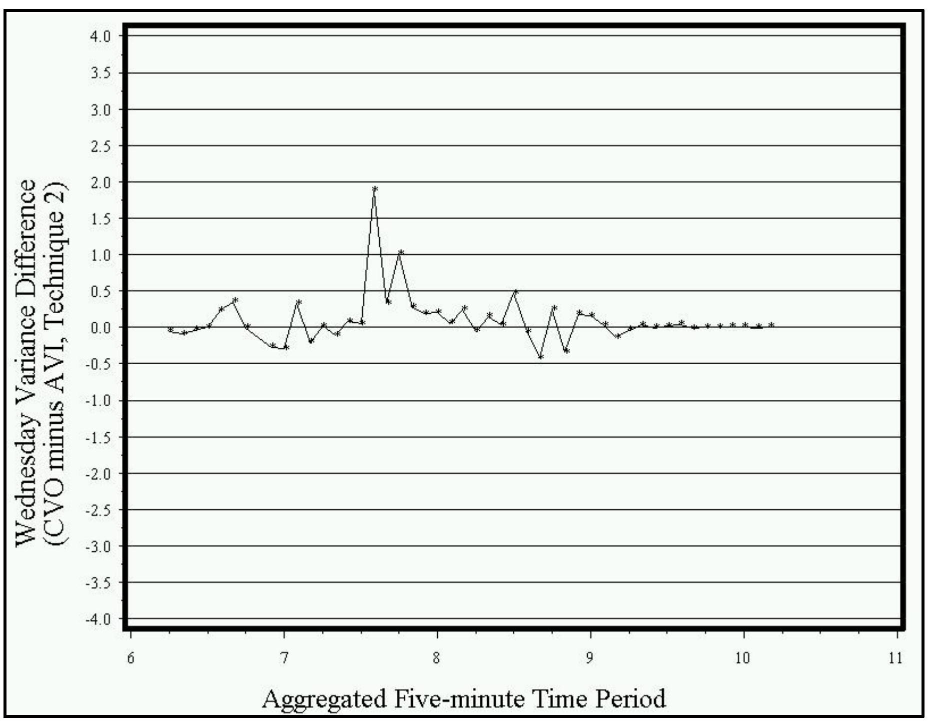

FIGURE B-124 Wednesday Variance Difference Between CVO and AVI with Technique Two

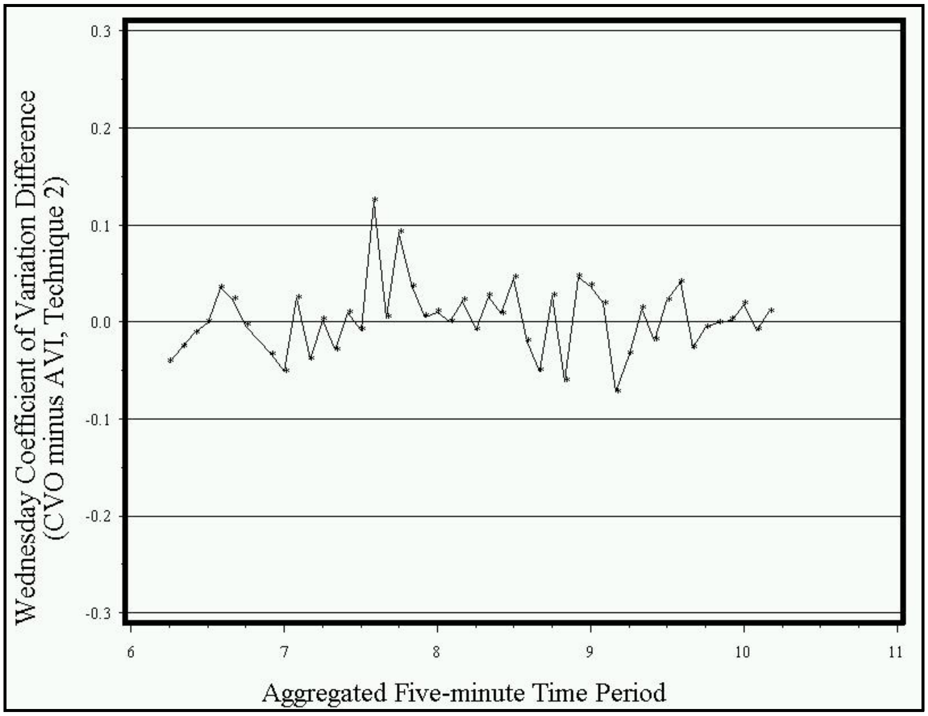

FIGURE B-125 Wednesday Coefficient of Variation Difference Between CVO and AVI with Technique Two

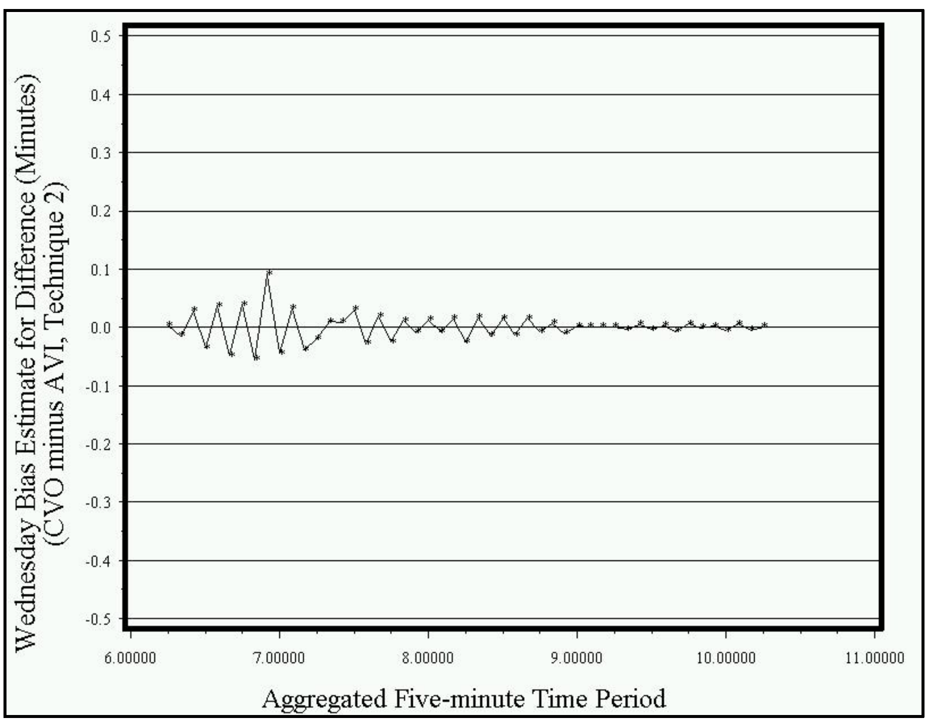

FIGURE B-126 Wednesday Bias Estimate for Difference Between CVO and AVI with Technique Two

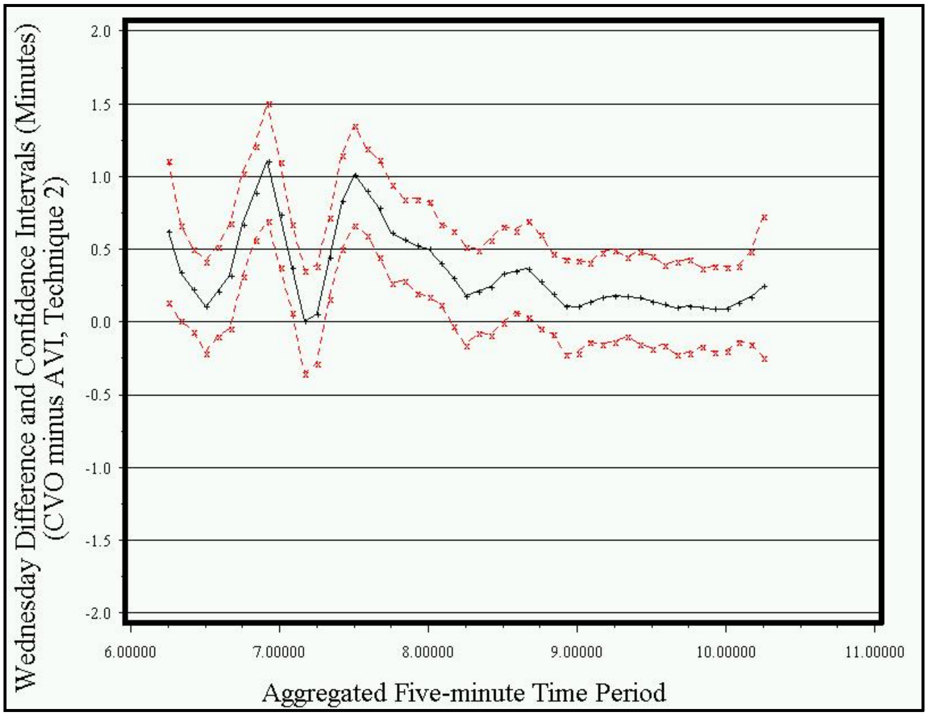

FIGURE B-127 Wednesday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

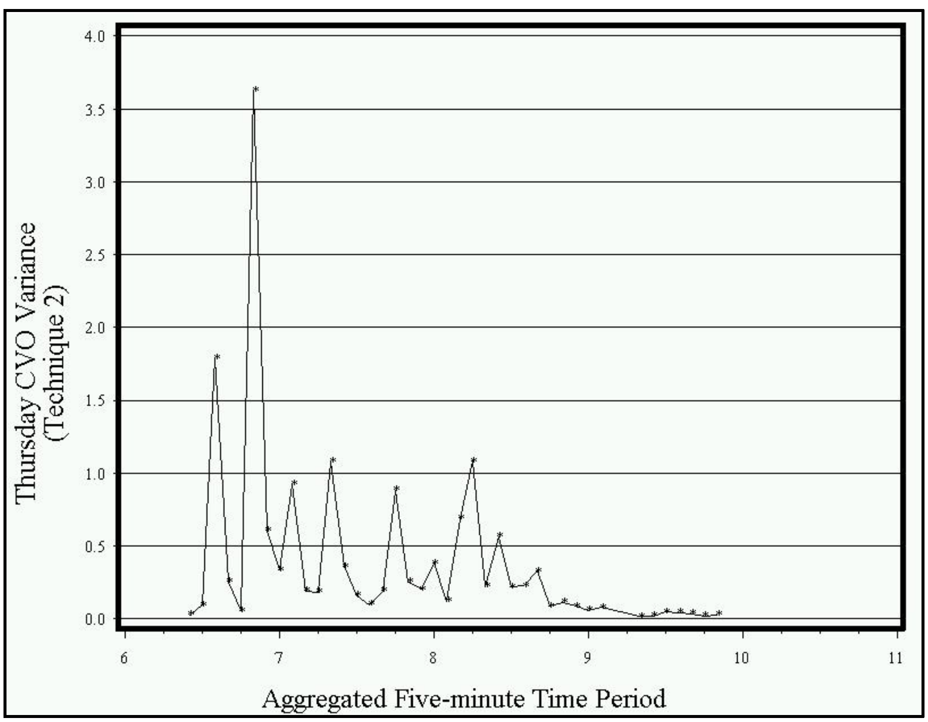

FIGURE B-128 Thursday CVO Variance with Technique Two

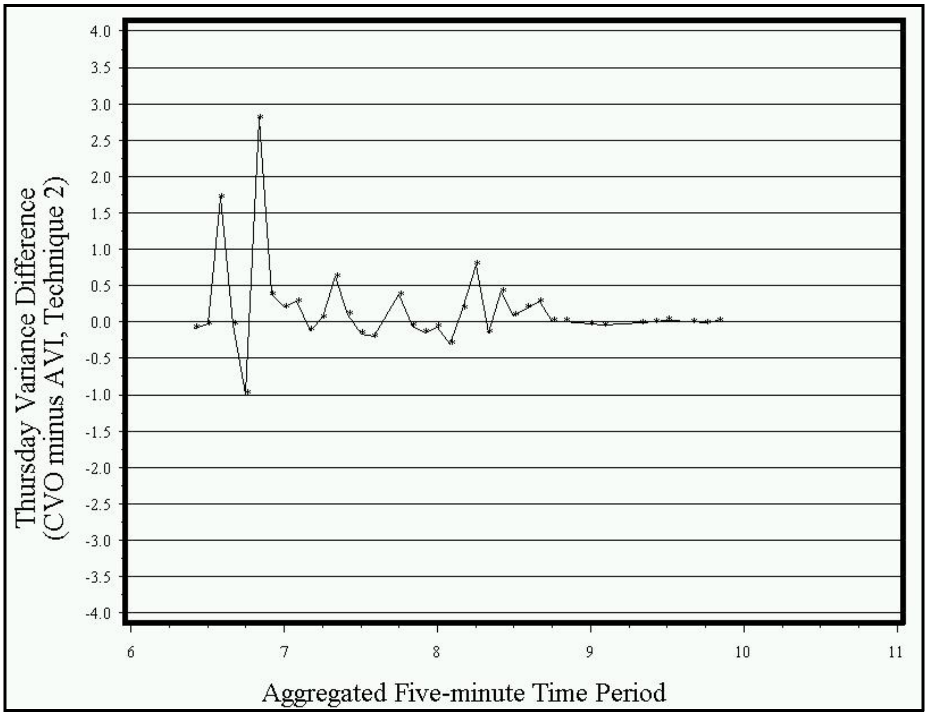

FIGURE B-129 Thursday Variance Difference Between CVO and AVI with Technique Two

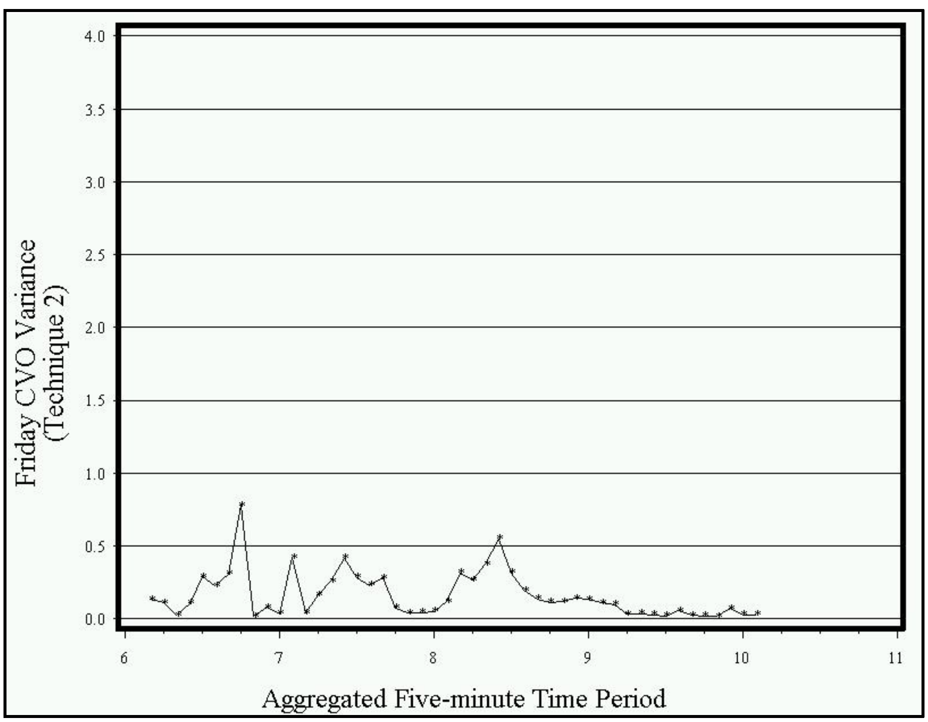

FIGURE B-130 Friday CVO Variance with Technique Two

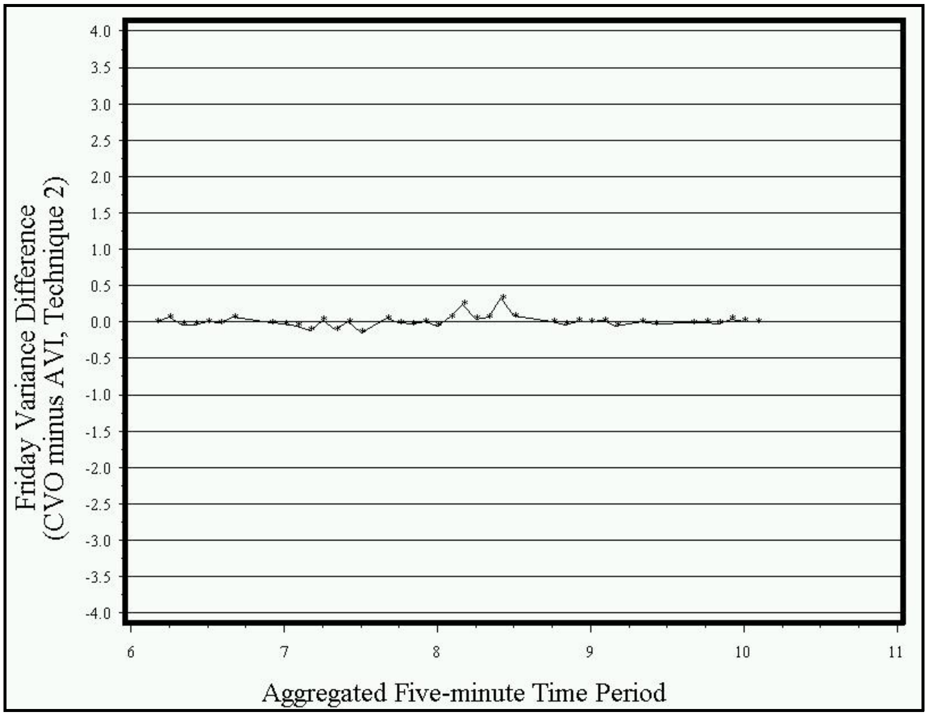

FIGURE B-131 Friday Variance Difference Between CVO and AVI with Technique Two

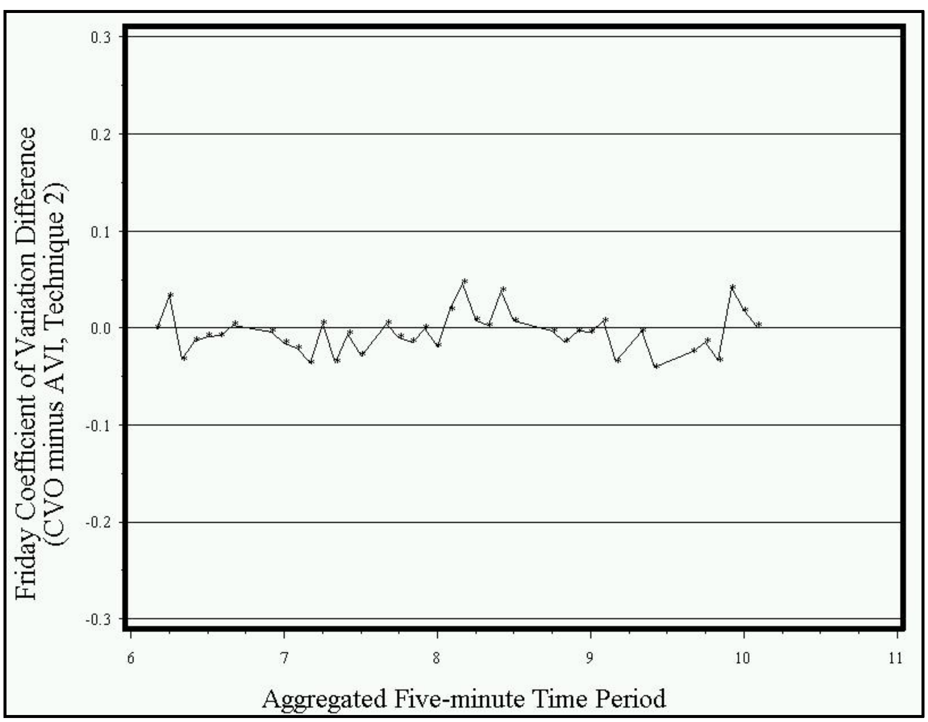

FIGURE B-132 Friday Coefficient of Variation Difference Between CVO and AVI with Technique Two

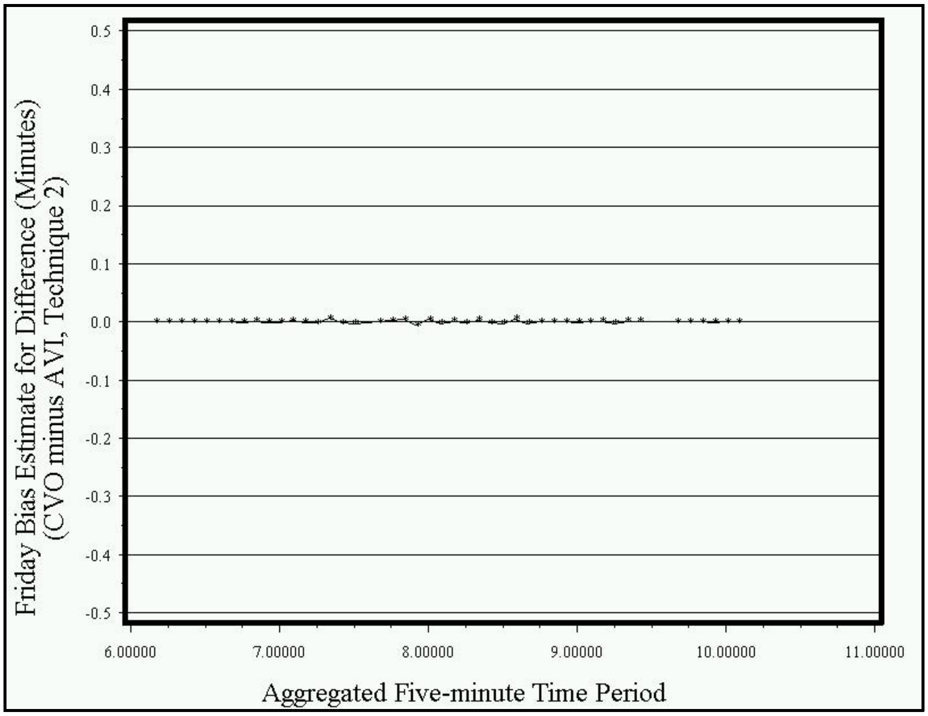

FIGURE B-133 Friday Bias Estimate for Difference Between CVO and AVI with Technique Two

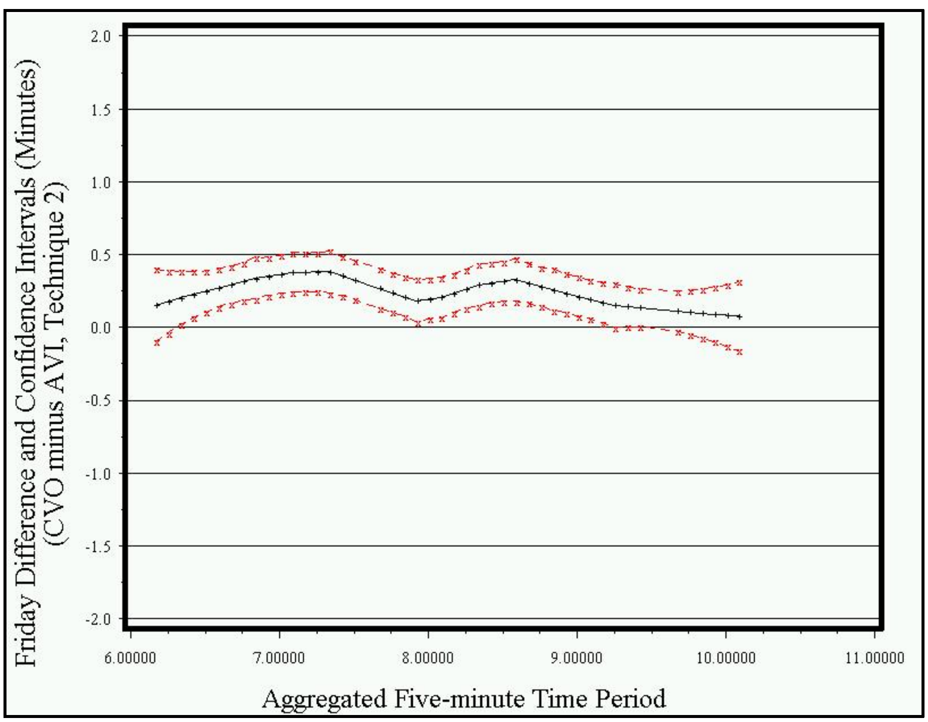

FIGURE B-134 Friday Difference and Confidence Intervals Including Correction for Estimated Bias for Technique Two

APPENDIX C

TABLE C-1 Percent Differences Between Inductance Loop and Test Vehicles for Monday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All Data	43	4.21	18.12	-35.89	73.07
		≥60 mph	22	5.95	15.37	-2.40	73.07
		31 to 59 mph	15	2.00	22.56	-35.89	43.25
		≤30 mph	6	3.35	17.71	-19.39	23.73
	Variance	All Data	22	1.13	9.71	-9.41	36.57
		≥60 mph	14	1.65	10.13	-4.59	36.57
		31 to 59 mph	5	-3.49	3.56	-9.41	-0.41
		≤30 mph	3	6.45	14.16	-2.65	22.76
	Coefficient of Variation	All Data	21	127.32	824.87	-94.80	–
		≥60 mph	13	-50.87	101.09	-94.47	277.81
		31 to 59 mph	5	-66.13	42.74	-94.80	8.98
		≤30 mph	3	–	–	-28.79	–

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE C-2 Percent Differences Between Inductance Loop and Test Vehicles for Tuesday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All Data	46	2.84	15.19	-27.23	59.66
		≥60 mph	17	6.38	4.84	-0.19	19.00
		31 to 59 mph	25	0.81	18.97	-27.23	59.66
		≤30 mph	4	0.44	18.56	-25.69	16.50
	Variance	All Data	21	-1.89	3.64	-12.89	2.01
		≥60 mph	7	-1.00	0.97	-3.00	-0.13
		31 to 59 mph	12	-1.92	3.61	-12.89	0.03
		≤30 mph	2	-4.83	9.68	-11.68	2.01
	Coefficient of Variation	All Data	20	-59.14	60.42	-96.53	140.05
		≥60 mph	7	-85.71	12.25	-95.53	-61.68
		31 to 59 mph	11	-51.35	71.37	-96.53	140.05
		≤30 mph	2	-8.98	82.94	-67.62	49.67

TABLE C-3 Percent Differences Between Inductance Loop and Test Vehicles for Friday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All Data	39	2.19	9.39	-18.80	30.82
		≥60 mph	18	5.62	4.46	-0.81	16.20
		31 to 59 mph	21	-0.76	11.43	-18.80	30.82
	Variance	All Data	25	-3.03	6.89	-31.37	3.40
		≥60 mph	11	-0.52	0.89	-2.41	0.00
		31 to 59 mph	14	-5.01	8.81	-31.37	3.40
	Coefficient of Variation	All Data	25	-33.01	101.32	-95.87	381.93
		≥60 mph	11	-26.28	56.96	-93.13	46.15
		31 to 59 mph	14	-38.31	128.01	-95.87	381.93

