# Traffic Data Quality Verification and Sensor Calibration for Weigh-In-Motion (WIM) Systems

**Final Report**

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Many state departments of transportation have been collecting various traffic data through the Automatic Traffic Recorder (ATR) and Weigh-in-Motion (WIM) systems as outlined in the Traffic Monitoring Guide (TMG) published by USDOT. A pooled fund study led by MnDOT was conducted in 2002 to determine traffic data editing procedures. It is challenging to identify potential problems associated with the collected data and ensure data quality. The WIM system itself presents difficulty in obtaining accurate data due to sensor characteristics, complex vehicle dynamics, and the pavement changes surrounding the sensor over time. To overcome these limitations, calibration procedures and other monitoring activities are essential to data reliability and accuracy. Current practice of WIM calibration procedures varies from organization to organization. This project aims to understand the characteristics of WIM measurements, identify different WIM operational modes, and develop mixture models for each operation period. Several statistical data analysis methodologies were explored to detect measurement drifts and support sensor calibration. A mixture modeling technique using Expectation Maximization (EM) algorithm and cumulative sum (CUSUM) methodologies were explored for data quality assurance. An adjusting CUSUM methodology was used to detect data anomaly. The results indicated that the adjusting CUSUM methodology was able to detect the sensor drifts. The CUSUM curves can trigger a potential drifting alert to the WIM manager. Further investigation was performed to compare the CUSUM deviation and the calibration adjustment. However, the analysis results did not indicate any relationship between the computed CUSUM deviation and the calibration adjustment.

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- Sushanth Kumar, a computer science graduate student, for his support on Weigh-In-Motion (WIM) data analysis.
- Benjamin Timerson and Mark Novak, Minnesota Department of Transportation (MnDOT), for providing WIM data and support.
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| | |
|---|---|
| AADT | Annual Average Daily Traffic |
| AADTT | Annual Average Daily Truck Traffic |
| AASHTO | American Association of State Highway and Transportation Officials |
| ARL | Average Run Length |
| ASTM | American Society for Testing and Materials |
| ATR | Automatic Traffic Recorder |
| CDF | Cumulative Distribution Function |
| CI | Confidence Interval |
| CTS | Center for Transportation Studies |
| CUSUM | Cumulative Sum |
| DI | Decision Interval |
| EM | Expectation Maximization |
| ESAL | Equivalent Single Axle Load |
| FHWA | Federal Highway Administration |
| ft | Feet |
| FXS | Front Axle Spacing |
| FXW | Front Axle Weight |
| GIS | Geographic Information System |
| GPS | Global Positioning System |
| GUI | Graphical Users Interface |
| GVW | Gross Vehicle Weight |
| IRD | International Road Dynamics, Inc. |
| ITS | Intelligent Transportation Systems |
| kips | kilo pound, a non-SI unit of force (1,000 pounds-force) |
| LTPP | Long Term Pavement Performance |
| MATLAB | Matrix Laboratory, Product of MathWorks, Inc. |
| MnDOT | Minnesota Depart of Transportation |
| MTO | Minnesota Traffic Observatory |
| MUTCD | Manual on Uniform Traffic Control Devices |

| | |
|---|---|
| NCHRP | National Cooperative Highway Research Program |
| RITA | Research & Innovative Technology Administration |
| SD | Standard Deviation |
| sec | Second |
| SPC | Statistical Process Control |
| SXW | Steering Axle Weight |
| TMAS | Travel Monitoring Analysis System |
| TMG | Traffic Monitoring Guide |
| UMN | University of Minnesota |
| USDOT | U.S. Department of Transportation |
| VC | Vehicle Class |
| VTRIS | Vehicle Travel Information System |
| WIM | Weigh-In-Motion |

# EXECUTIVE SUMMARY

As stated in the Federal Highway Administration (FHWA) Traffic Monitoring Guide (TMG) supplement in 2008, travel monitoring data should be submitted to the FHWA via the Travel Monitoring Analysis System (TMAS). TMAS includes the monthly volume data for traffic volume trends and will include vehicle classification and truck weight data that in the past were processed with the Vehicle Travel Information System (VTRIS). Many State Departments of Transportation (DOT) have been collecting various traffic data through the Automatic Traffic Recorder (ATR) and Weigh-in-Motion (WIM) systems. With the significant amount of data being collected on a daily basis, it requires substantial amount of effort to verify data and ensure data quality. It is challenging to identify potential problems associated with the collected data and sensor errors. A pooled fund study led by Minnesota Department of Transportation (MnDOT) was conducted in 2002 to determine traffic data quality and editing procedures.