TABLE C-4 Percent Differences Between Inductance Loop and CVO for Monday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All Data	38	2.60	23.09	-32.44	77.52
		≥60 mph	9	1.02	1.90	-1.72	3.82
		31 to 59 mph	22	3.81	28.50	-32.44	77.52
		≤30 mph	7	0.83	20.63	-21.27	34.20
	Variance	All Data	38	0.58	7.93	-12.32	34.28
		≥60 mph	9	-0.95	0.29	-1.40	-0.51
		31 to 59 mph	22	-0.30	8.16	-12.32	34.28
		≤30 mph	7	5.33	11.03	-11.19	21.70
	Coefficient of Variation	All Data	38	23.84	427.17	-96.32	–
		≥60 mph	9	-90.82	4.73	-95.78	-80.37
		31 to 59 mph	22	-57.04	76.93	-96.32	260.49
		≤30 mph	7	425.44	934.15	-66.47	–

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE C-5 Percent Differences Between Inductance Loop and CVO for Tuesday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All Data	31	3.49	22.06	-32.34	81.19
		≥60 mph	5	3.85	4.46	0.62	11.69
		31 to 59 mph	21	3.34	25.92	-32.34	81.19
		≤30 mph	5	3.77	16.44	-24.70	14.20
	Variance	All Data	31	0.14	6.45	-8.47	24.21
		≥60 mph	5	-1.30	0.58	-1.94	-0.49
		31 to 59 mph	21	-0.60	5.64	-8.49	21.16
		≤30 mph	5	4.66	11.04	-2.27	24.21
	Coefficient of Variation	All Data	31	-37.55	122.26	-97.40	524.11
		≥60 mph	5	-85.17	14.18	-97.40	-62.09
		31 to 59 mph	21	-65.61	49.73	-95.24	111.57
		≤30 mph	5	127.94	241.54	-59.20	524.11

TABLE C-6 Percent Differences Between Inductance Loop and CVO for Friday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All Data	20	0.07	8.67	-24.08	21.14
		≥60 mph	3	2.44	1.83	0.84	4.43
		31 to 59 mph	17	-0.34	9.36	-24.08	21.14
	Variance	All Data	20	-0.86	3.28	-10.12	9.05
		≥60 mph	3	-0.78	0.43	-1.09	-0.28
		31 to 59 mph	17	-0.88	3.57	-10.12	9.05
	Coefficient of Variation	All Data	20	-53.70	54.82	-93.24	104.04
		≥60 mph	3	-87.97	4.04	-91.49	-83.56
		31 to 59 mph	17	-47.66	57.51	-93.24	104.04

TABLE C-7 Percent Differences Between CVO and Test Vehicles for Monday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Monday	Mean	All Data	37	2.58	12.14	-20.73	58.33
		≥60 mph	18	4.36	3.72	-2.79	13.50
		31 to 59 mph	13	0.44	19.27	-20.73	58.33
		≤30 mph	6	1.89	9.98	-15.80	12.67
	Variance	All Data	19	0.11	3.40	-9.41	6.56
		≥60 mph	11	0.42	1.78	-4.10	2.53
		31 to 59 mph	5	0.25	6.32	-9.41	6.56
		≤30 mph	3	-1.25	2.17	-3.20	1.08
	Coefficient of Variation	All Data	18	113.92	233.38	-94.63	621.69
		≥60 mph	10	150.52	252.70	-67.73	621.69
		31 to 59 mph	5	8.13	73.58	-94.63	91.32
		≤30 mph	3	168.21	354.54	-38.85	577.59

TABLE C-8 Percent Differences Between CVO and Test Vehicles for Tuesday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Tuesday	Mean	All Data	29	1.62	7.54	-13.38	16.40
		≥60 mph	9	9.37	4.18	2.69	16.40
		31 to 59 mph	16	-2.14	6.49	-13.38	10.30
		≤30 mph	4	-0.79	3.26	-2.94	3.96
	Variance	All Data	15	-0.48	4.18	-12.45	4.37
		≥60 mph	5	0.75	1.32	-0.70	1.87
		31 to 59 mph	8	-0.35	2.99	-7.33	2.13
		≤30 mph	2	-4.04	11.89	-12.45	4.37
	Coefficient of Variation	All Data	14	191.42	362.11	-72.90	–
		≥60 mph	5	68.65	119.88	-52.78	240.62
		31 to 59 mph	7	326.48	477.78	-35.53	–
		≤30 mph	2	25.61	139.32	-72.90	124.12

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE C-9 Percent Differences Between CVO and Test Vehicles for Thursday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Thursday	Mean	All Data	24	3.29	6.54	-12.73	19.44
		≥60 mph	4	5.58	1.54	3.96	7.19
		31 to 59 mph	16	2.57	7.80	-12.73	19.44
		≤30 mph	4	3.86	3.31	0.46	6.98
	Variance	All Data	16	-2.29	5.56	-16.30	3.72
		≥60 mph	4	1.00	1.96	-0.60	3.72
		31 to 59 mph	9	-2.73	5.99	-16.30	3.31
		≤30 mph	3	-5.34	6.78	-11.77	-1.74
	Coefficient of Variation	All Data	16	212.74	580.73	-80.89	–
		≥60 mph	4	614.53	–	-20.36	–
		31 to 59 mph	9	88.91	247.20	-80.89	651.76
		≤30 mph	3	48.51	188.88	-69.80	266.34

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE C-10 Percent Differences Between CVO and Test Vehicles for Friday by Congestion Level

Day	Travel Time Variable	Congestion Level	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Friday	Mean	All Data	20	2.76	7.00	-12.23	16.80
		≥60 mph	5	5.89	5.32	-2.69	10.95
		31 to 59 mph	15	1.72	7.33	-12.23	16.80
	Variance	All Data	13	-2.72	8.89	-30.86	3.88
		≥60 mph	3	1.26	2.29	-0.38	3.88
		31 to 59 mph	10	-3.92	9.87	-30.86	2.18
	Coefficient of Variation	All Data	13	144.90	349.06	-75.37	–
		≥60 mph	3	565.02	560.10	-19.21	–
		31 to 59 mph	10	18.87	127.53	-75.37	371.21

Note: Cells with differences greater than one thousand are indicated with a "–."

TABLE C-11 Travel Time Characteristic Averages for All Days and All Data Sources

Travel Time Variable	Data Source	Number of Observations	Mean
Mean	Inductance Loops	192	2.90
	Test Vehicles	170	2.81
	CVO	115	3.17
Variance	Inductance Loops	192	0.05
	Test Vehicles	91	0.07
	CVO	115	0.07
Coefficient of Variation	Inductance Loops	192	0.03
	Test Vehicles	91	0.06
	CVO	115	0.08

TABLE C-12 Travel Time Characteristic Averages for All Days for Inductance Loop Data by Congestion Level for All Days Together

Travel Time Variable	Data Source	Number of Observations	Mean
Mean	≥60 mph	104	2.54
	31 to 59 mph	74	2.83
	≤30 mph	14	5.94
Variance	≥60 mph	104	0.01
	31 to 59 mph	74	0.04
	≤30 mph	14	0.42
Coefficient of Variation	≥60 mph	104	0.01
	31 to 59 mph	74	0.03
	≤30 mph	14	0.10

TABLE C-13 Travel Time Characteristic Averages for All Days for Test Vehicles by Congestion Level for All Days Together

Travel Time Variable	Data Source	Number of Observations	Mean
Mean	≥60 mph	82	2.30
	31 to 59 mph	74	2.81
	≤30 mph	14	5.82
Variance	≥60 mph	47	0.02
	31 to 59 mph	38	0.11
	≤30 mph	6	0.27
Coefficient of Variation	≥60 mph	47	0.05
	31 to 59 mph	38	0.09
	≤30 mph	6	0.07

TABLE C-14 Travel Time Characteristic Averages for All Days for CVO by Congestion Level for All Days Together

Travel Time Variable	Data Source	Number of Observations	Mean
Mean	≥60 mph	23	2.35
	31 to 59 mph	76	2.82
	≤30 mph	16	6.04
Variance	≥60 mph	23	0.03
	31 to 59 mph	76	0.07
	≤30 mph	16	0.15
Coefficient of Variation	≥60 mph	23	0.07
	31 to 59 mph	76	0.08
	≤30 mph	16	0.05

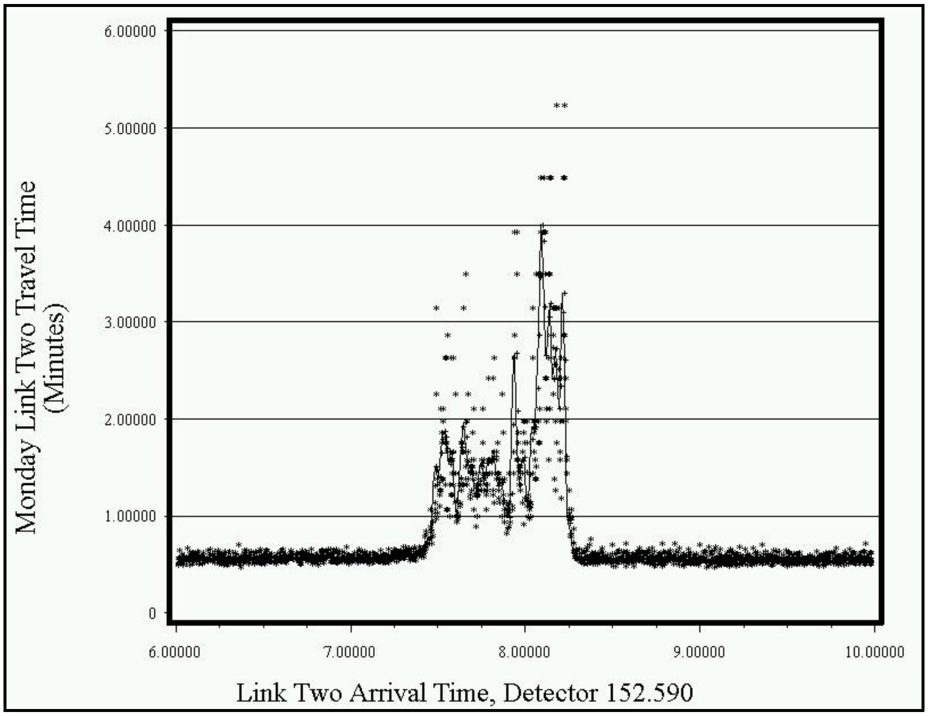

FIGURE C-1 Loess Travel Time Predicted Values for Monday Inductance Loop Data from Detector 152.590

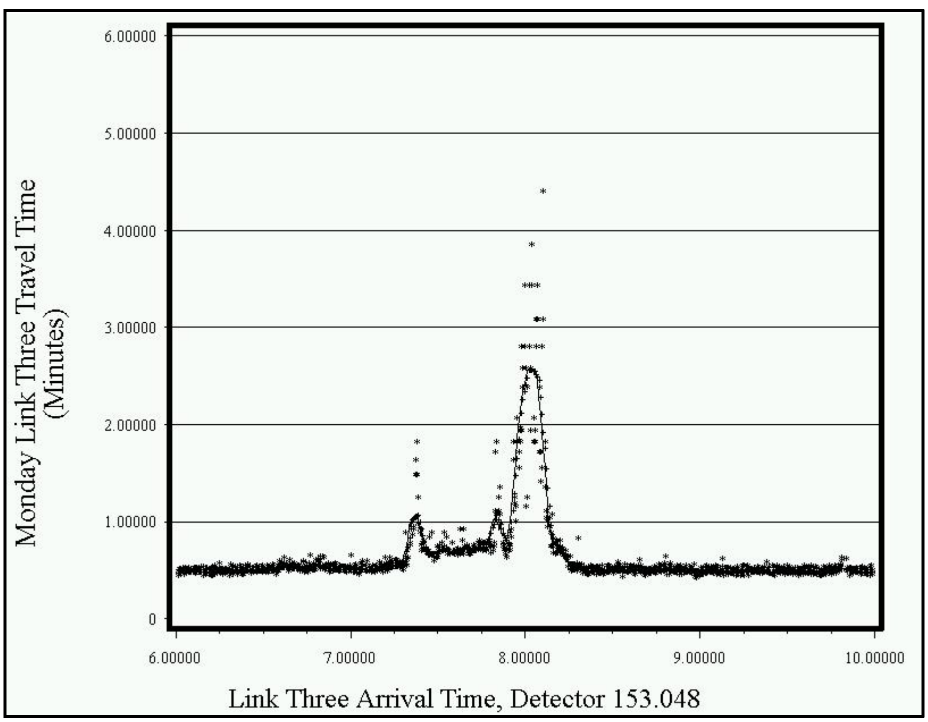

FIGURE C-2 Loess Travel Time Predicted Values for Monday Inductance Loop Data from Detector 153.048

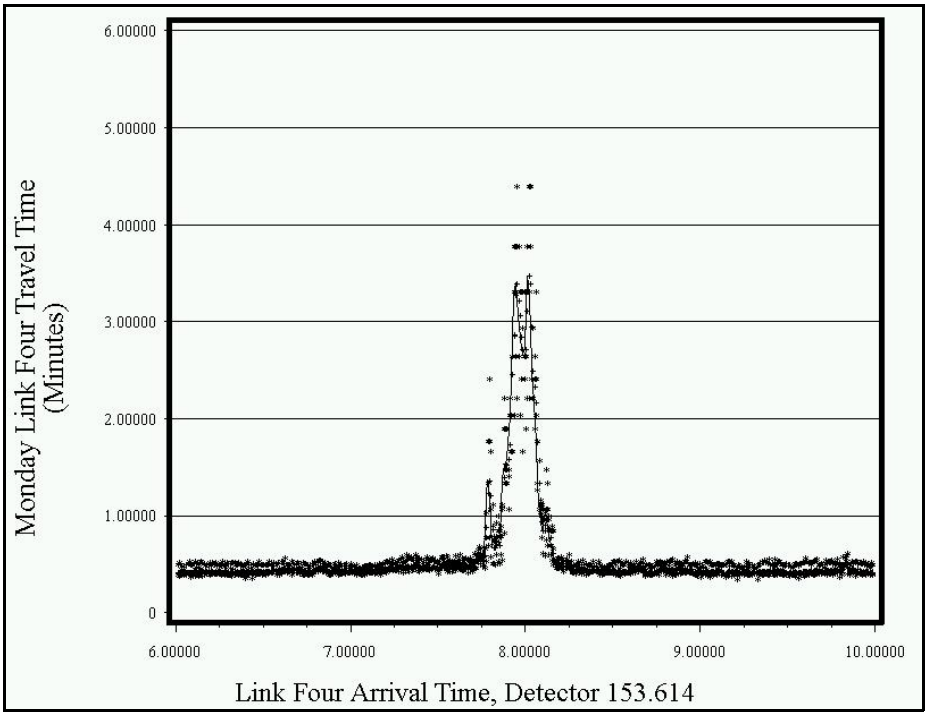

FIGURE C-3 Loess Travel Time Predicted Values for Monday Inductance Loop Data from Detector 153.614

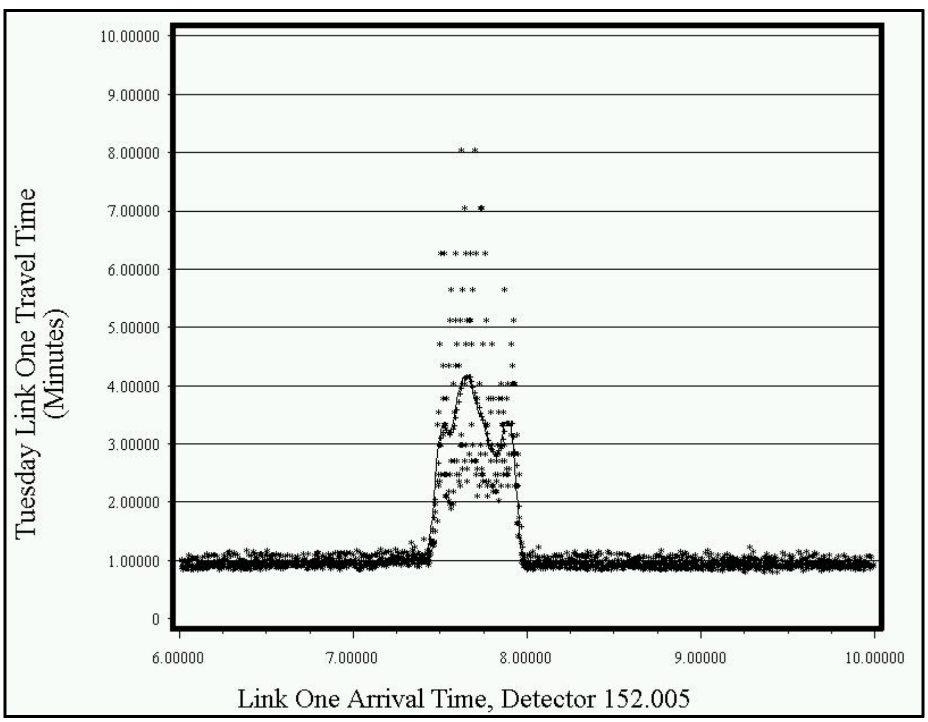

FIGURE C-4 Loess Travel Time Predicted Values for Tuesday Inductance Loop Data from Detector 152.005

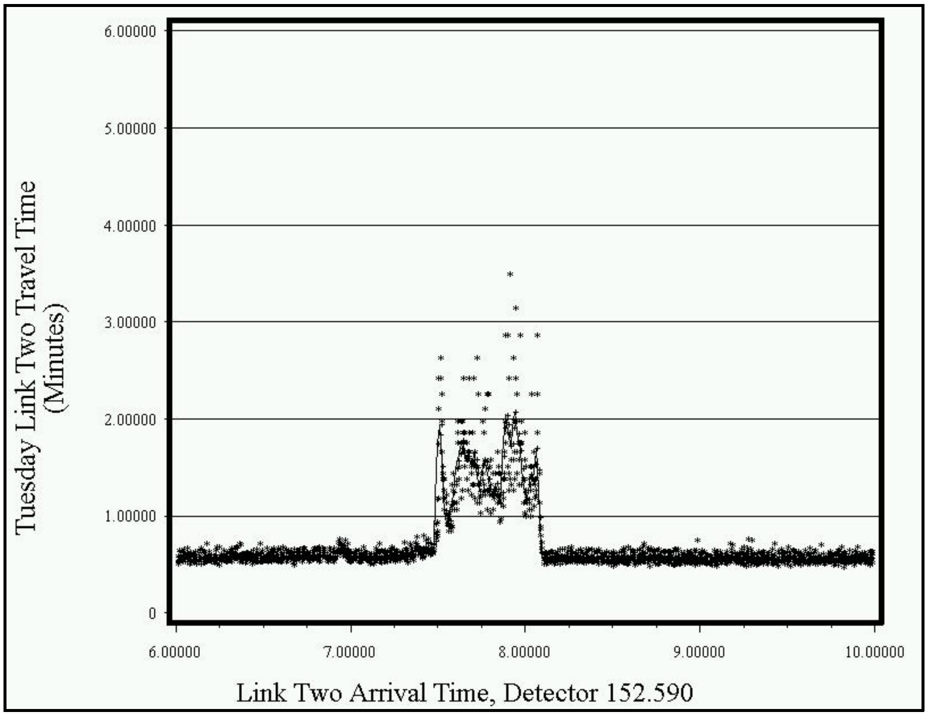

FIGURE C-5 Loess Travel Time Predicted Values for Tuesday Inductance Loop Data from Detector 152.590

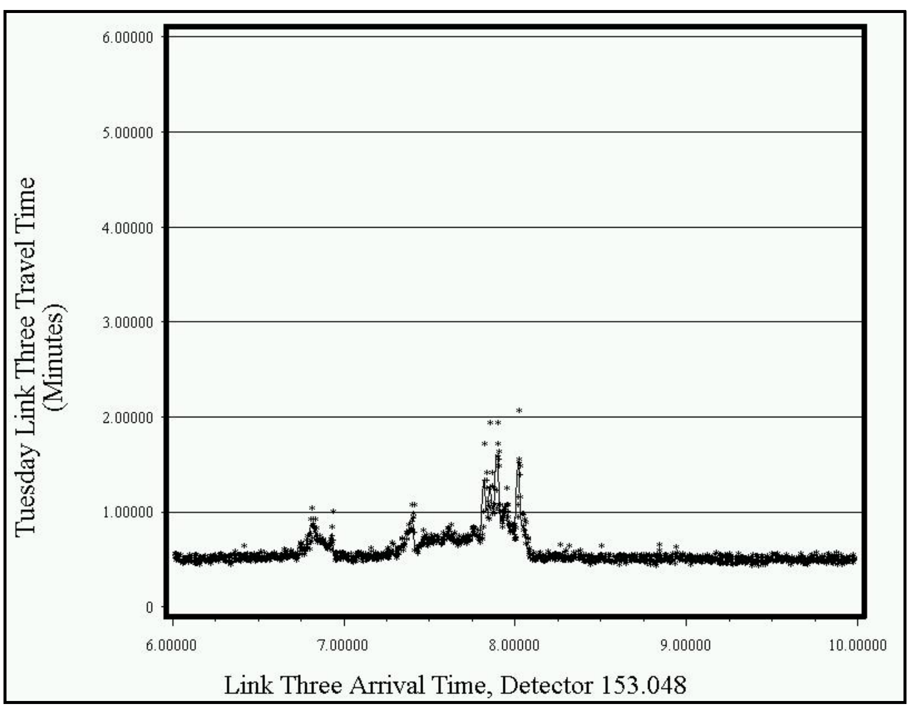

FIGURE C-6 Loess Travel Time Predicted Values for Tuesday Inductance Loop Data from Detector 153.048

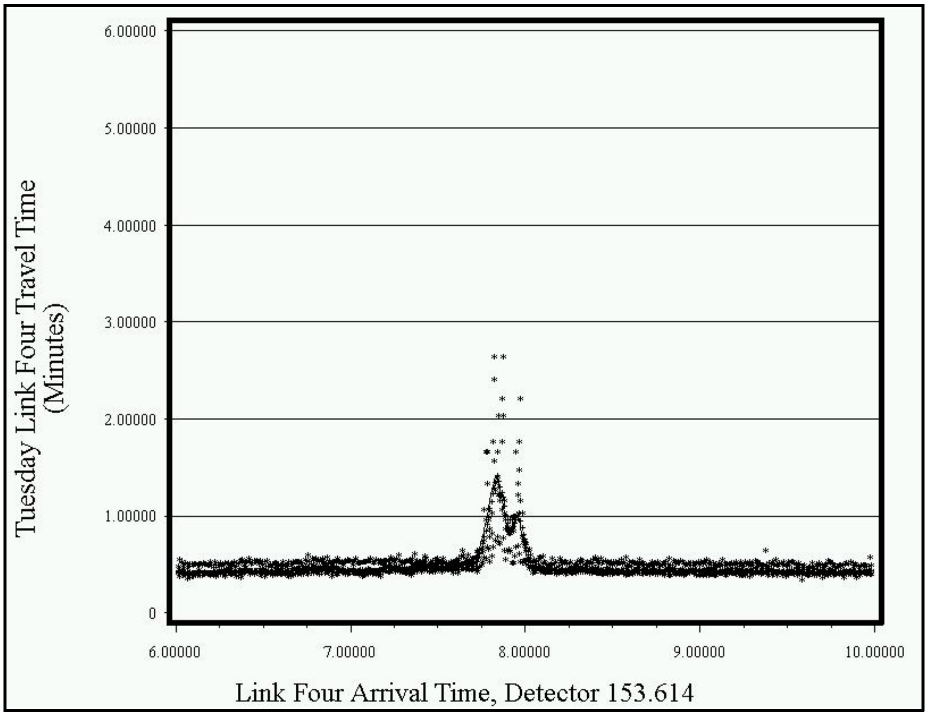

FIGURE C-7 Loess Travel Time Predicted Values for Tuesday Inductance Loop Data from Detector 153.614

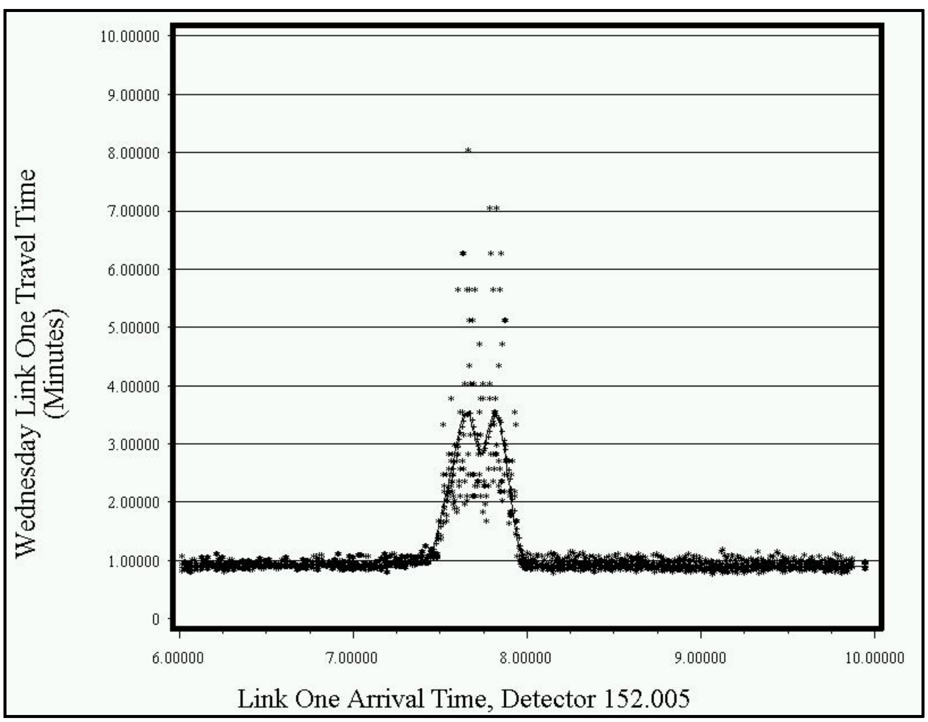

FIGURE C-8 Loess Travel Time Predicted Values for Wednesday Inductance Loop Data from Detector 152.005

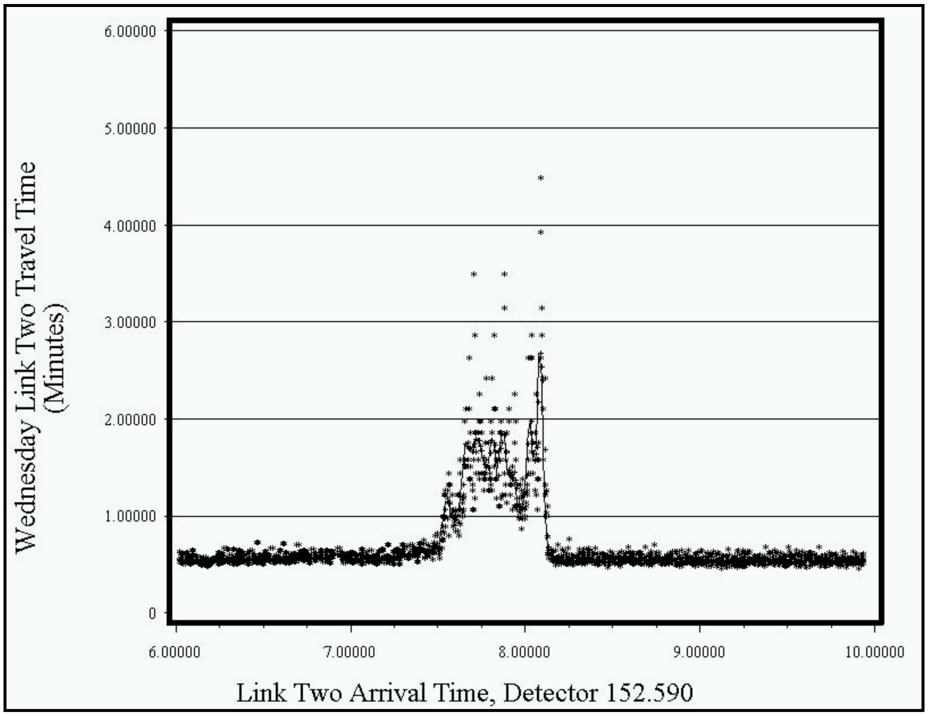

FIGURE C-9 Loess Travel Time Predicted Values for Wednesday Inductance Loop Data from Detector 152.590

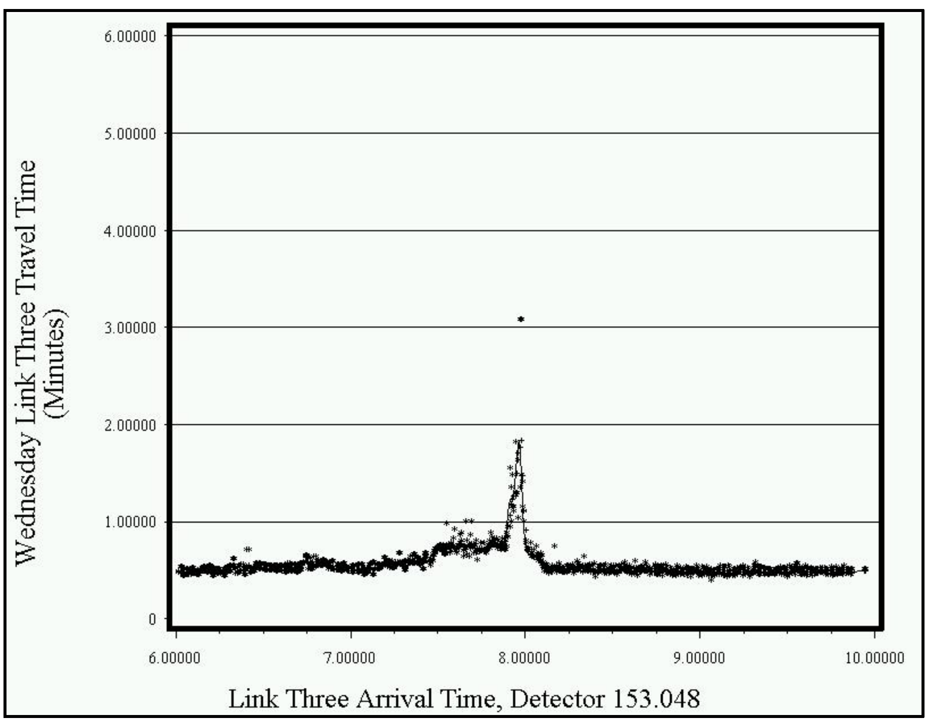

FIGURE C-10 Loess Travel Time Predicted Values for Wednesday Inductance Loop Data from Detector 153.048

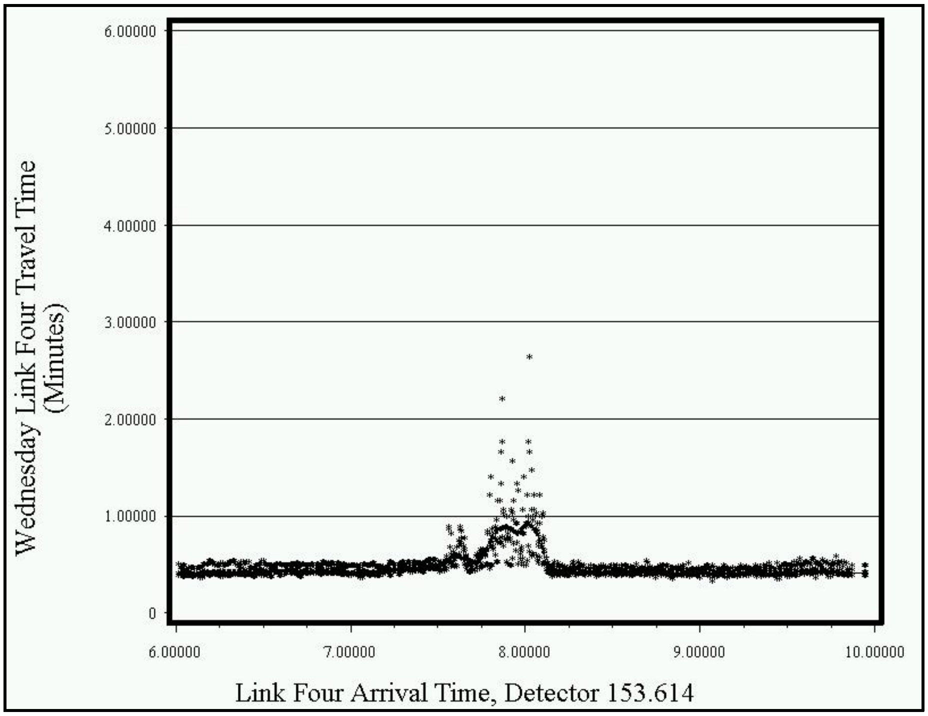

FIGURE C-11 Loess Travel Time Predicted Values for Wednesday Inductance Loop Data from Detector 153.614

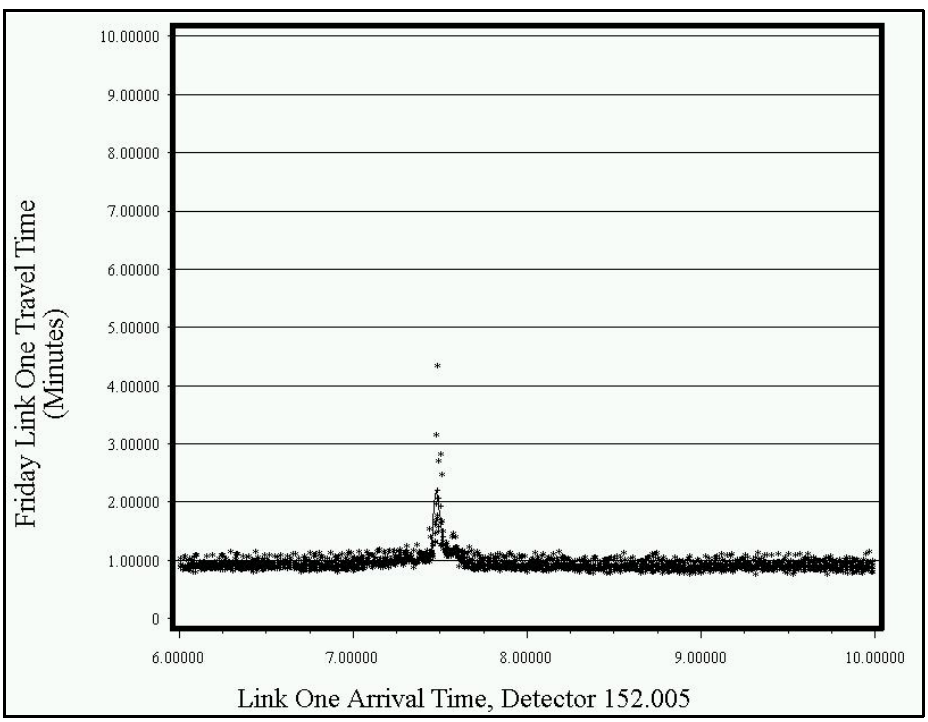

FIGURE C-12 Loess Travel Time Predicted Values for Friday Inductance Loop Data from Detector 152.005

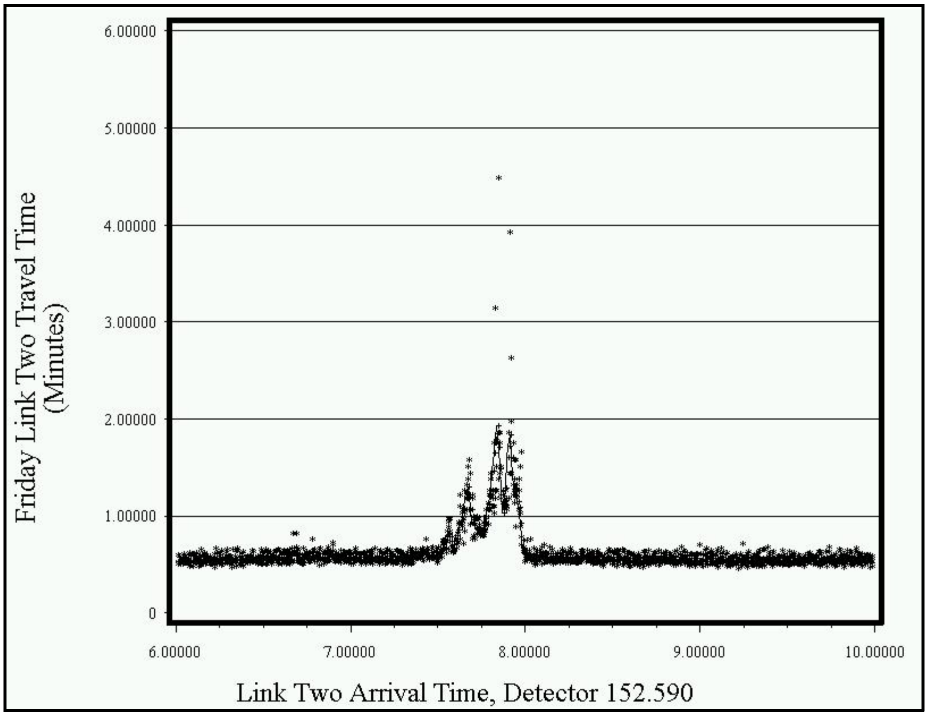

FIGURE C-13 Loess Travel Time Predicted Values for Friday Inductance Loop Data from Detector 152.590

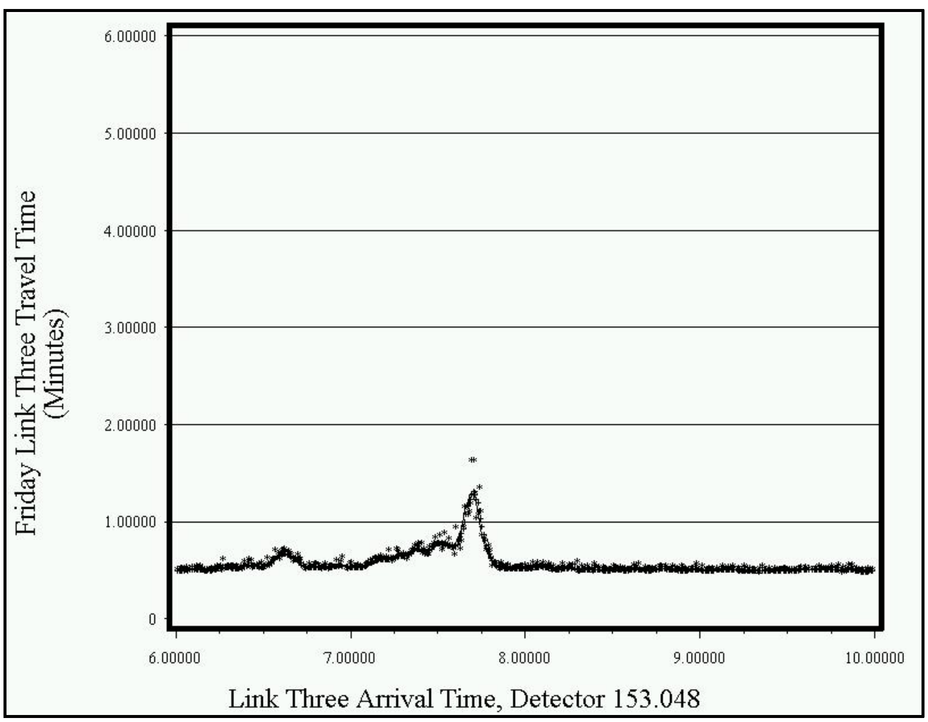

FIGURE C-14 Loess Travel Time Predicted Values for Friday Inductance Loop Data from Detector 153.048

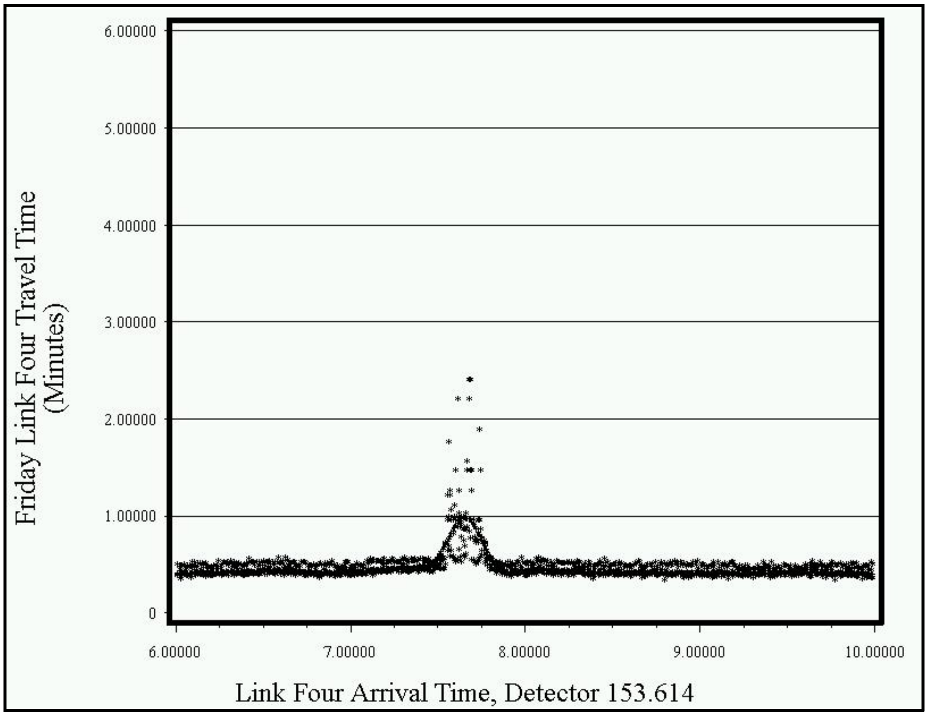

FIGURE C-15 Loess Travel Time Predicted Values for Friday Inductance Loop Data from Detector 153.614

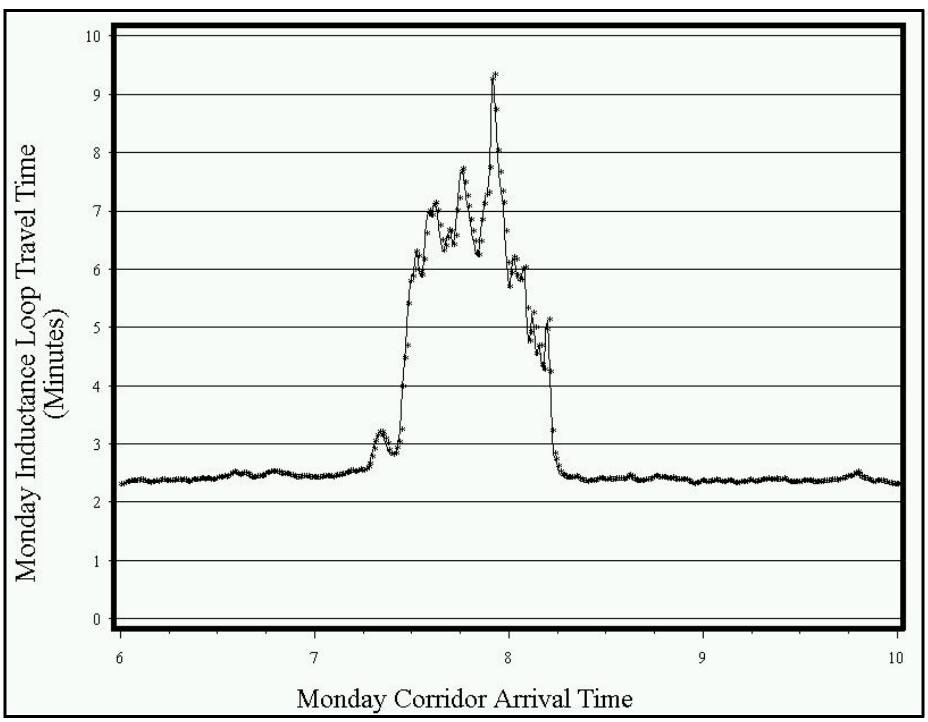

FIGURE C-16 Study Corridor Travel Time Estimate from Inductance Loop Detector Data for Monday

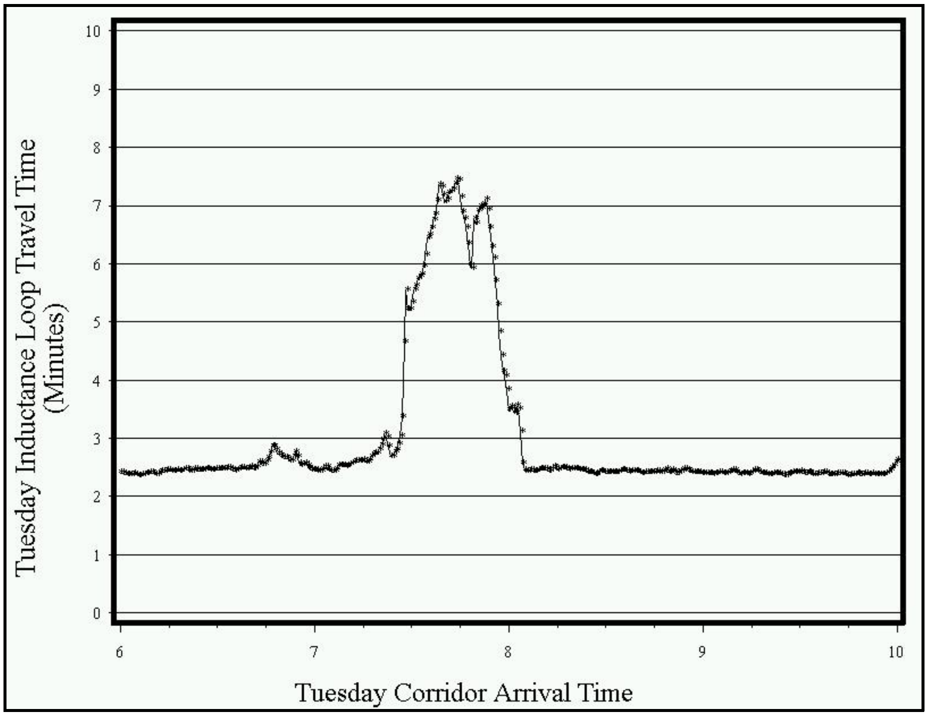

FIGURE C-17 Study Corridor Travel Time Estimate from Inductance Loop Detector Data for Tuesday

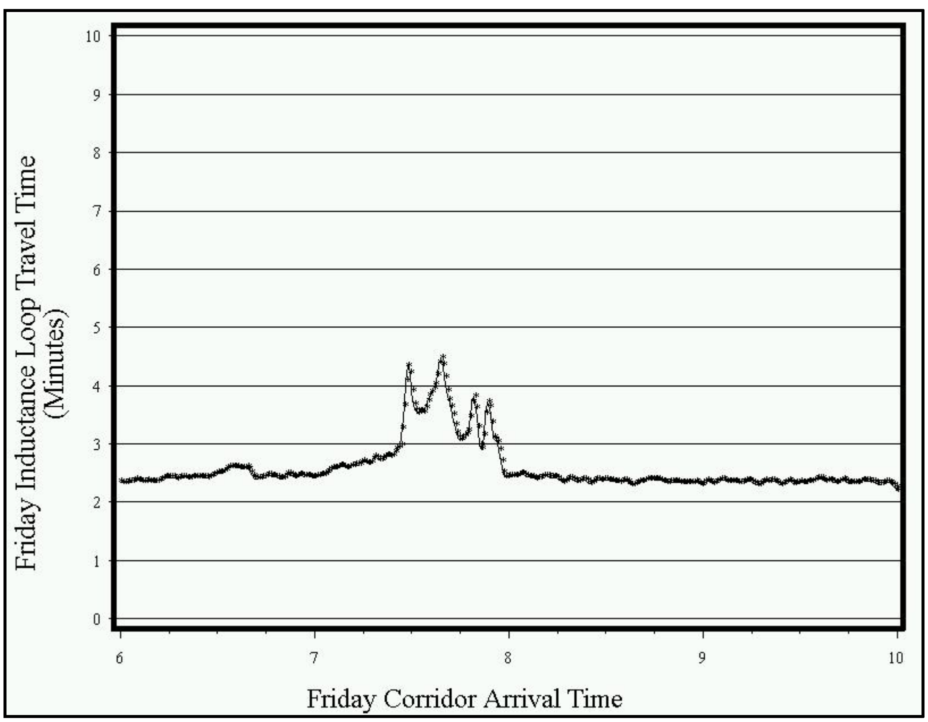

FIGURE C-18 Study Corridor Travel Time Estimate from Inductance Loop Detector Data for Friday

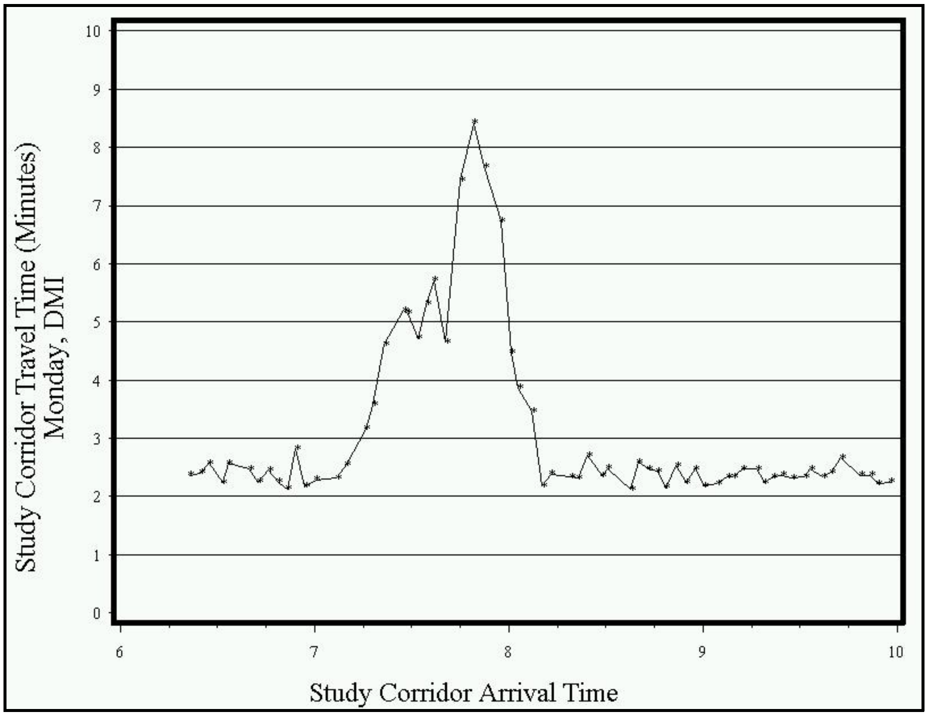

FIGURE C-19 Study Corridor Travel Time Estimate from Test Vehicle Data for Monday

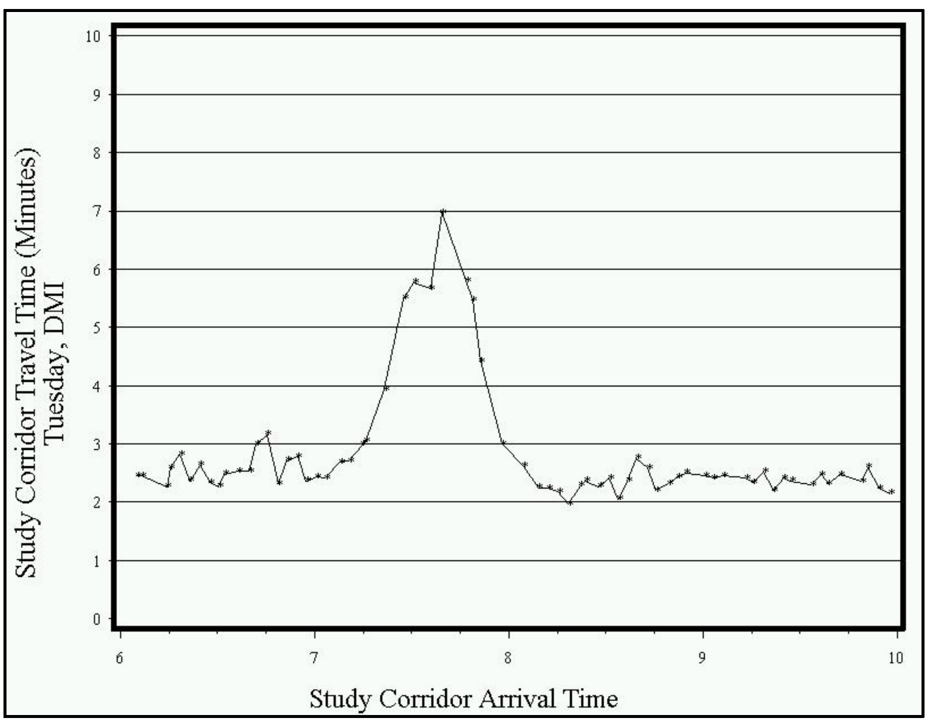

FIGURE C-20 Study Corridor Travel Time Estimate from Test Vehicle Data for Tuesday