The WIM system itself presents difficulty in obtaining accurate data due to sensor characteristics, complex vehicle dynamics, and the pavement changes surrounding the sensor over time. WIM sensor is sensitive to vehicle speed, weather, and smoothness of payment. WIM data biases, drifting over time, and seasonal effects have made the calibration process more challenging. To overcome these limitations, calibration procedures and other monitoring activities are essential to data reliability and accuracy. Current practice of WIM sensor calibration procedures varies from organization to organization. MnDOT uses a fully loaded test truck (typically around 80 kips) to calibrate WIM sensors at least twice a year.

Due to the WIM sensor characteristic that it tends to drift over time by various factors, there is a need to develop statistically quality control methodology to alert the WIM system operator or manager when the health of WIM sensors begin to deteriorate. This research aims to understand the characteristics of WIM measurements, identify different WIM operational modes, and develop mixture models for each operation period. This study explores several statistical data analysis methodologies to detect WIM sensor drifts and support WIM calibration. A mixture modeling technique using Expectation Maximization (EM) algorithm was used to divide the vehicle class 9 Gross Vehicle Weight (GVW) into three normally distributed components, i.e., unloaded, partially loaded, and fully loaded trucks. In addition to the GVW for vehicle class 9, steering axle weight for vehicle class 2, 3, and 9 were also analyzed to examine potential trend of data drifting by comparing the historical variations with calibration dates. The objective is to monitor the health of WIM systems though multiple measures to effectively determine if a calibration is needed.

Many WIM performance monitoring methodologies and calibration procedures were proposed for vehicle class 9 five-axle tractor-semitrailers. Formal monitoring using statistical quality control is needed to assure data quality and support decision making in determining when calibration is needed.

Cumulative sum (CUSUM) chart is a commonly used quality control method to detect deviations from benchmark values. The CUSUM methodologies were explored to detect potential drifts of WIM systems. An adjusting CUSUM methodology was used to detect anomaly. The adjusting CUSUM curve was reset back to zero whenever a WIM calibration was performed. Decision Interval (DI) and allowance reference of adjusting CUSUM were also implemented to detect a process shift in mean that changes from general horizontal motion to a non horizontal linear drift. A known period of WIM data set with no sensor drifts was used to develope the corresponding reference allowance (k) and DI (h) for anomaly detection.

The results indicated that the adjusting CUSUM methodology was able to detect the sensor drifts prior to the actual calibration. The CUSUM curves can trigger an alert to the WIM manager or operator that the WIM sensor may drift further from normal operation if the CUSUM curves do not fall back inside the DI band within a time period (1-2 weeks). Further investigation was performed to compare the CUSUM deviation and the calibration adjustment and to study possible relationship. However, the analysis results did not indicate any relationship between the derived CUSUM deviation and the calibration adjustment.

# 1. INTRODUCTION

## 1.1 Background

One of the key tasks for the traffic data analyst is to monitor WIM sensor output, maintain its accuracy, and conduct calibration when needed. The Traffic Monitoring Guide (TMG), published by USDOT 2001, provides information and guidance to state and local agencies on data collection methodologies. According to the guide, Minnesota Department of Transportation (MnDOT) and other state DOTs have installed several Automated Traffic Recorder (ATR) and Weigh-In-Motion (WIM) sensors on major roadways and bridges to collect vehicle classification, speed and weight data. Collected ATR/WIM traffic data are usually post-processed to support traffic load forecasting, pavement design and analysis, infrastructure investment decision making, and transportation planning.

However, due to the increasing amount of data and its complexity, a traffic data quality control tool is needed to verify data quality automatically and support sensor calibration effectively. The WIM calibration steps were specified in the Long Term Pavement Performance (LTPP) Program. Calibration criteria were integrated in the LTPP software for quality control before uploading to LTPP database. Several weight accuracy matrices, such as steer axle weight, axle spacing, Gross Vehicle Weight (GVW), and traffic volume by class, were recommended by FHWA. Using GVW distribution for statistical analysis has been an ongoing challenge due to subjective visual interpretation and incapable of identifying drifts.

Regarding previous related work, Davis (1997) (1) developed an empirical Bayes method for estimating Annual Average Daily Traffic (AADT) from short portable counts that accounted for possible uncertainty when adjusting the short count for seasonal and day-of-week effects, and (2) computed portable count sampling plans which were sufficient to identify the appropriate factor group corrections for a non-ATR site. This involved fitting statistical models and estimating monthly and day-of-week adjustment factors for MnDOT's rural ATRs. In a later project (Davis and Yang, 1999) we extended these methods to accommodate classification counts, using data from FHWA's Long Term Pavement Performance Project. This has given us substantial experience working the data from ATRs and classification counters.

## 1.2 Research Objectives

The objective of this project is to characterize the WIM sensor measurements and develop probability models to effectively detect sensor drifts and reliably identify when sensor calibration is needed. In order to achieve this goal, the characteristics of WIM sensors were studied and the key parameters that influence the sensor output were identified. For example, Gross vehicle Weight (GVW) and Steering Axle Weight (SXW) of class 9 vehicles. Separate probability model for data under normal operation and data needed calibration were formulated and studied. Probability models were integrated with a set of possible symptom and causes for system diagnosis and anomaly detection. The integrated prototype was verified through a different set of WIM data to evaluate its performance on data quality control. The goal is to develop a methodology that can make recommendation for potential improvements in the current WIM calibration procedures. As a result of improvement on WIM calibration, it will provide more reliable and accurate traffic data across the state for roadway design, planning, forecast, and investment decision making.