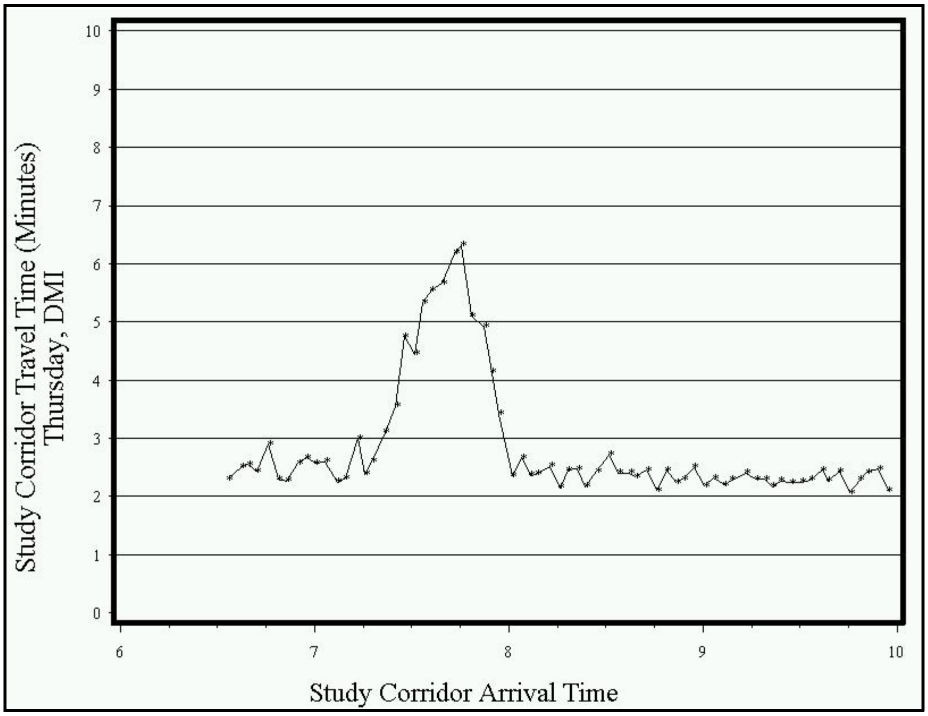

FIGURE C-21 Study Corridor Travel Time Estimate from Test Vehicle Data for Thursday

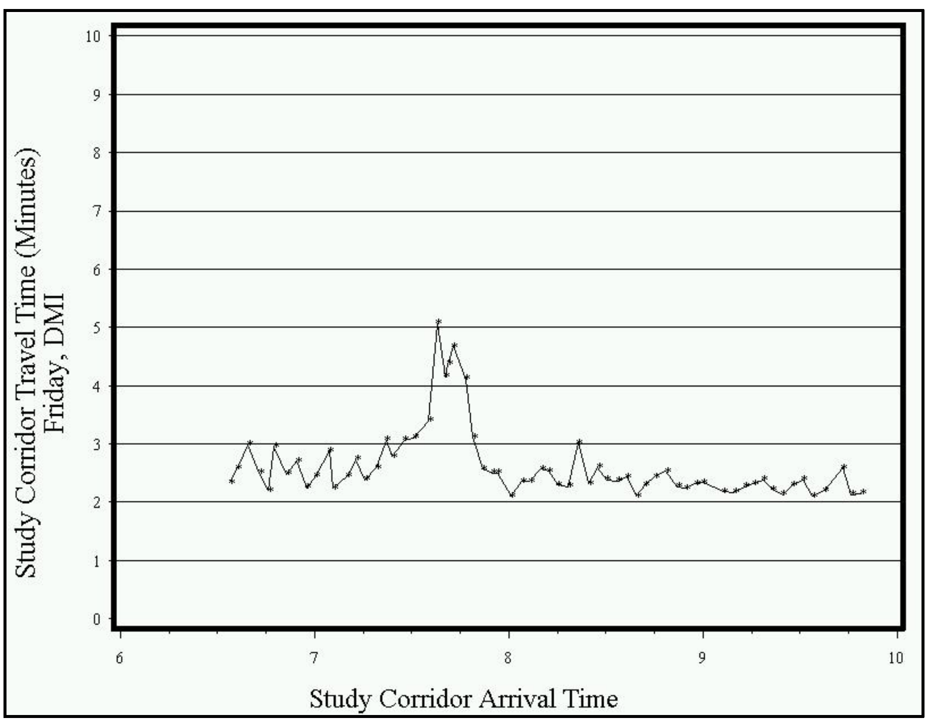

FIGURE C-22 Study Corridor Travel Time Estimate from Test Vehicle Data for Friday

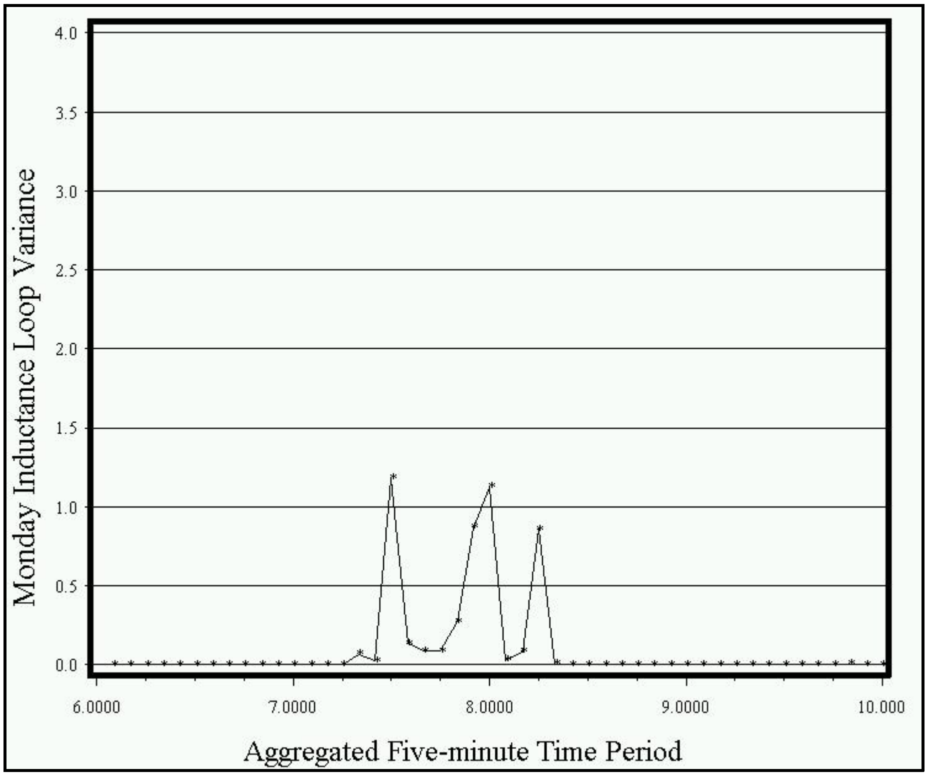

FIGURE C-23 Monday Inductance Loop Variance

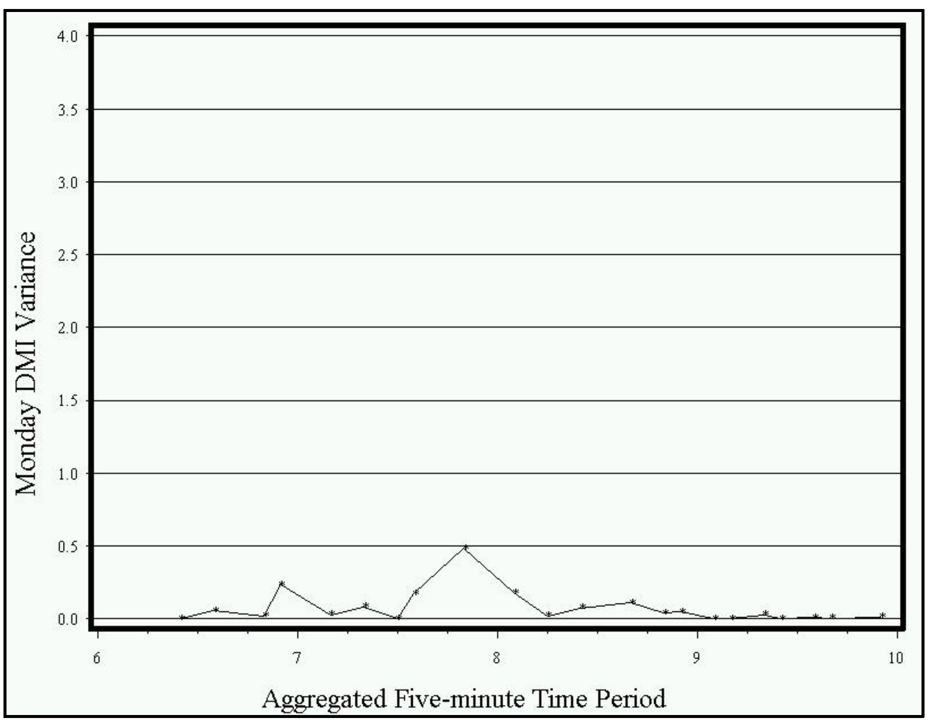

FIGURE C-24 Monday Test Vehicle Variance

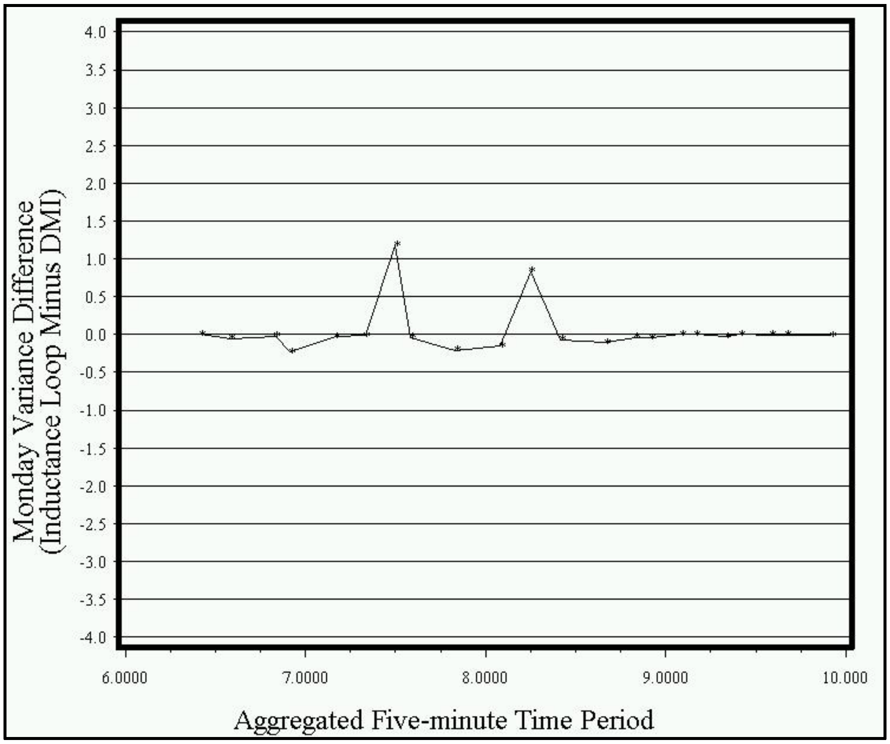

FIGURE C-25 Monday Variance Difference Between Inductance Loop and Test Vehicle

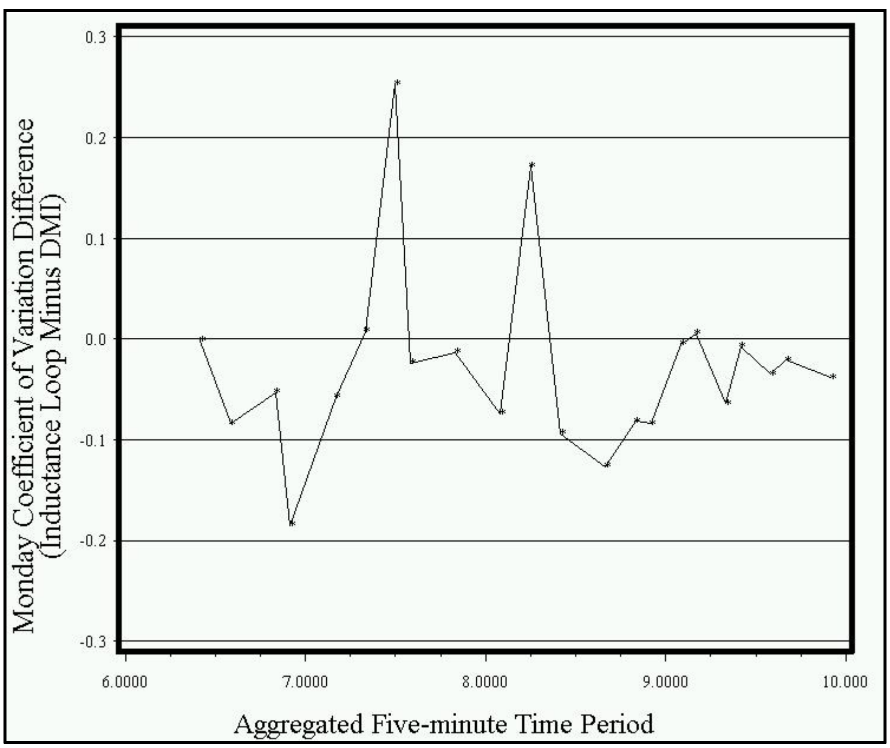

FIGURE C-26 Monday Coefficient of Variation Difference Between Inductance Loop and Test Vehicles

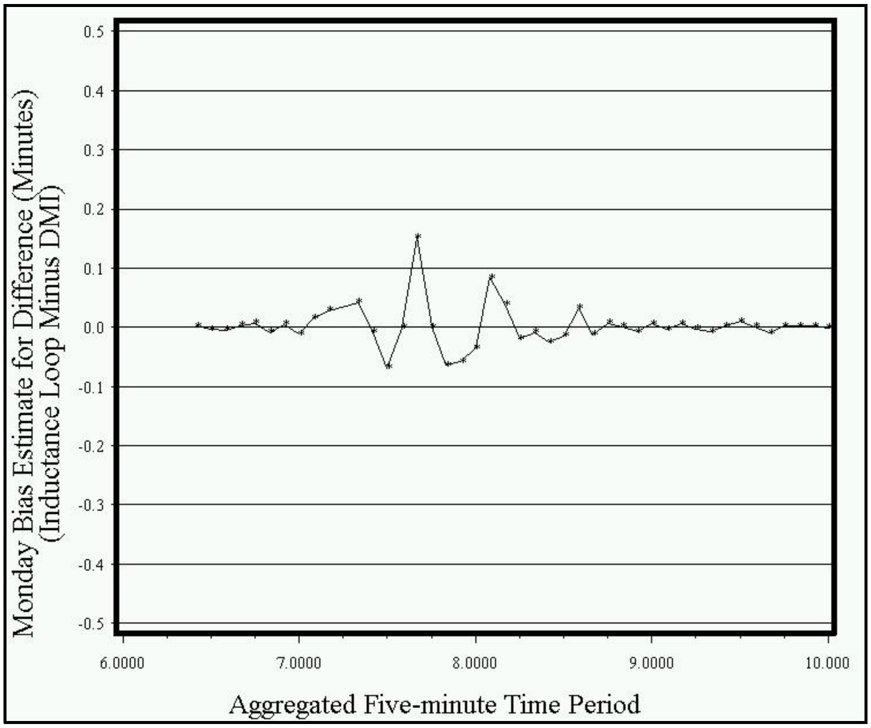

FIGURE C-27 Monday Bias Estimate for Differences Between Inductance Loop and Test Vehicles

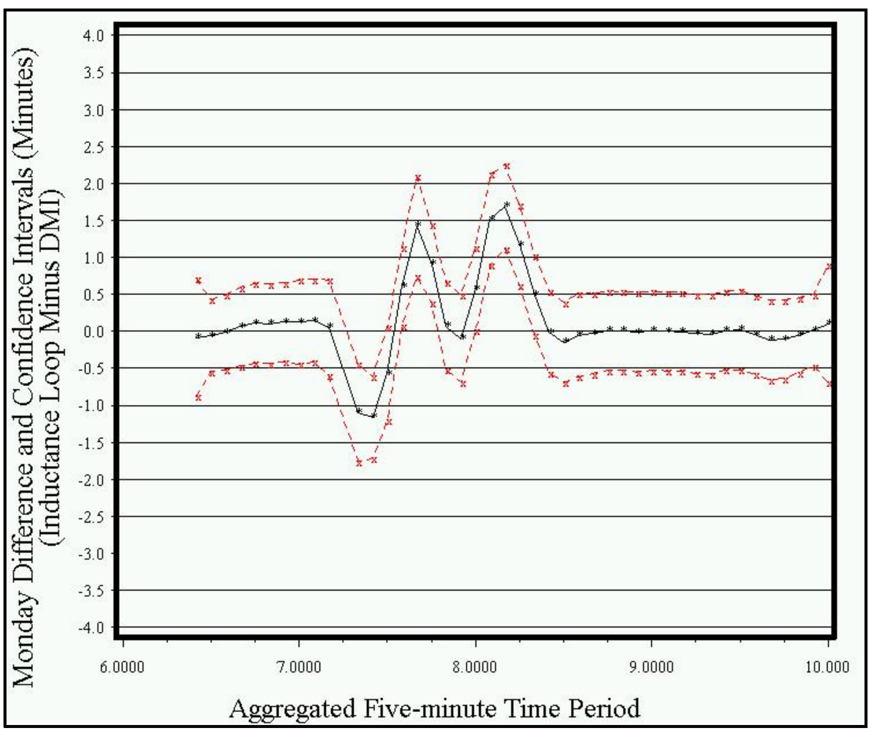

FIGURE C-28 Monday Difference Between Inductance Loop and Test Vehicle and Confidence Intervals Including Correction for Estimated Bias

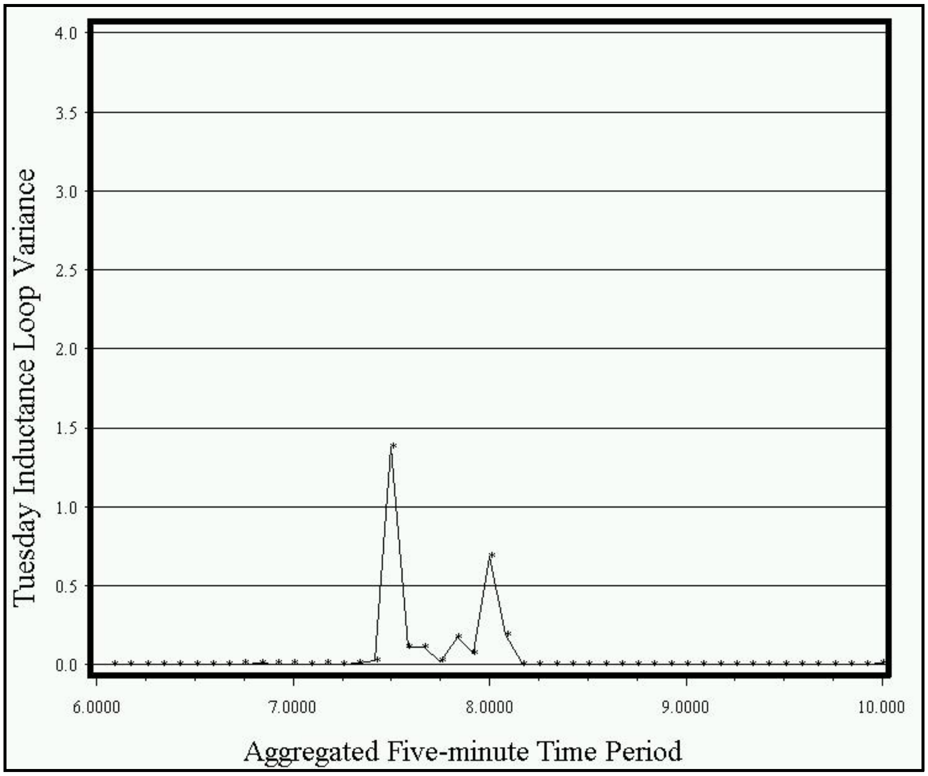

FIGURE C-29 Tuesday Inductance Loop Variance

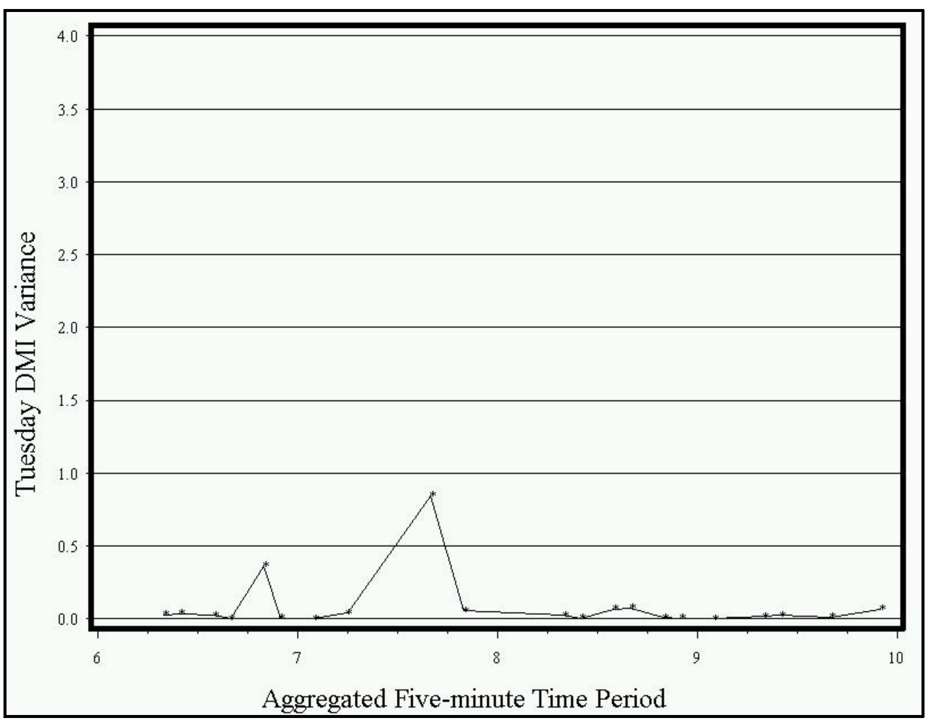

FIGURE C-30 Tuesday Test Vehicle Variance

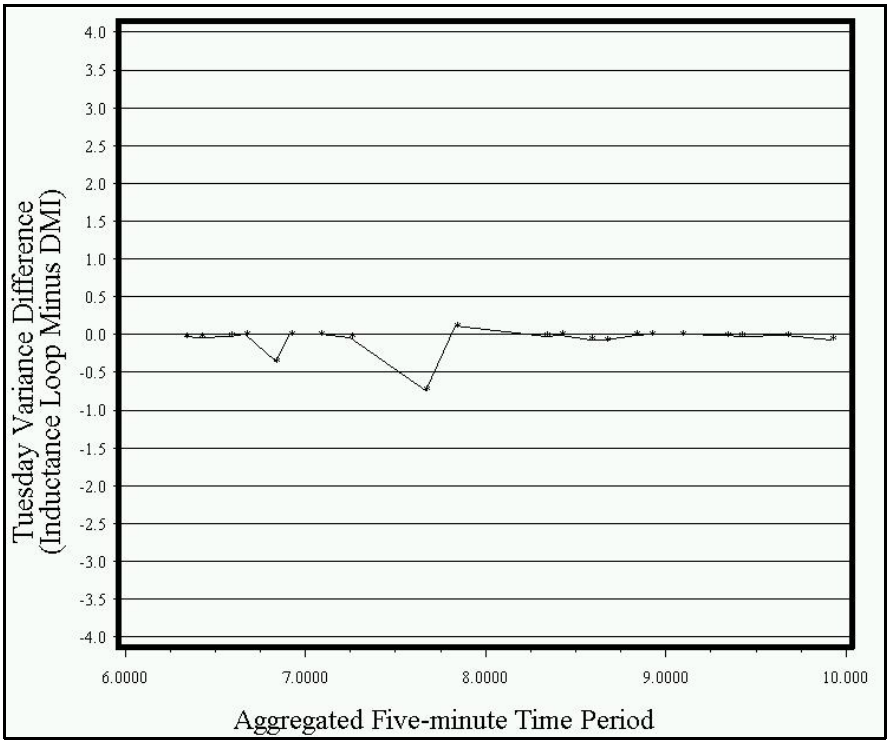

FIGURE C-31 Tuesday Variance Difference Between Inductance Loop and Test Vehicle

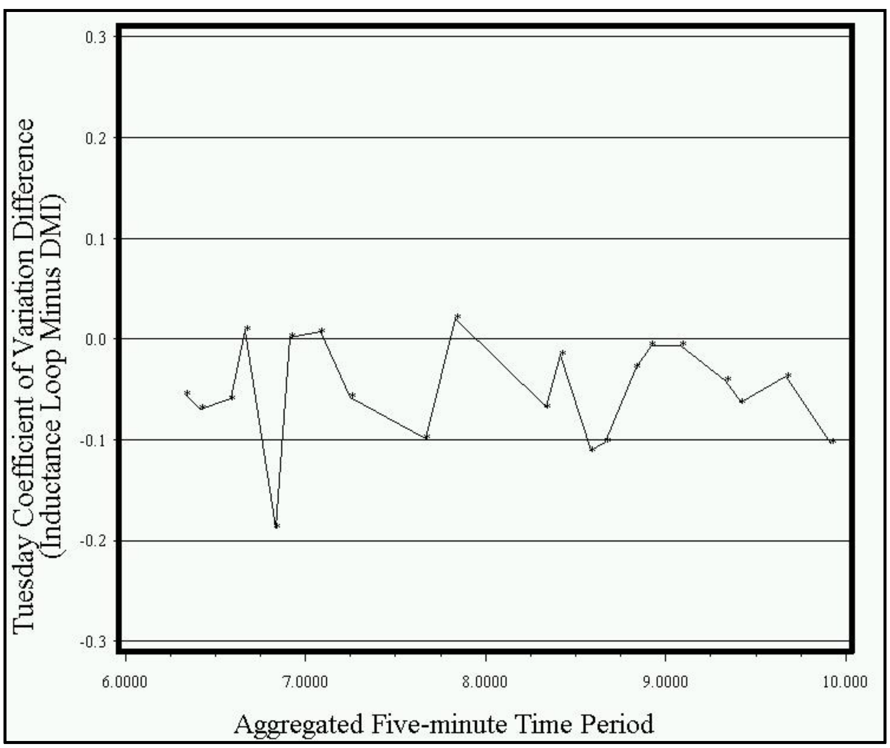

FIGURE C-32 Tuesday Coefficient of Variation Difference Between Inductance Loop and Test Vehicles

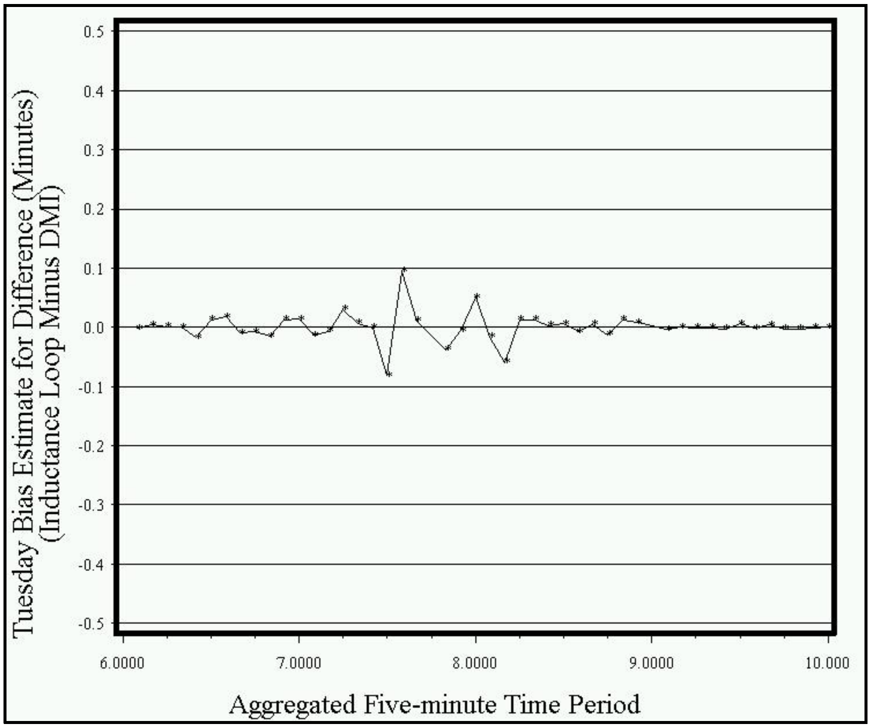

FIGURE C-33 Tuesday Bias Estimate for Differences Between Inductance Loop and Test Vehicles

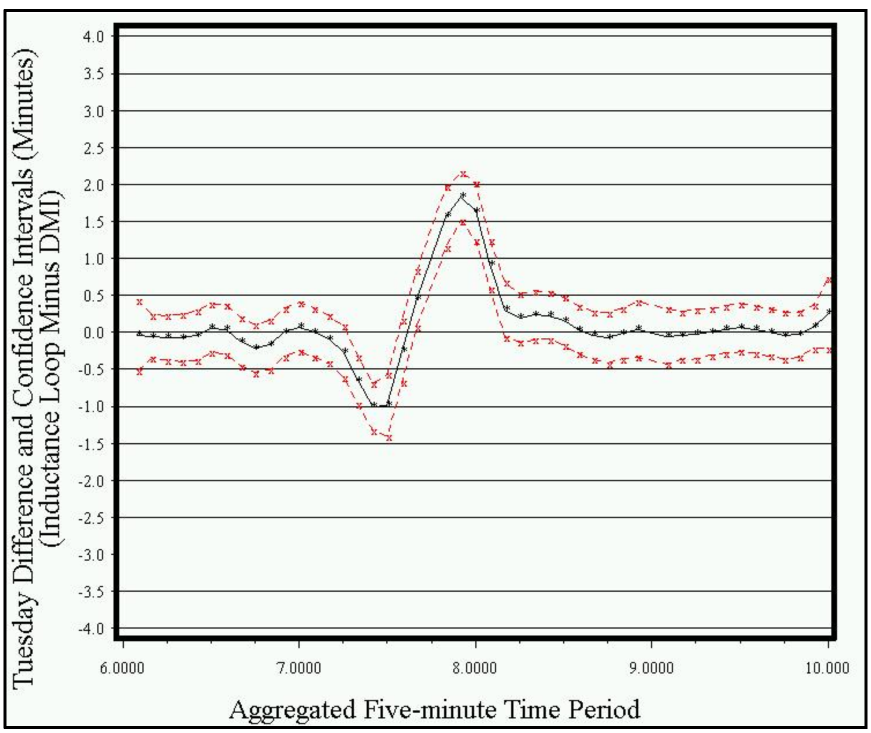

FIGURE C-34 Tuesday Difference Between Inductance Loop and Test Vehicle and Confidence Intervals Including Correction for Estimated Bias

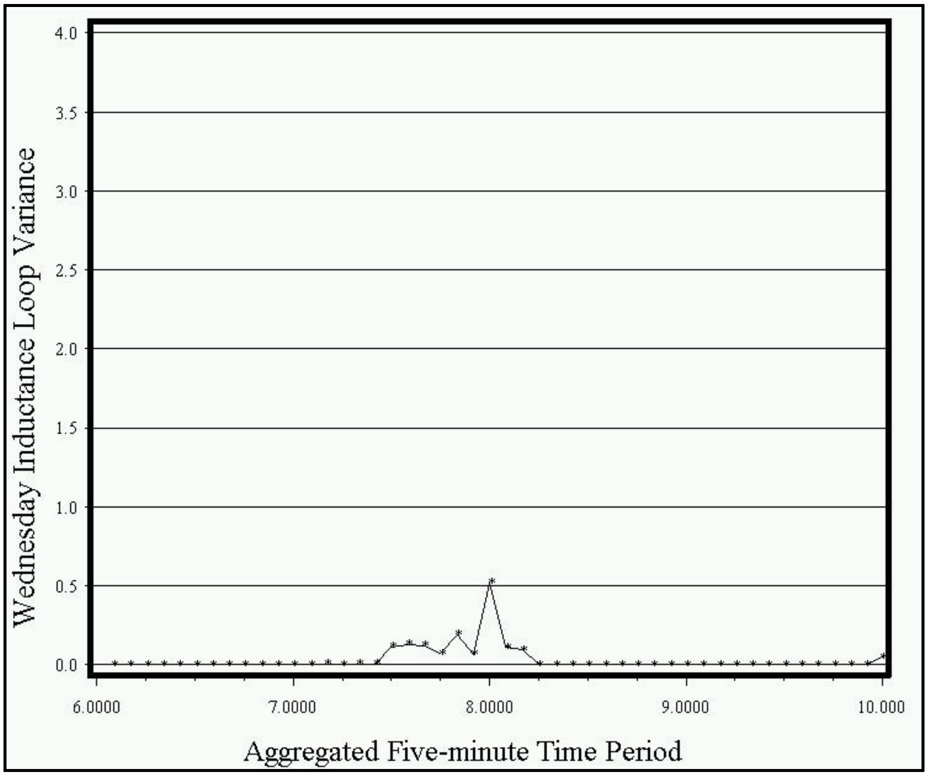

FIGURE C-35 Wednesday Inductance Loop Variance

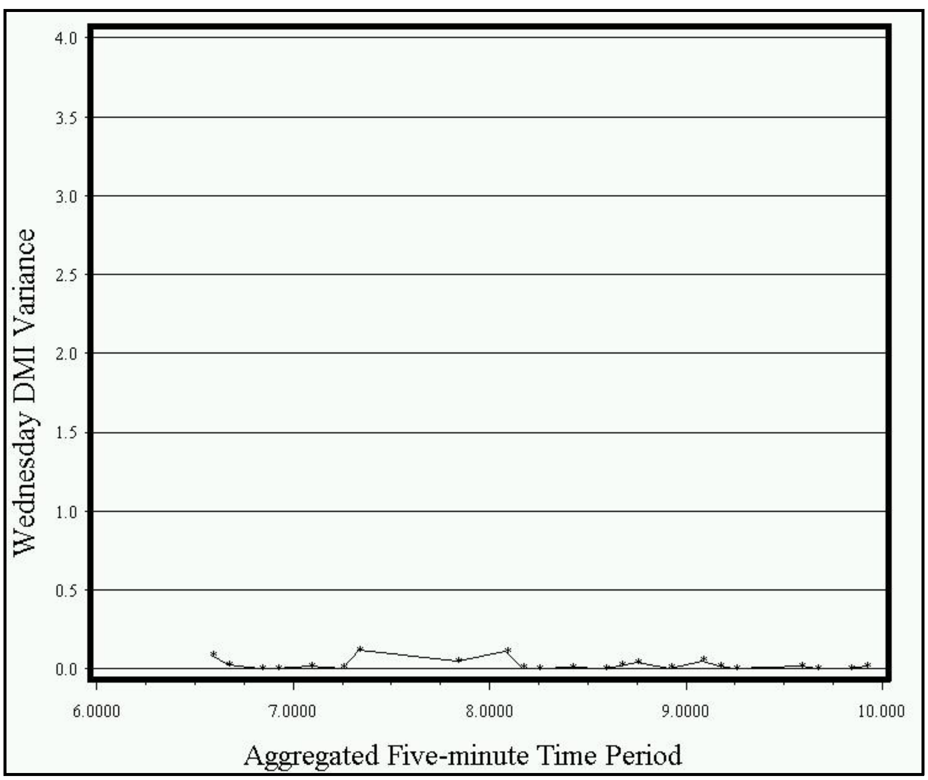

FIGURE C-36 Wednesday Test Vehicle Variance

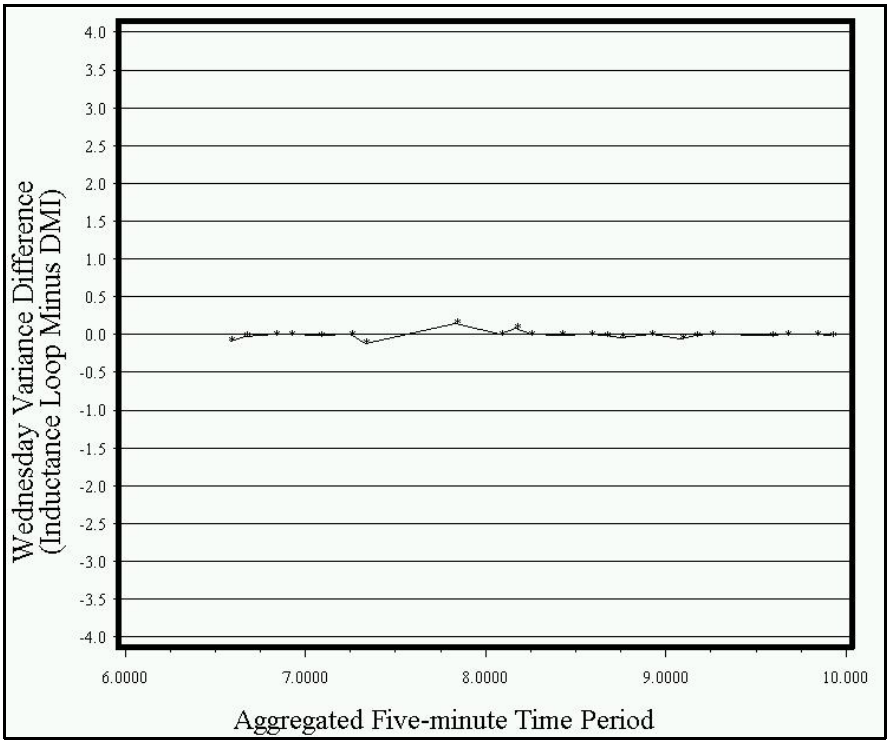

FIGURE C-37 Wednesday Variance Difference Between Inductance Loop and Test Vehicle

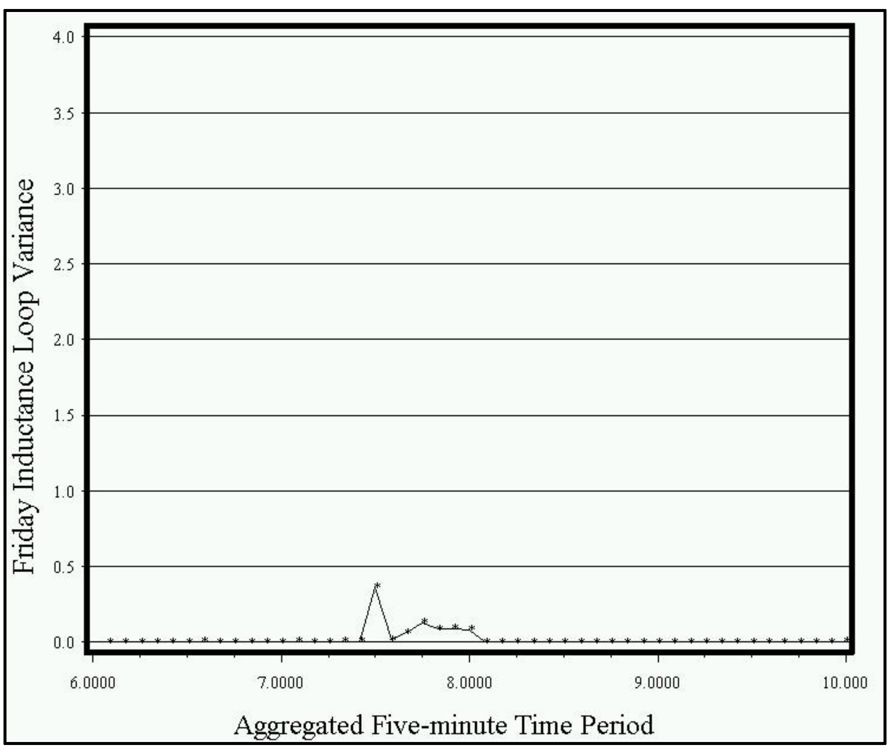

FIGURE C-38 Friday Inductance Loop Variance

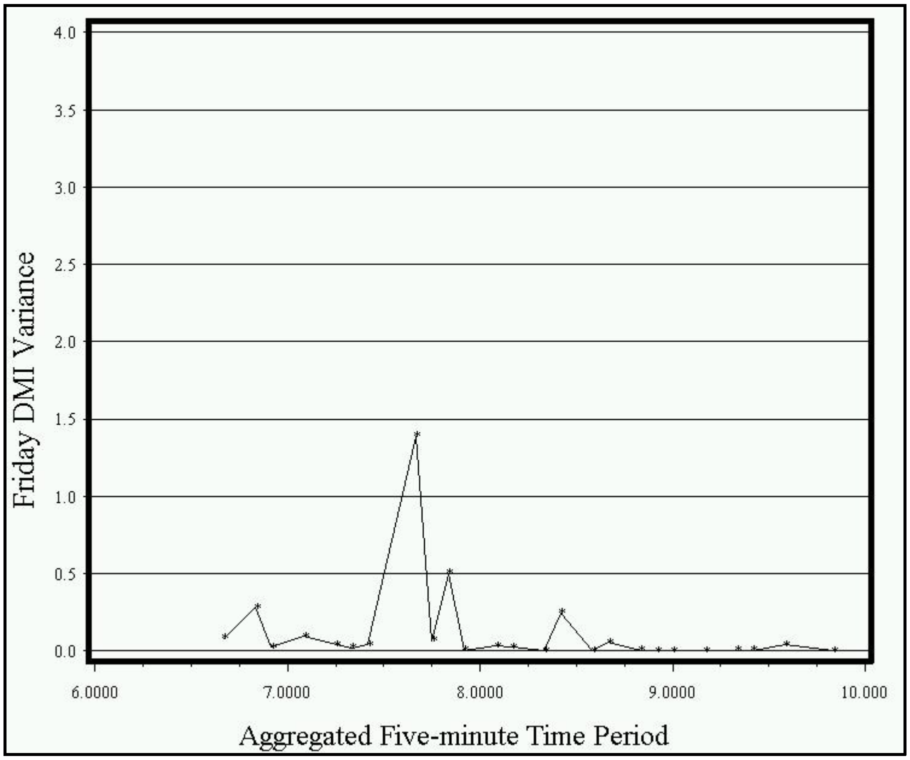

FIGURE C-39 Friday Test Vehicle Variance

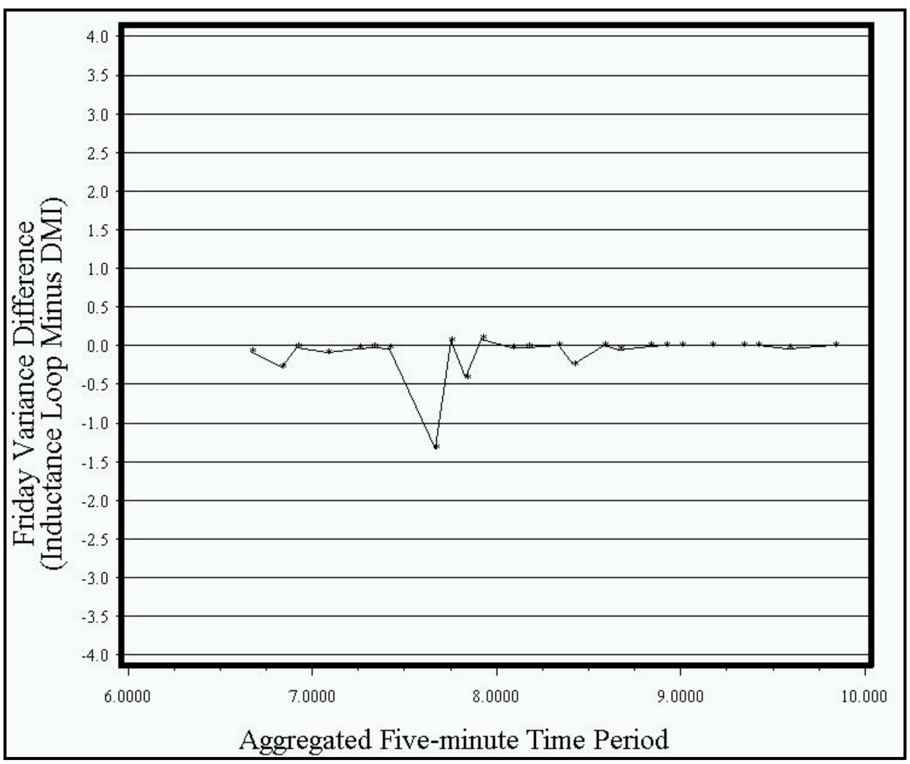

FIGURE C-40 Friday Variance Difference Between Inductance Loop and Test Vehicle

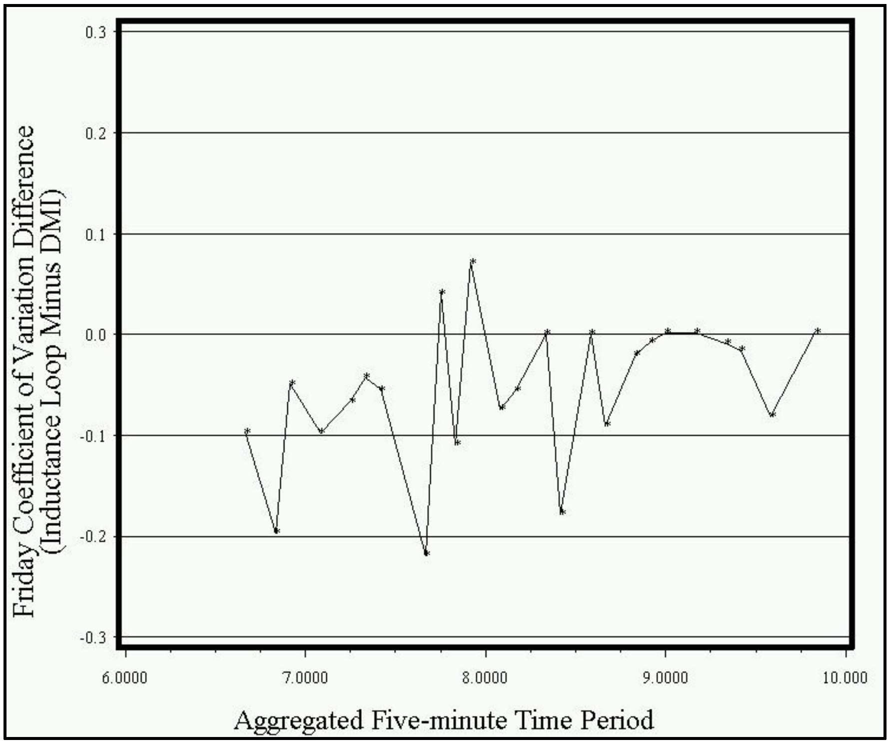

FIGURE C-41 Friday Coefficient of Variation Difference Between Inductance Loop and Test Vehicles

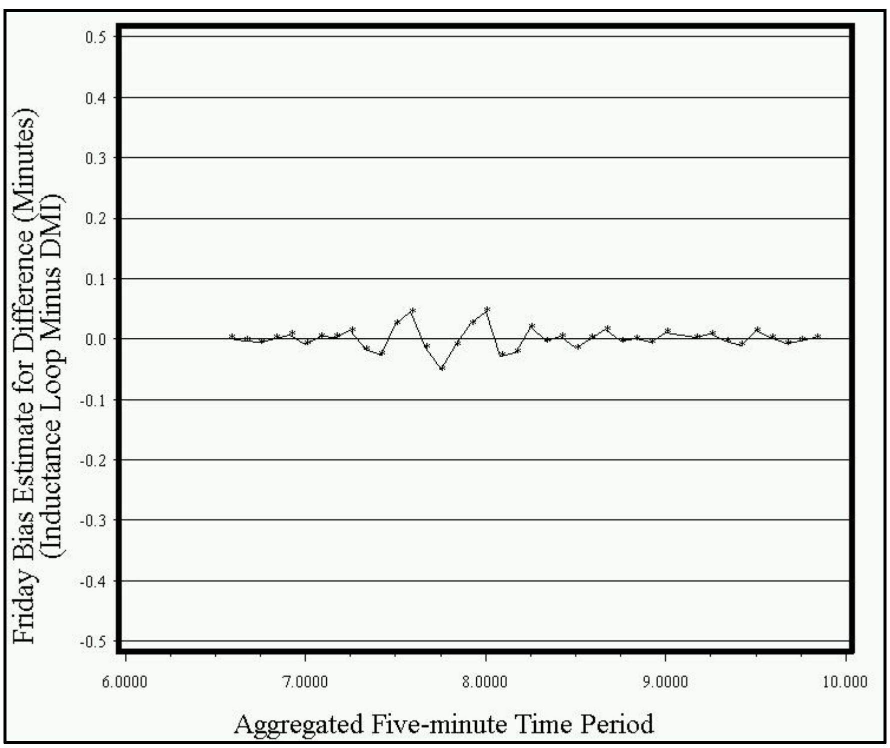

FIGURE C-42 Friday Bias Estimate for Differences Between Inductance Loop and Test Vehicles

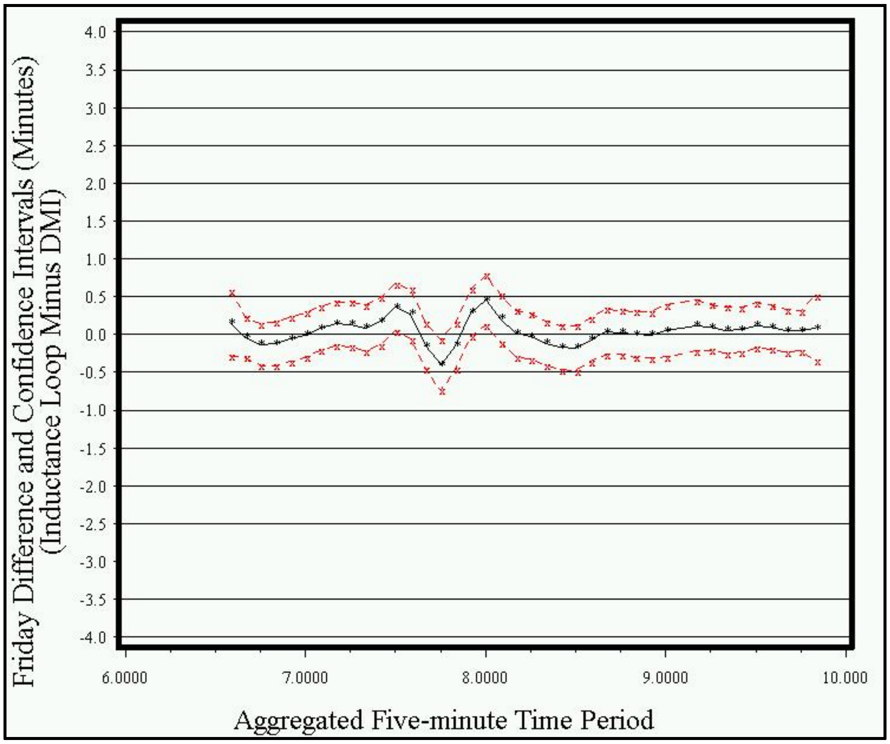

FIGURE C-43 Friday Difference Between Inductance Loop and Test Vehicle and Confidence Intervals Including Correction for Estimated Bias

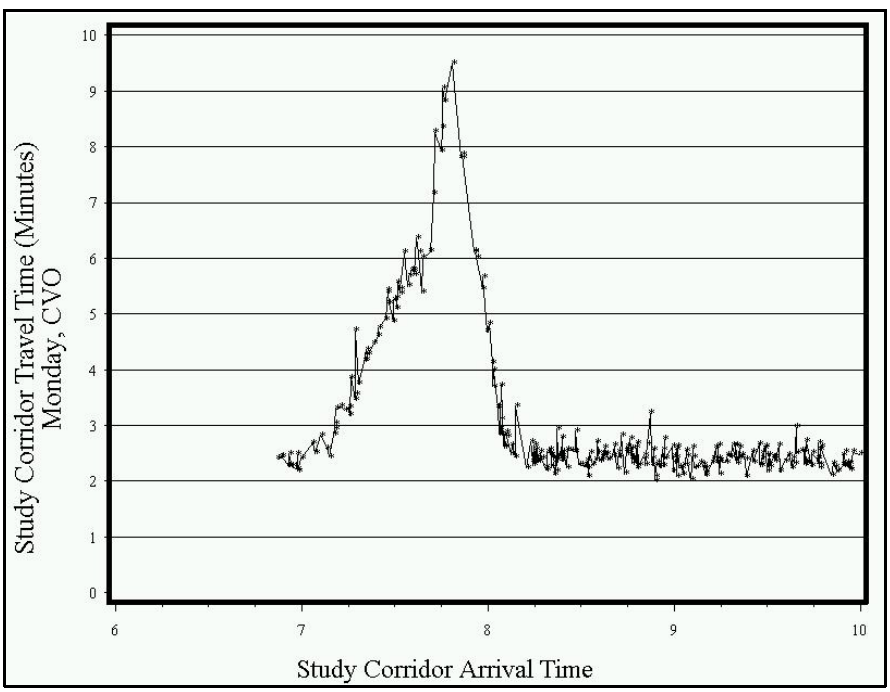

FIGURE C-44 Study Corridor Travel Time Estimate from CVO for Monday

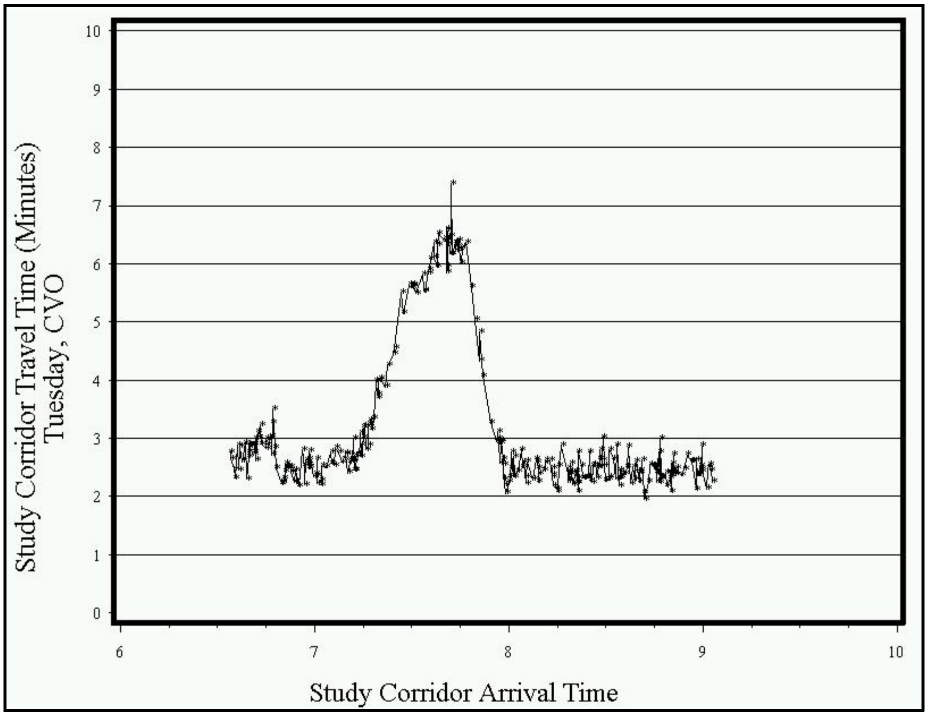

FIGURE C-45 Study Corridor Travel Time Estimate from CVO for Tuesday

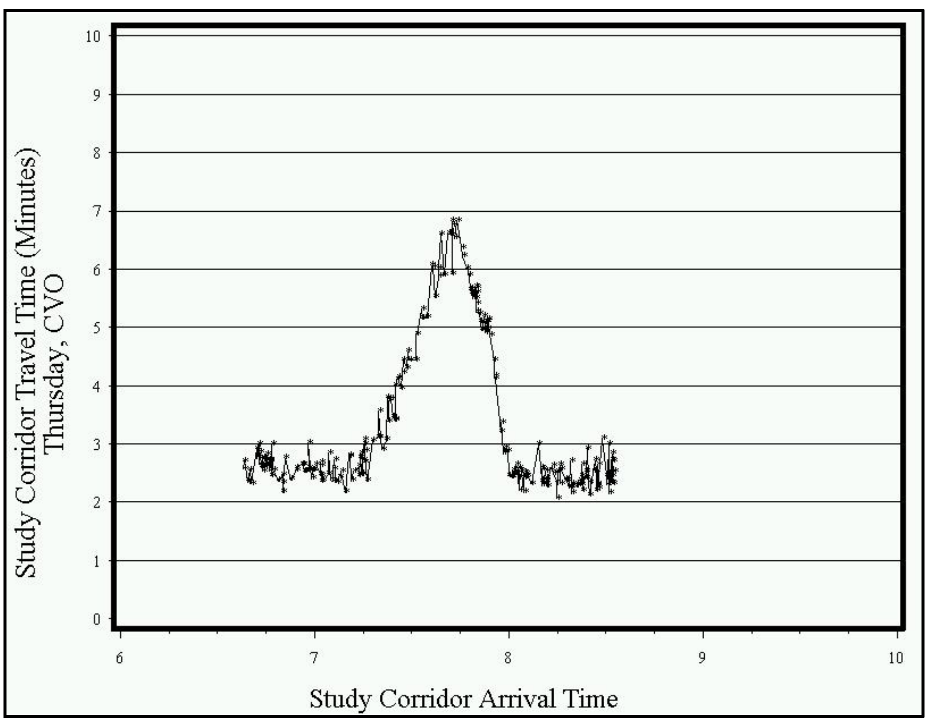

FIGURE C-46 Study Corridor Travel Time Estimate from CVO for Thursday

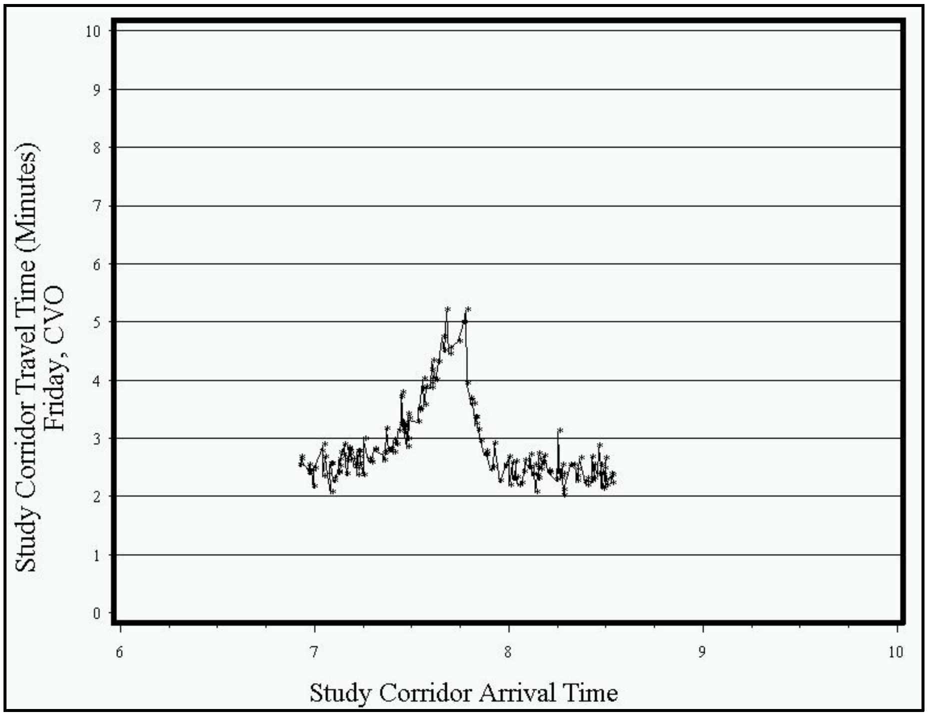

FIGURE C-47 Study Corridor Travel Time Estimate from CVO for Friday

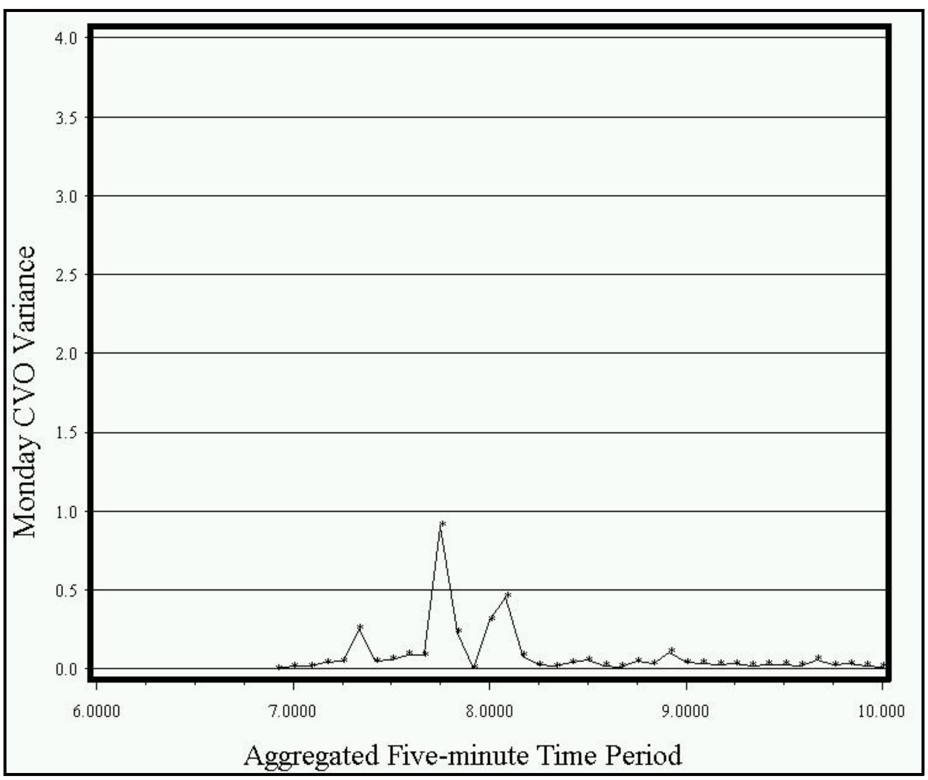

FIGURE C-48 Monday CVO Variance

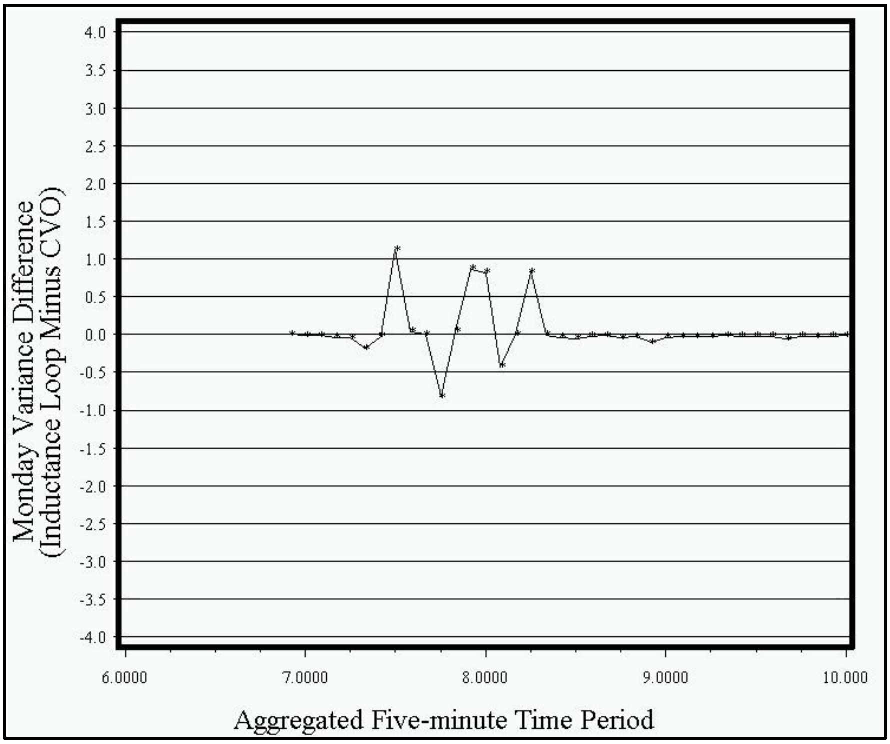

FIGURE C-49 Monday Variance Difference Between Inductance Loop and CVO

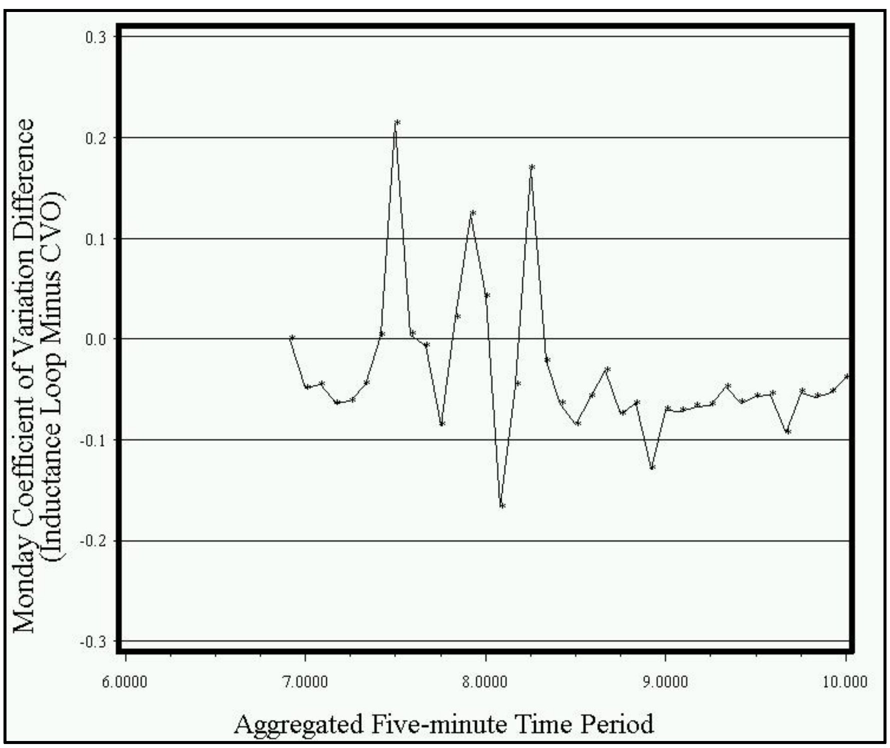

FIGURE C-50 Monday Coefficient of Variation Difference Between Inductance Loop and CVO

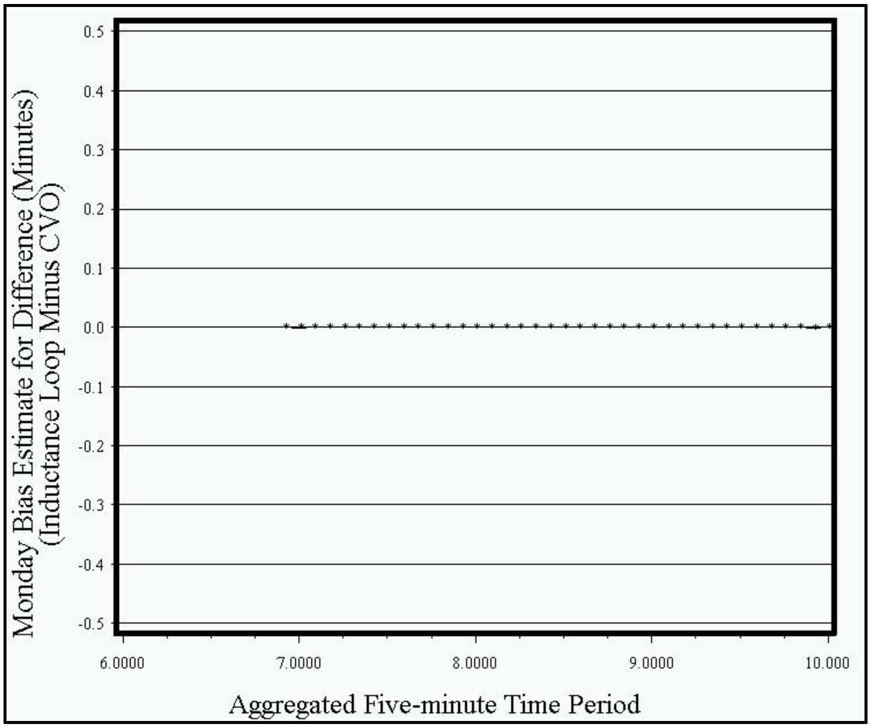

FIGURE C-51 Monday Bias Estimate for Differences Between Inductance Loop and CVO

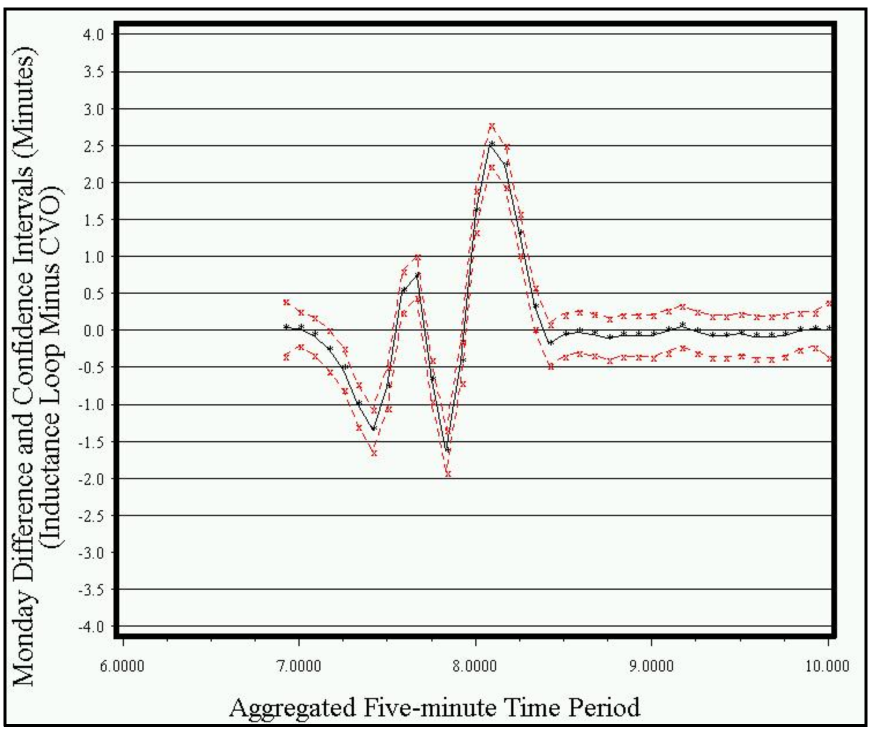

FIGURE C-52 Monday Difference Between Inductance Loop and CVO and Confidence Intervals Including Correction for Estimated Bias

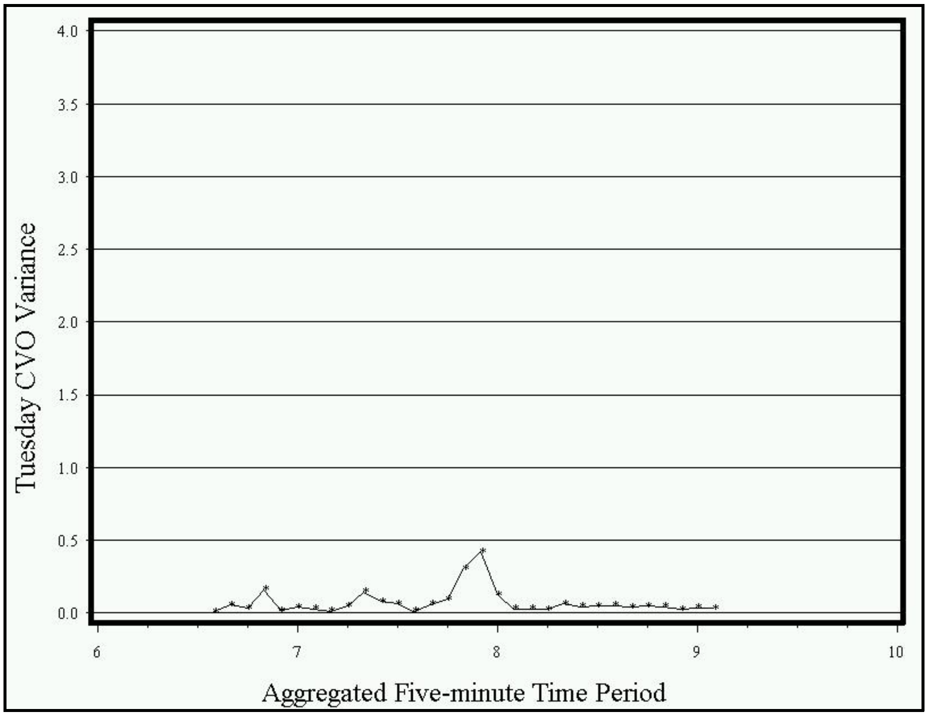

FIGURE C-53 Tuesday CVO Variance

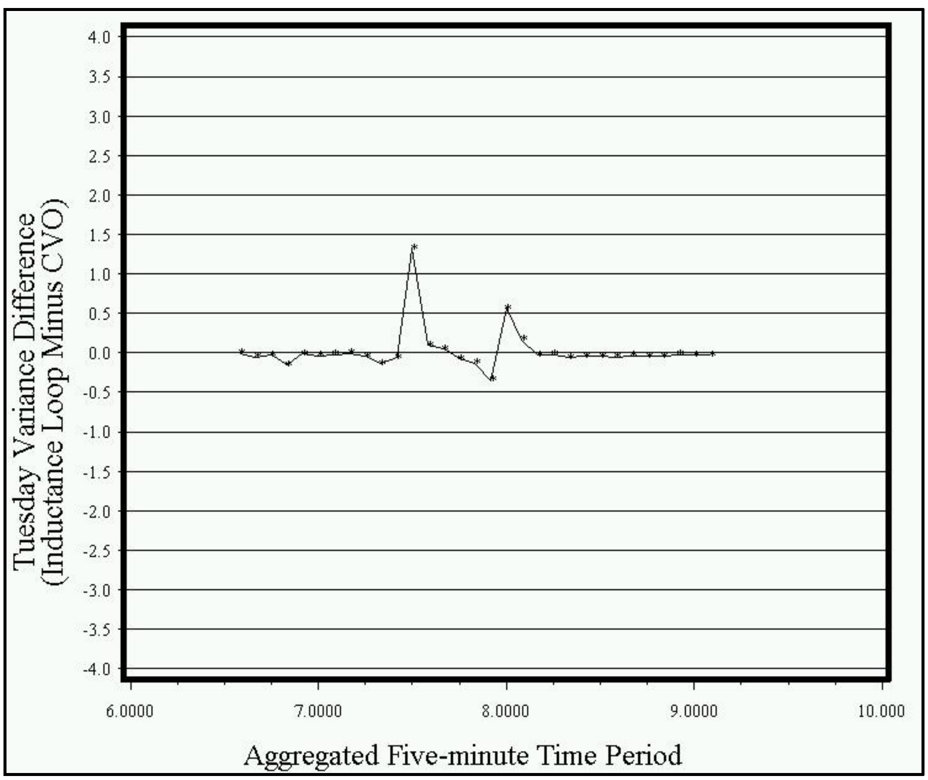

FIGURE C-54 Tuesday Variance Difference Between Inductance Loop and CVO

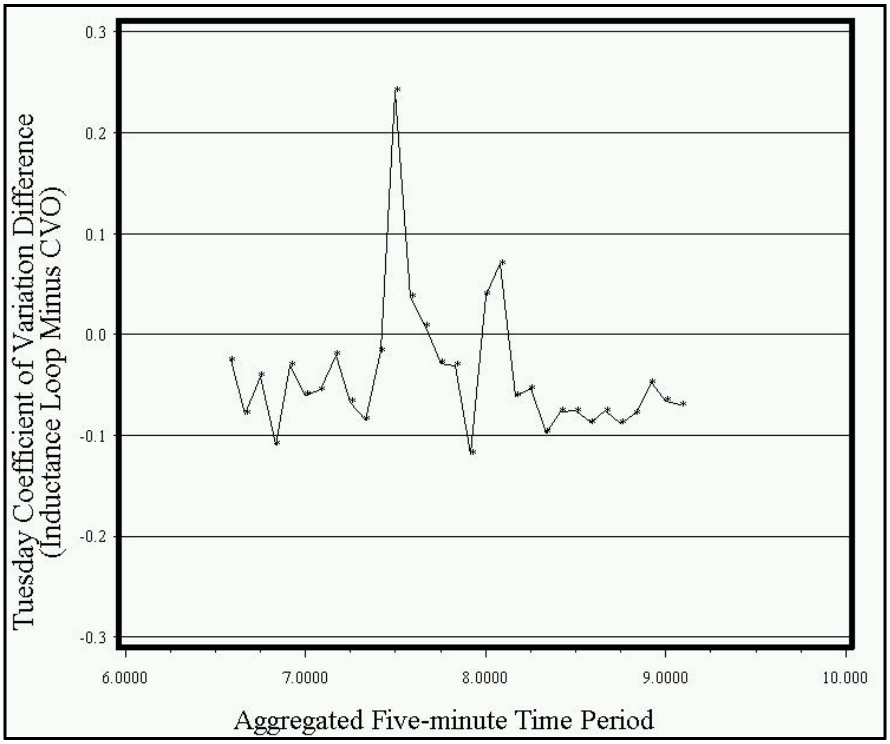

FIGURE C-55 Tuesday Coefficient of Variation Difference Between Inductance Loop and CVO

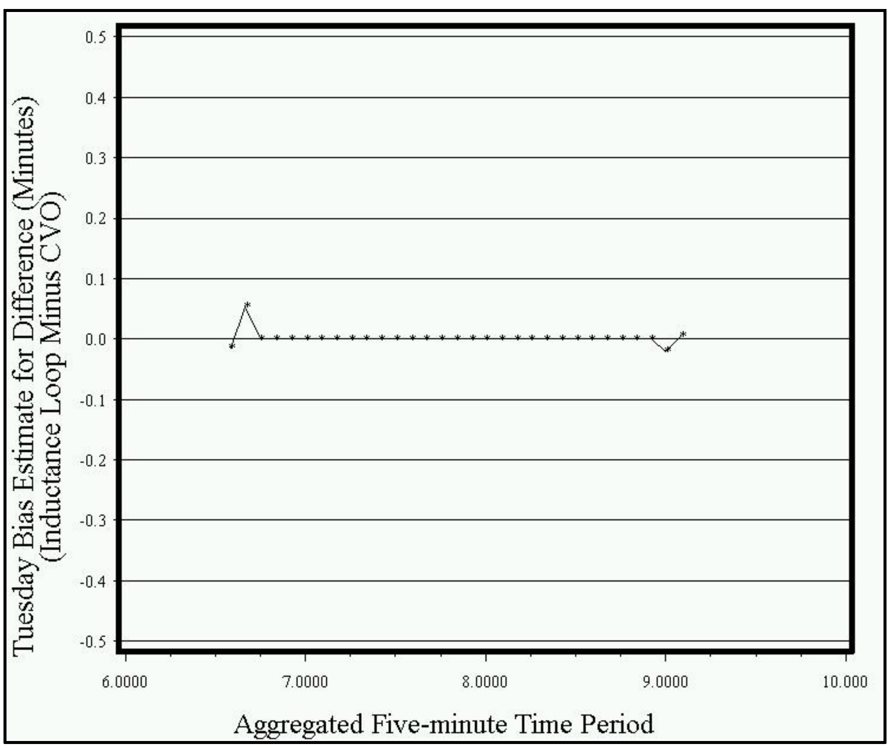

FIGURE C-56 Tuesday Bias Estimate for Differences Between Inductance Loop and CVO

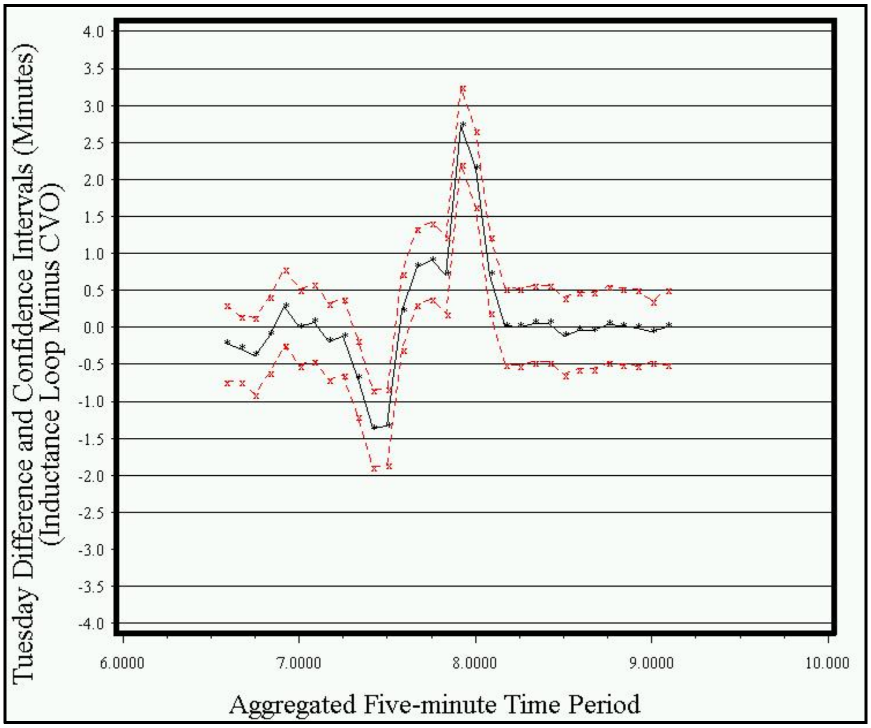

FIGURE C-57 Tuesday Difference Between Inductance Loop and CVO and Confidence Intervals Including Correction for Estimated Bias

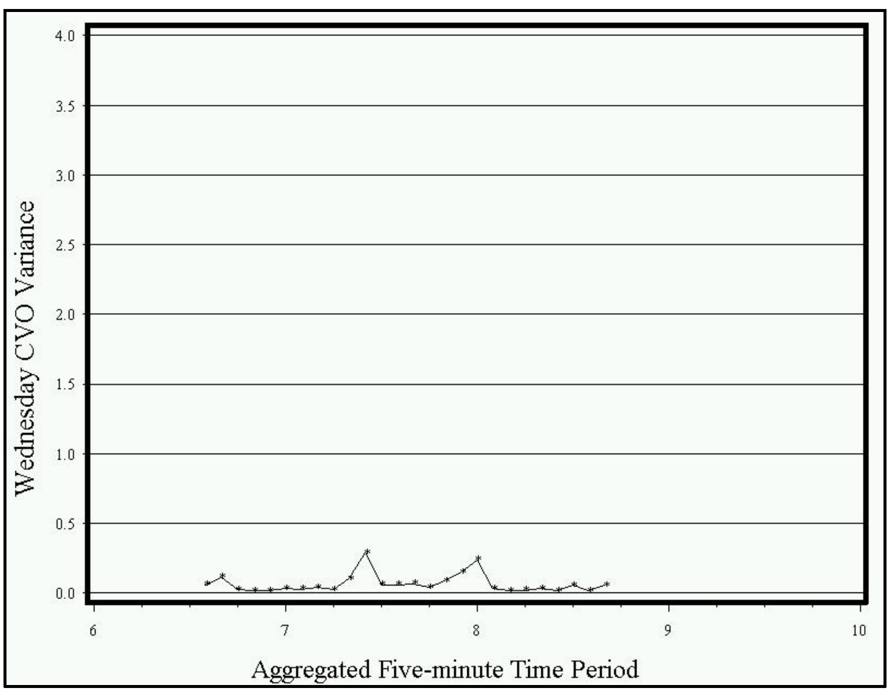

FIGURE C-58 Wednesday CVO Variance

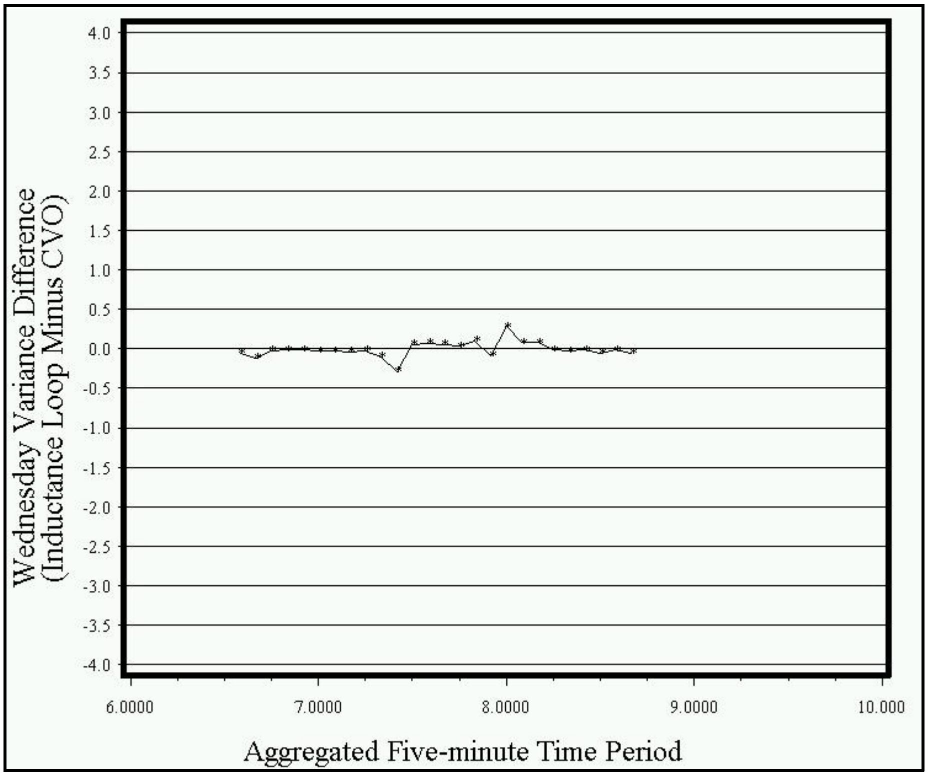

FIGURE C-59 Wednesday Variance Difference Between Inductance Loop and CVO

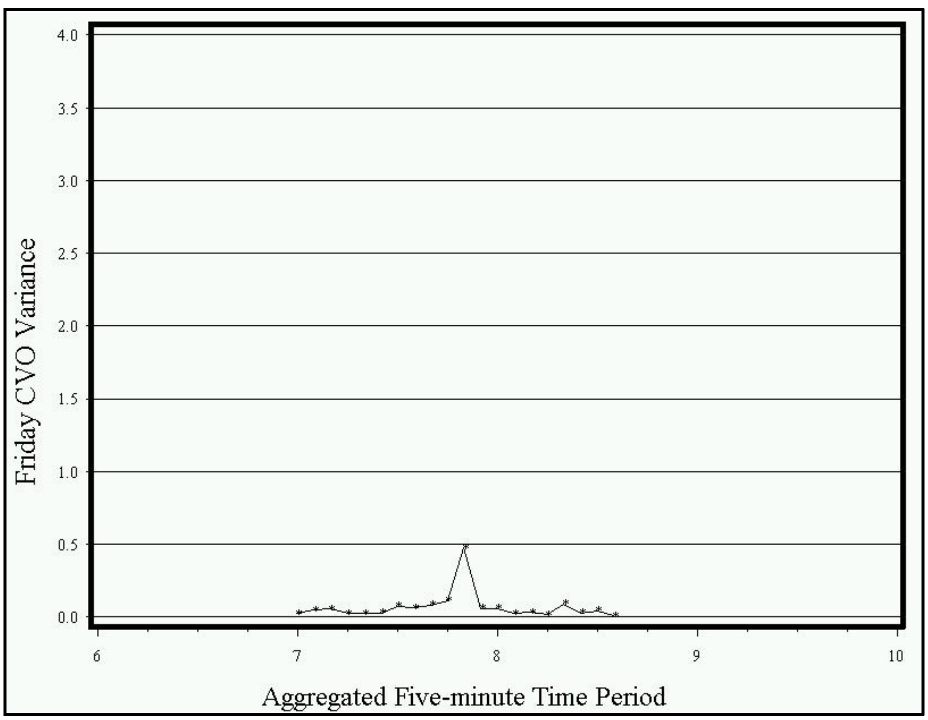

FIGURE C-60 Friday CVO Variance

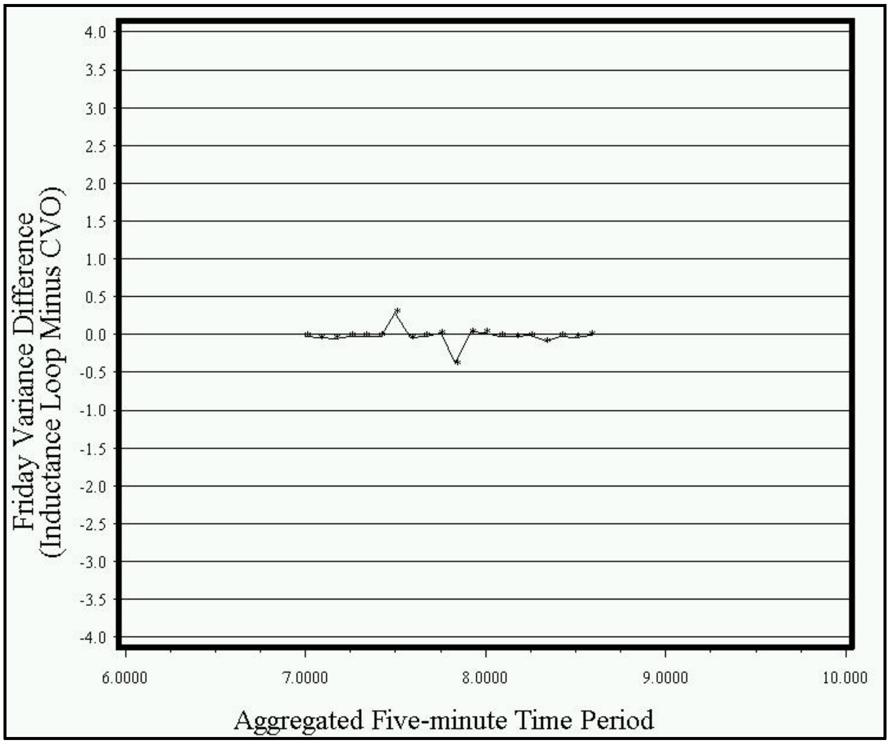

FIGURE C-61 Friday Variance Difference Between Inductance Loop and CVO

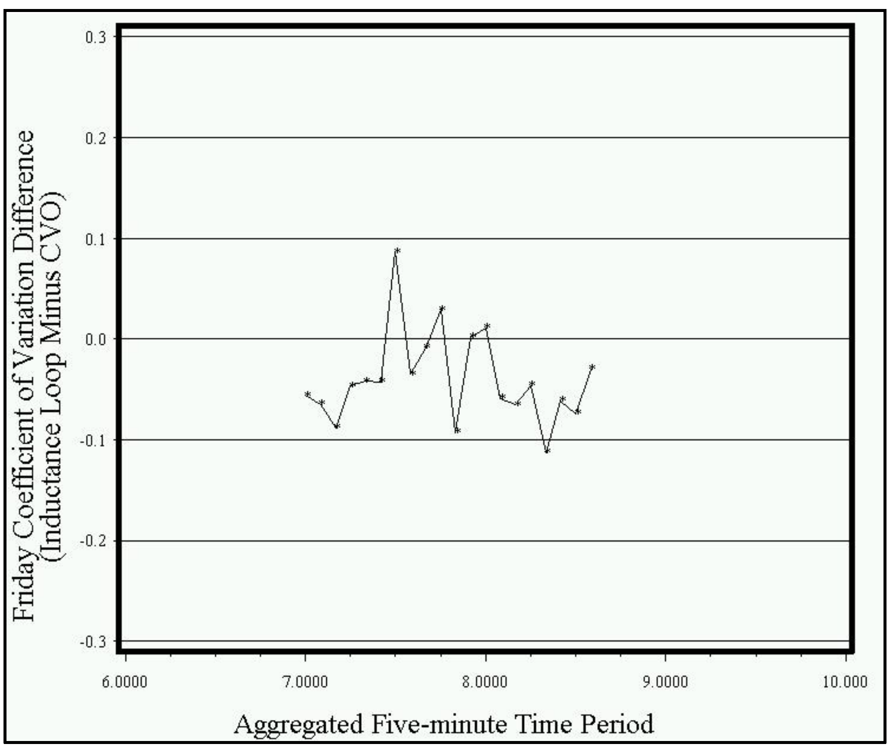

FIGURE C-62 Friday Coefficient of Variation Difference Between Inductance Loop and CVO

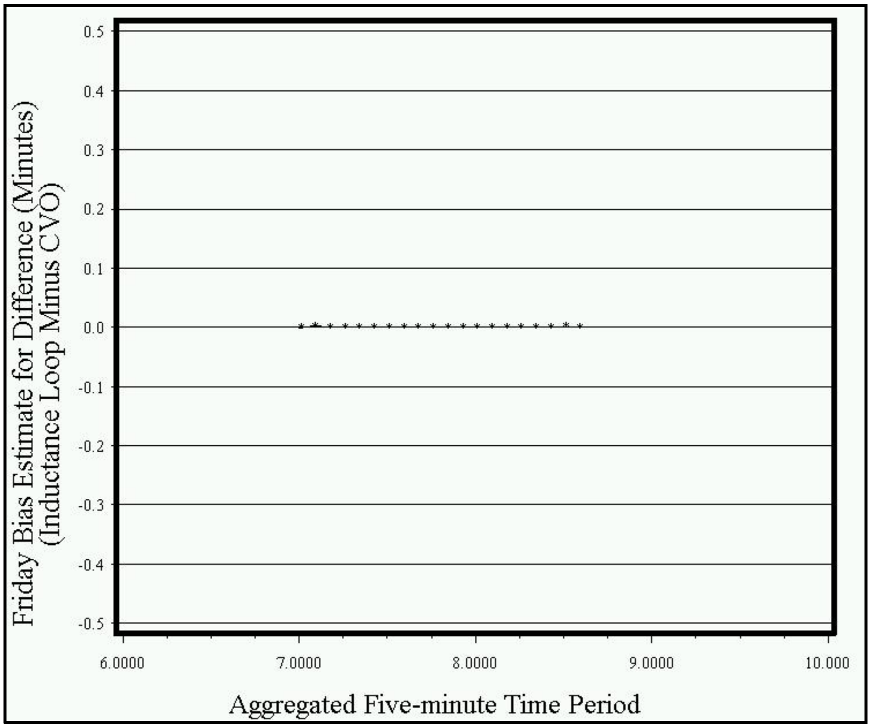

FIGURE C-63 Friday Bias Estimate for Differences Between Inductance Loop and CVO

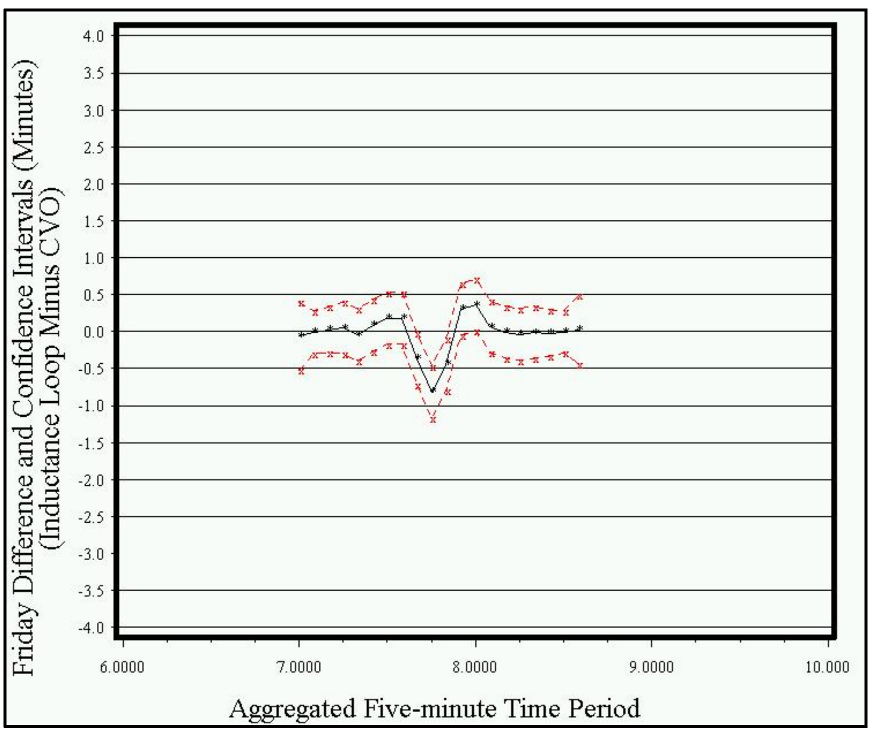

FIGURE C-64 Friday Difference Between Inductance Loop and CVO and Confidence Intervals Including Correction for Estimated Bias

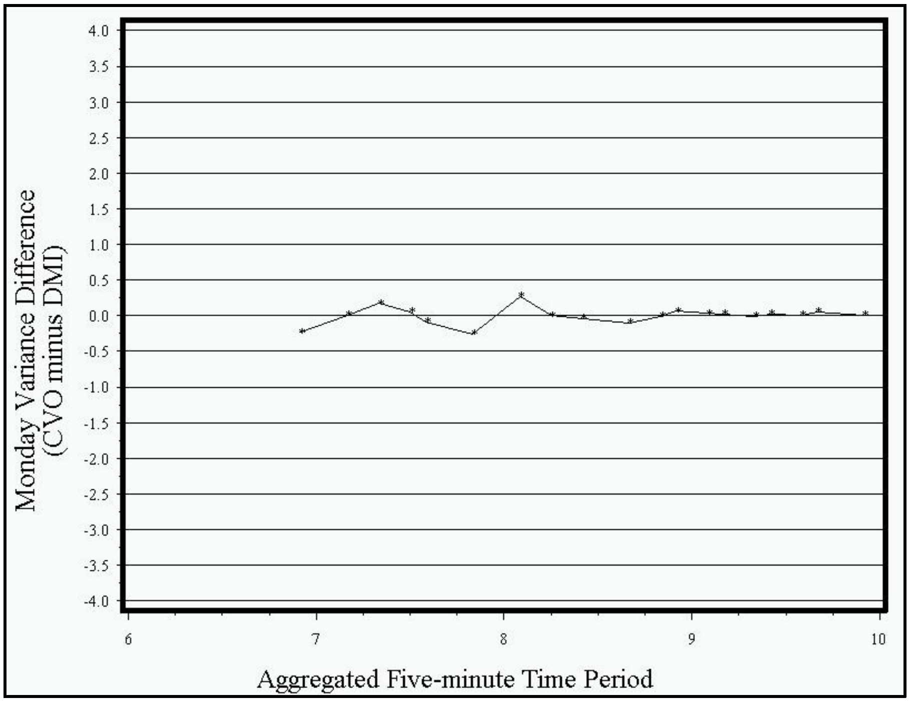

FIGURE C-65 Monday Variance Difference Between CVO and Test Vehicles

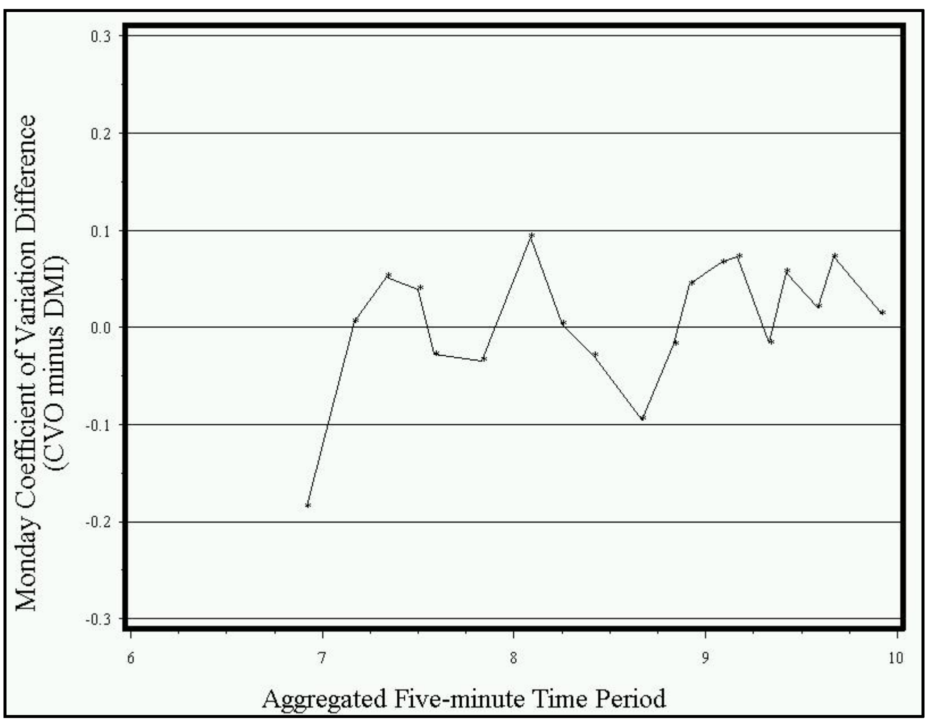

FIGURE C-66 Monday Coefficient of Variation Difference Between CVO and Test Vehicles

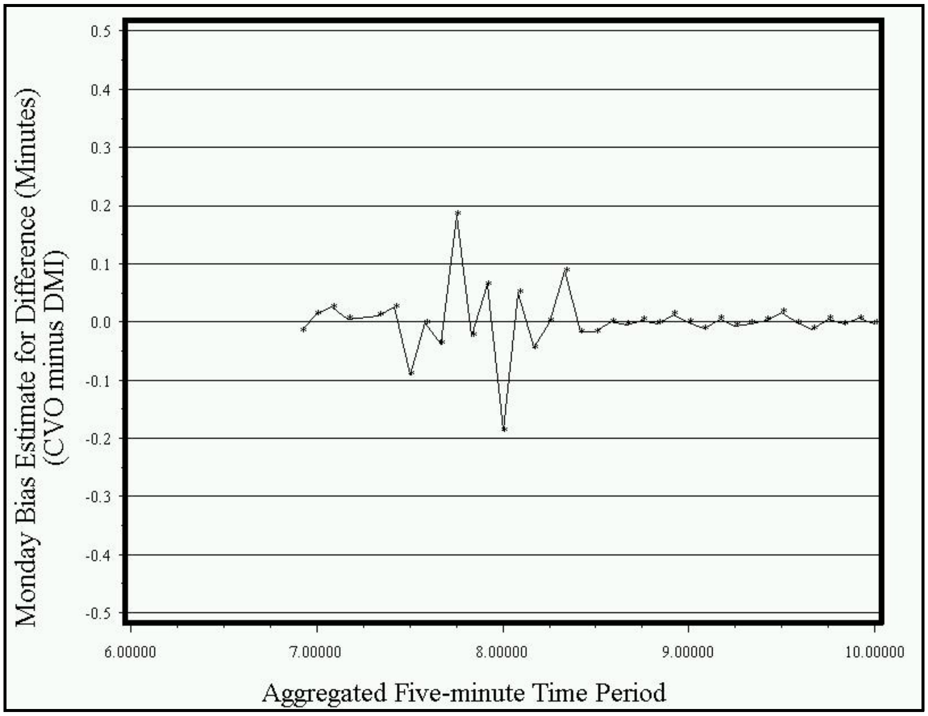

FIGURE C-67 Monday Bias Estimate for Differences Between CVO and Test Vehicles

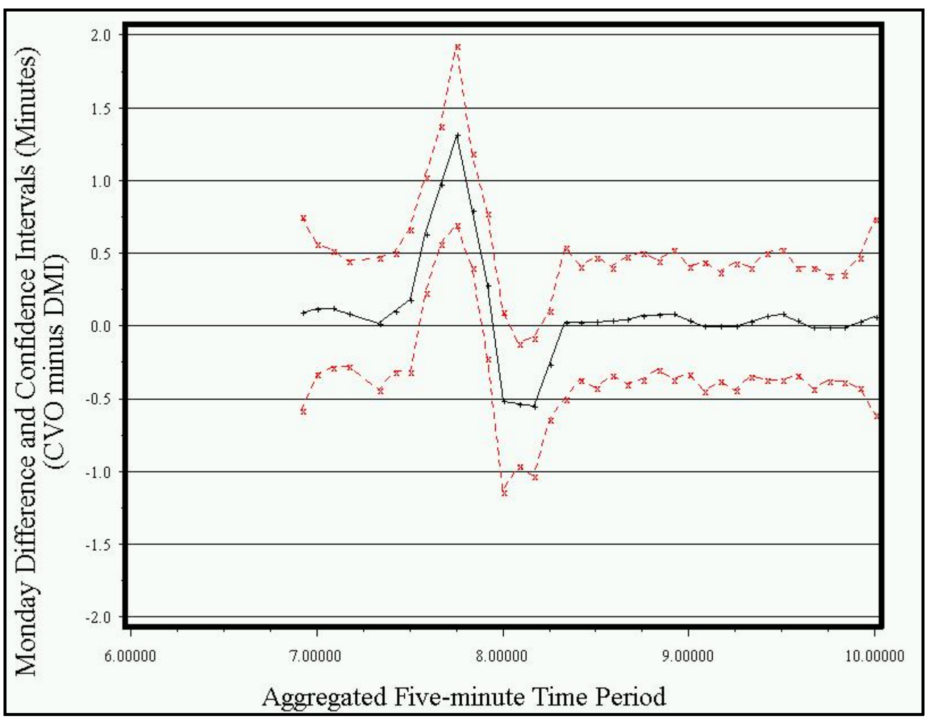

FIGURE C-68 Monday Difference Between CVO and Test Vehicles and Confidence Intervals Including Correction for Estimated Bias

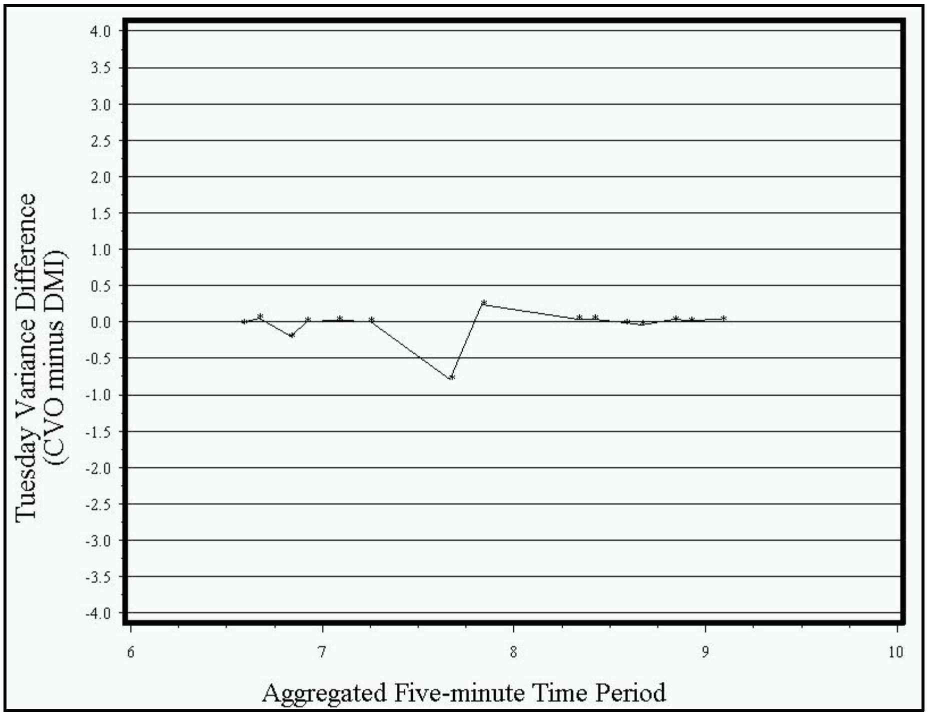

FIGURE C-69 Tuesday Variance Difference Between CVO and Test Vehicles

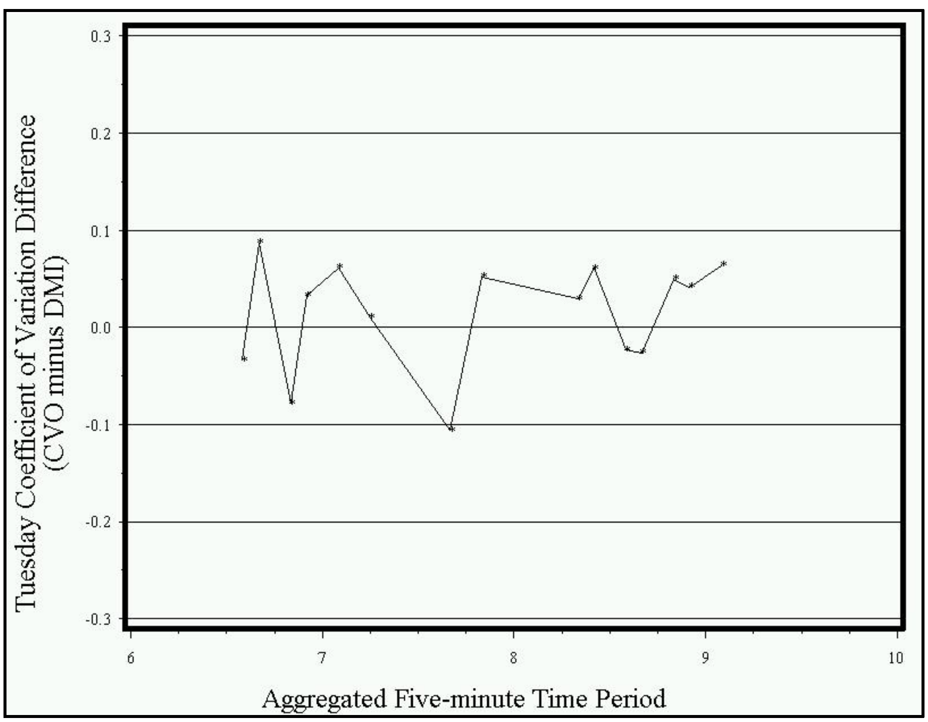

FIGURE C-70 Tuesday Coefficient of Variation Difference Between CVO and Test Vehicles

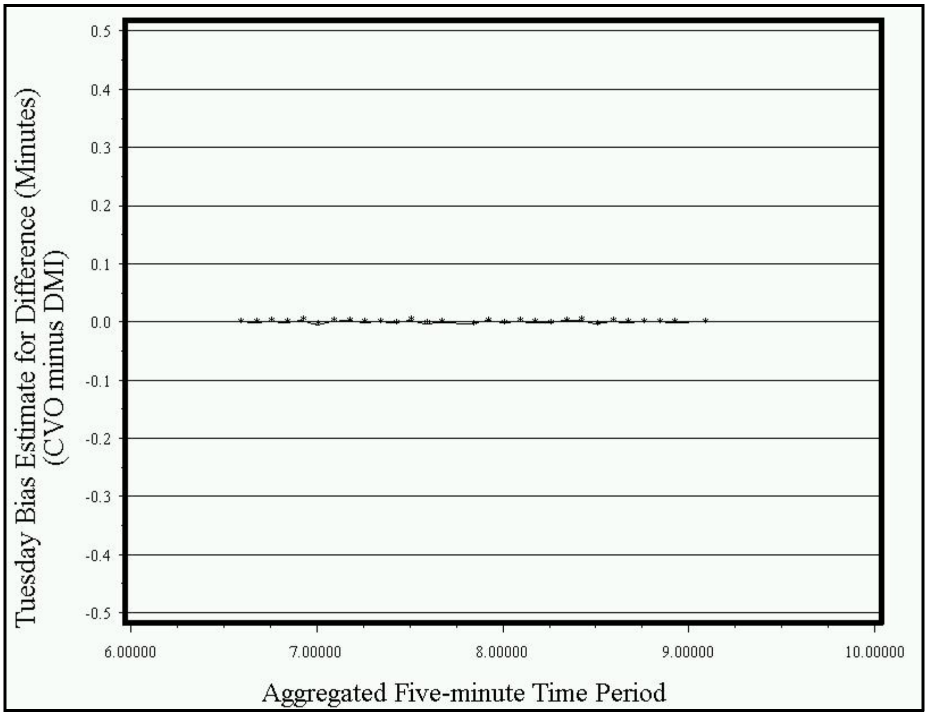

FIGURE C-71 Tuesday Bias Estimate for Differences Between CVO and Test Vehicles

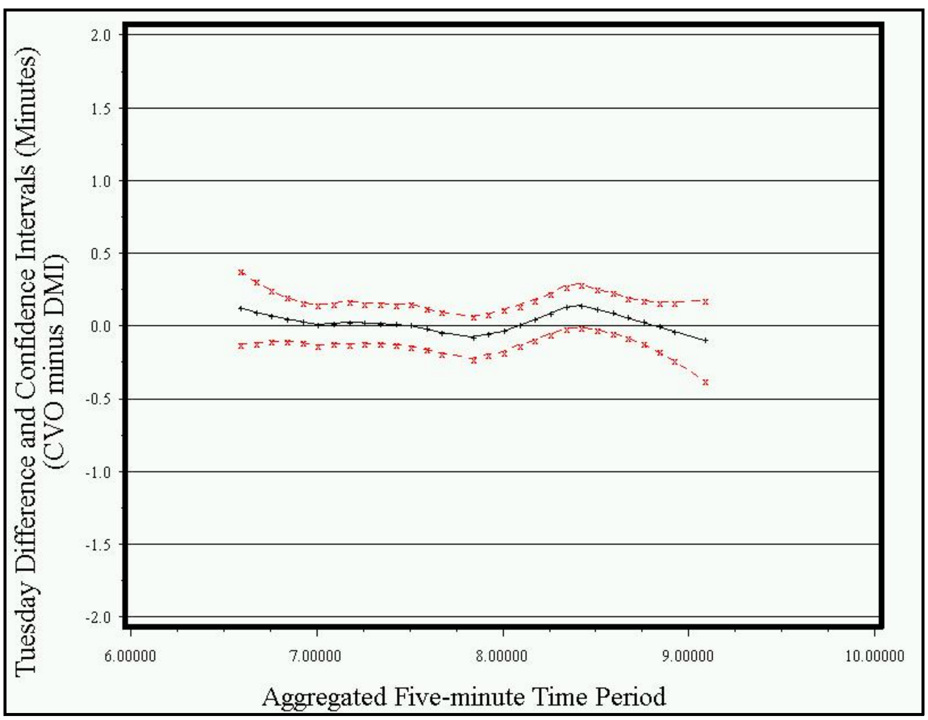

FIGURE C-72 Tuesday Difference Between CVO and Test Vehicles and Confidence Intervals Including Correction for Estimated Bias

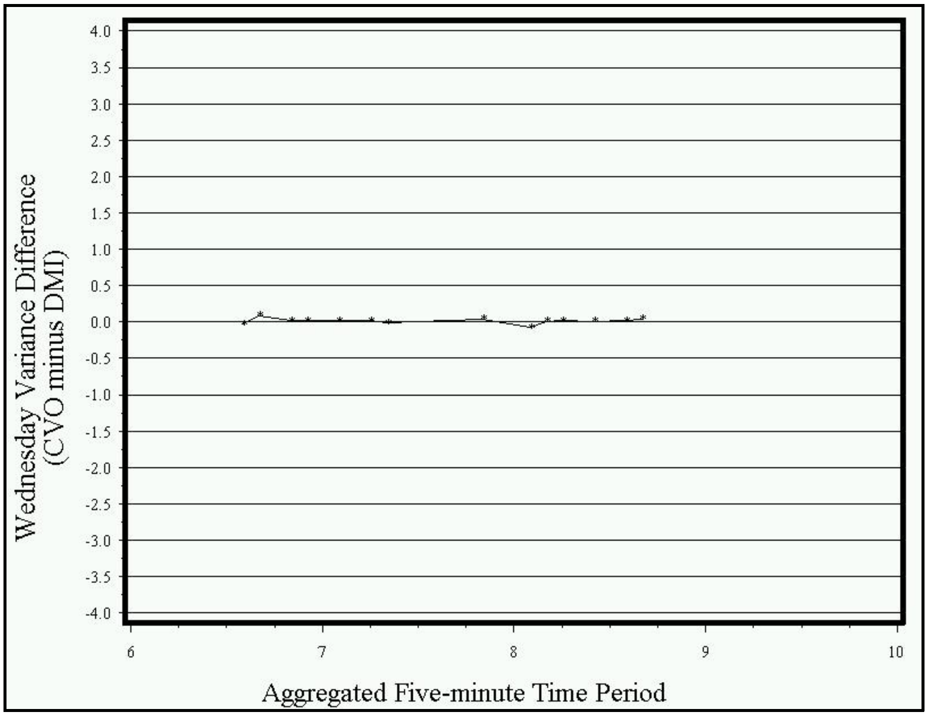

FIGURE C-73 Wednesday Variance Difference Between CVO and Test Vehicles

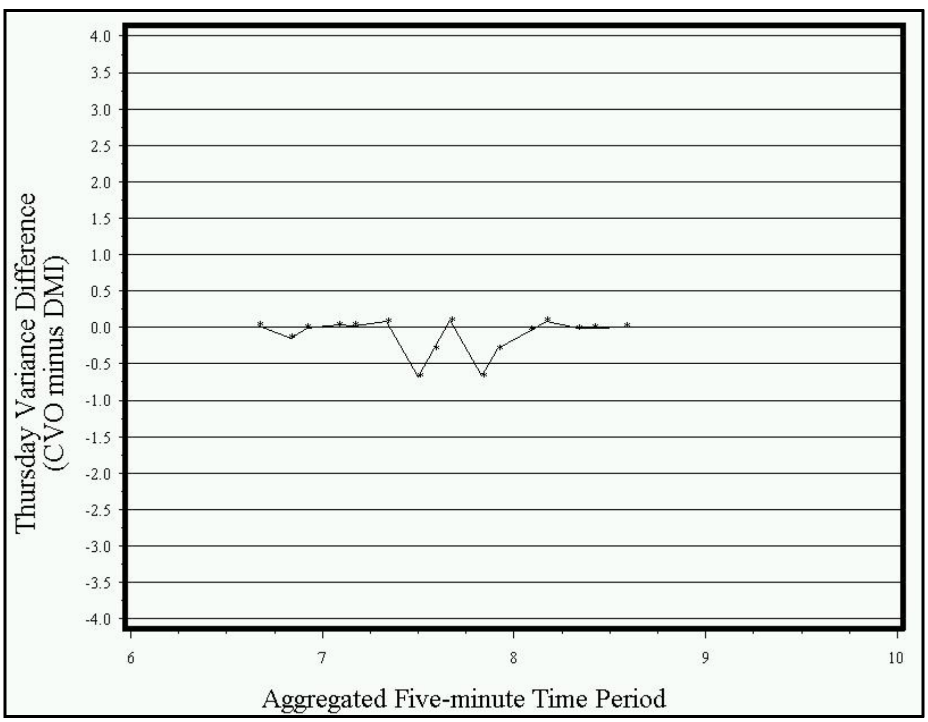

FIGURE C-74 Thursday Variance Difference Between CVO and Test Vehicles

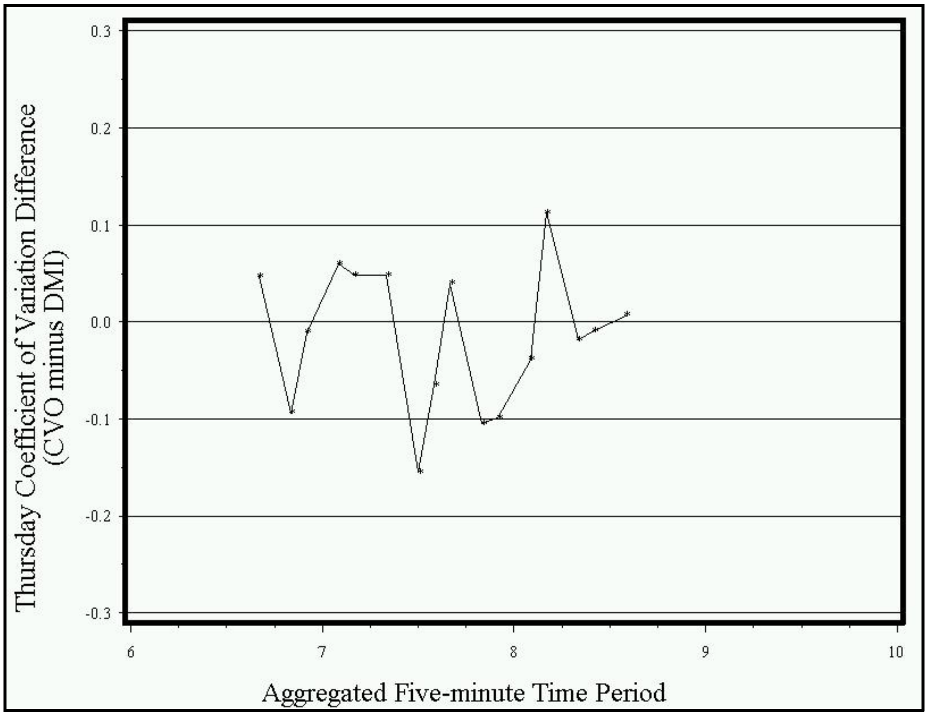

FIGURE C-75 Thursday Coefficient of Variation Difference Between CVO and Test Vehicles

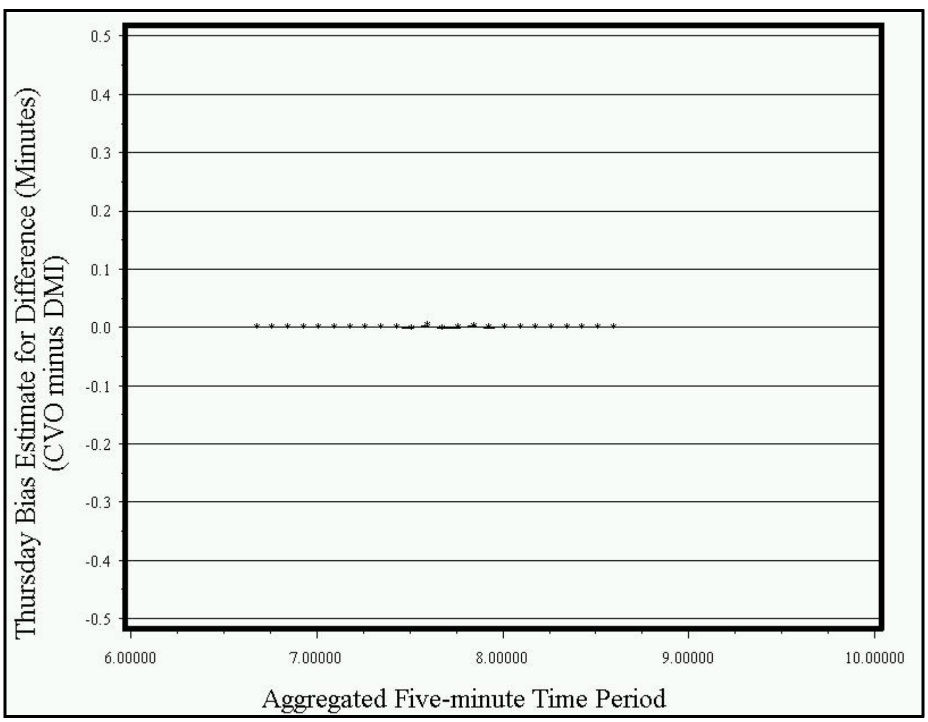

FIGURE C-76 Thursday Bias Estimate for Differences Between CVO and Test Vehicles

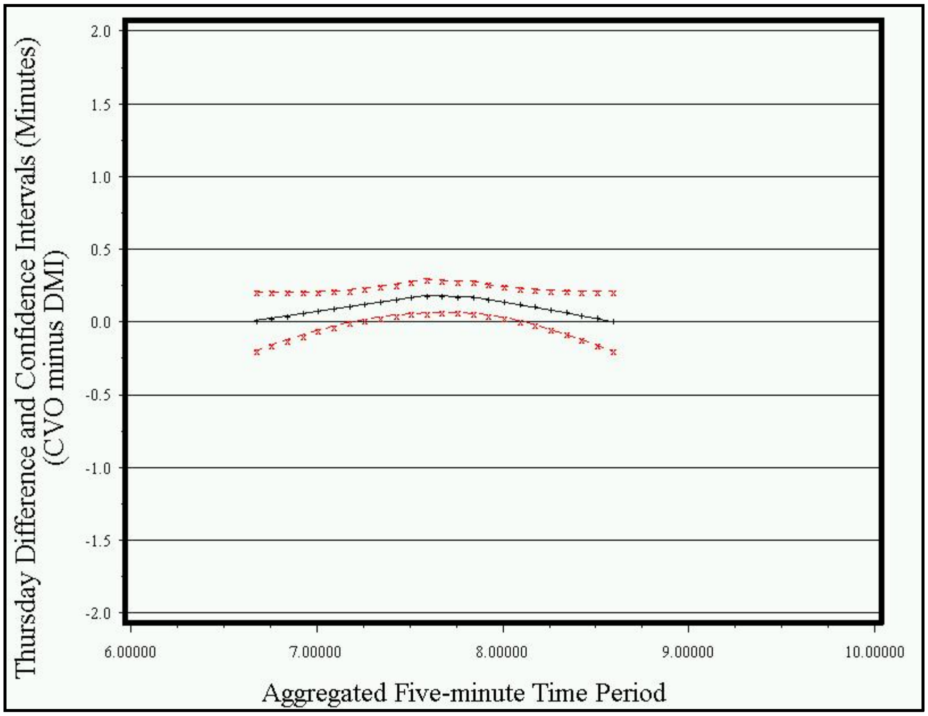

FIGURE C-77 Thursday Difference Between CVO and Test Vehicles and Confidence Intervals Including Correction for Estimated Bias

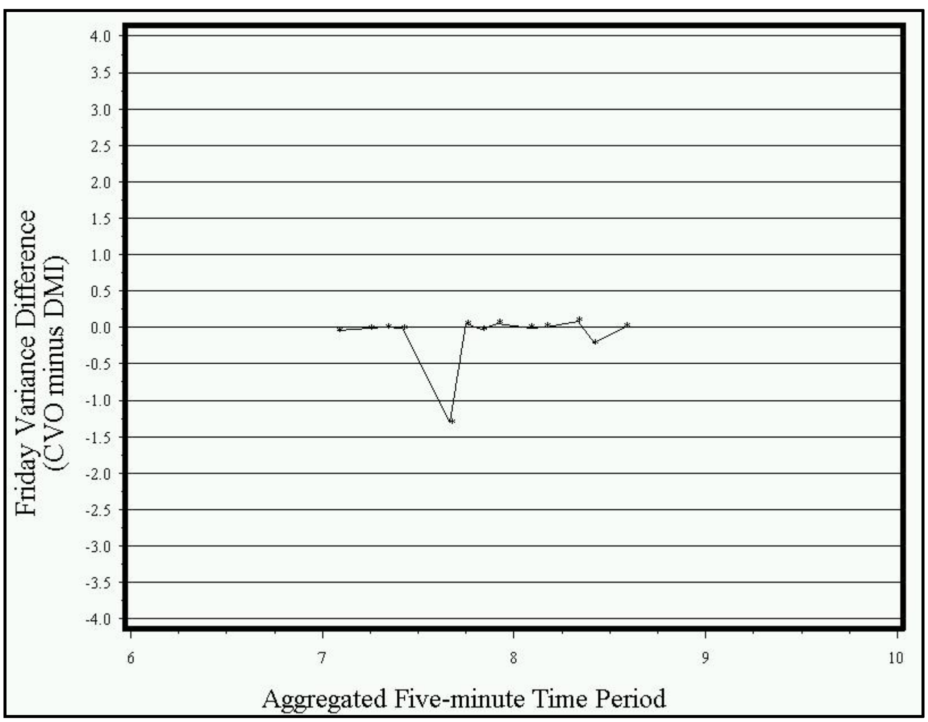

FIGURE C-78 Friday Variance Difference Between CVO and Test Vehicles

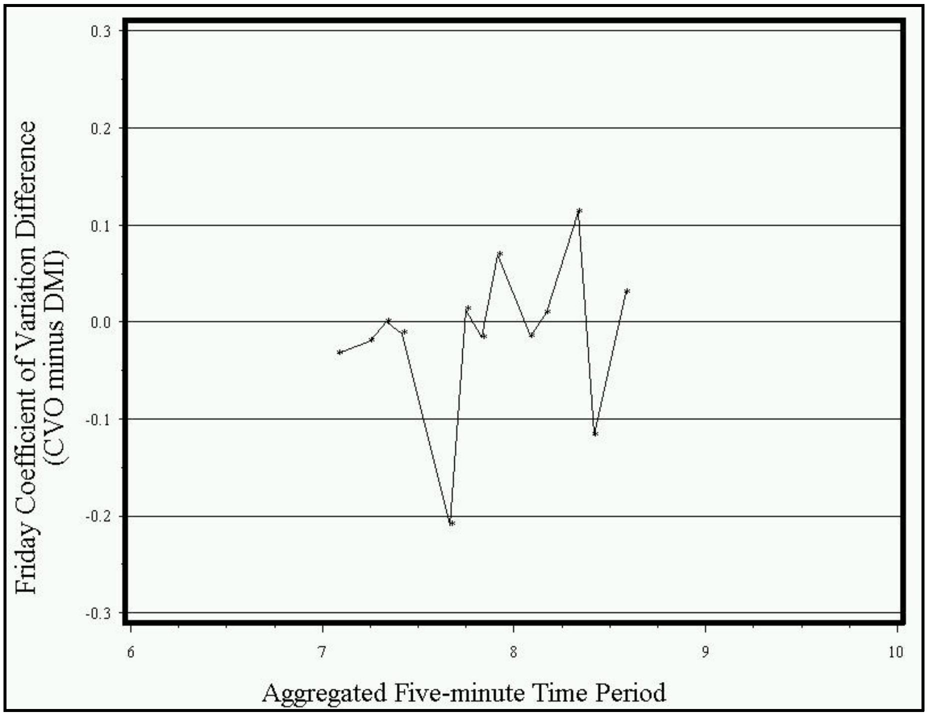

FIGURE C-79 Friday Coefficient of Variation Difference Between CVO and Test Vehicles

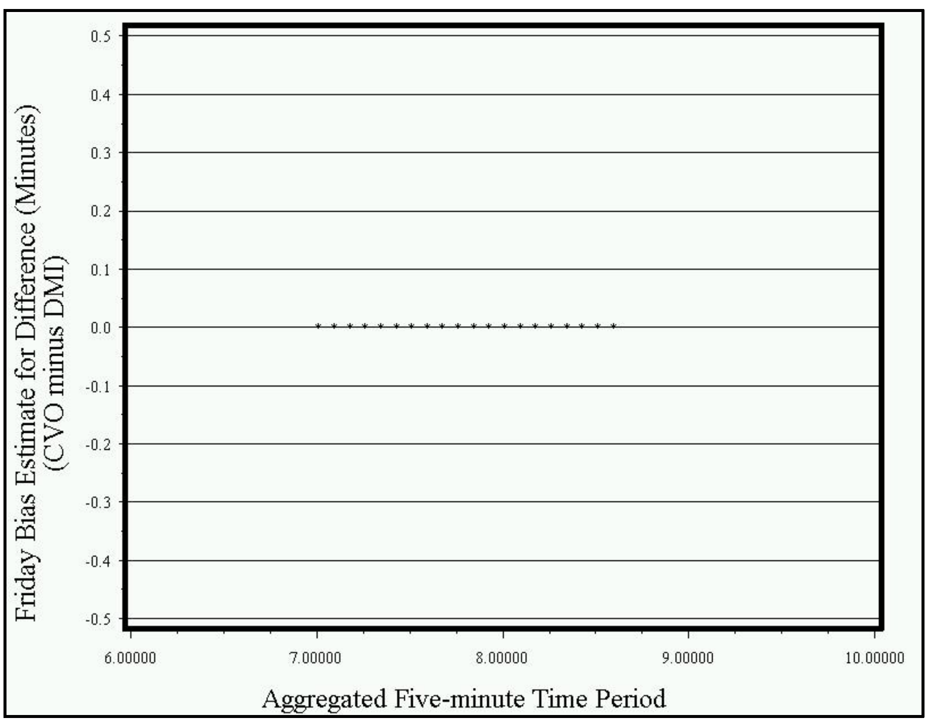

FIGURE C-80 Friday Bias Estimate for Differences Between CVO and Test Vehicles

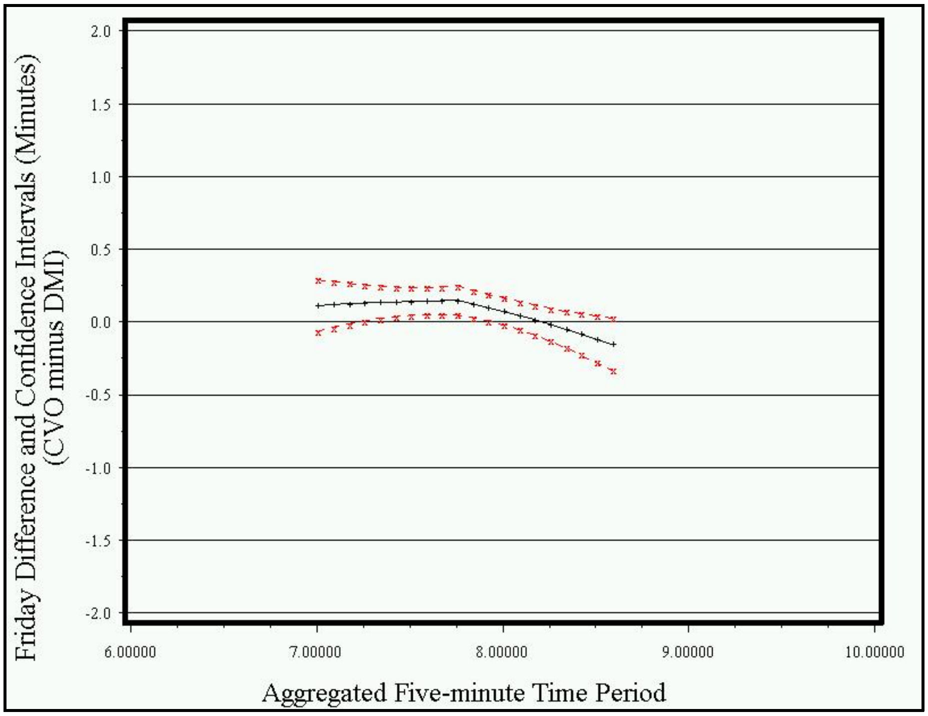

FIGURE C-81 Friday Difference Between CVO and Test Vehicles and Confidence Intervals Including Correction for Estimated Bias