### 1.3 Literature Review

Weigh-In-Motion (WIM) systems have been widely used to collect the traffic loading data to support traffic load forecasting (Qu et al., 1997; Lee & Nabil, 1998; Seegmiller, 2006; and Ramachandran, 2009), pavement design and analysis (NCHRP, 2004; Elkins, 2008), infrastructure investment decision making, and transportation planning. MnDOT and other state DOTs collect WIM data every year to meet federal traffic reporting requirements as part of the Long Term Pavement Performance Program (LTPP) and Vehicle Travel Information System (VTRIS). Traffic data quality control procedures were recommended to address general traffic data quality issues (Nichols & Bullock, 2004; Turner, 2007). However, WIM sensor measurements drift over time due to its sensitivity on road surface smoothness, temperature, vehicle dynamics, and many other factors.

The American Society for Testing and Materials (ASTM) has developed a standard specification for highway WIM systems. The procedure for WIM acceptance and calibration involves using a combination of test trucks and statically-weighed, randomly-selected vehicles from the traffic stream. The standard specifies that each type of WIM system shall be capable of performing weight measurements within 15% for heavy-duty vehicles gross weight and 30% for a single axle weight for 95% of all vehicles weight (ASTM, 1994). Although this is an improved method, it is impractical to use in most cases due to the unavailability of static scales at most portable WIM sites.

Dahlin (1992) proposed a WIM performance monitoring methodology and calibration procedure for class 9 five-axle tractor-semitrailers. He recommended three measures for WIM data quality analysis, including bimodal Gross Vehicle Weight (GVW), front axle weight, and flexible Equivalent Single Axle Load (ESAL) factor. Han et al. (1995) used statistical quality control methods to monitor WIM systems based on Dahlin’s 3 classes of GVW. However, the proposed statistical quality control methodology was unusable due to calibration drift.

Later Ott and Papagiannakis (1996) investigated using class 9 steering axle weights for monitoring 2 subgroups (less and greater than 50 kips). Static and dynamic GVW variations were estimated to generate anticipated Confidence Interval (CI) plots for a WIM station. Nichols and Cetin (2007) introduced multi-component mixture models to characterize class 9 GVW distributions which is consist of several homogeneous, normally distributed, subpopulations. Expectation Maximization (EM) algorithm was then used to estimate subpopulation parameters. They illustrated several patterns suggesting calibration drift and component failure.

FHWA has developed a framework that provides guidelines and methodologies for calculating data quality measures for various applications (FHWA 2004, Turner 2002). The data quality measurement framework suggested 6 fundamental measures (accuracy, completeness, validity, timeliness, coverage and accessibility) for traffic data quality. These quality parameters are often user-specific or application-specific. They are typically derived from either the underlying quality indicators or other quality parameters (Wang et al. 2001). Traditionally, traffic data quality control is performed manually. However, due to the increasing data volume and complexity, a logical structure for evaluating traffic data is needed. A pooled fund study (Flinner, 2002) led by MnDOT was conducted in 2002 to determine traffic data editing procedures. As a result of the study, 120 traffic data quality rules were generated. However, the study was not able to “develop software to assist in the evaluation of the rule base and to put revised software into production” due to extensive data system integration and testing were needed.

Cumulative Sum (CUSUM) chart is a commonly used quality control method to detect deviations from benchmark values. Hawkins & Olwell (1998) used the CUSUM charts and charting as Statistical Process Control (SPC) tools for quality improvement. Luceño (2004) used generalized CUSUM charts to detect level shifts in auto correlated noise. Lin et al. (2007) developed an adaptive CUSUM algorithm to robustly detect anomaly. The cumulative sum of difference between each measurement and the benchmark value is calculated as the CUSUM value. In addition to the regular CUSUM charts, an adjusting CUSUM methodology will be used to for data quality assurance in this study.

### 1.4 Summary of Weigh-In-Motion (WIM) Data

The Weigh-In-Motion (WIM) data was collected from continuous traffic counting sites located on interstate highways, US routes and Minnesota routes throughout the state. Please see Appendix A for a list of WIM sites in Minnesota. These sites collect data on vehicle volume, class, speed and weight. Of particular interest is the calibration of the sensors which collect these data and studying them to determine when calibration is needed and when inaccurate measurement or sensor drift occurs. Monthly comprehensive WIM reports published by MnDOT are available online at http://www.dot.state.mn.us/traffic/data/reports-monthly-wim.html.

The first phase of this project consists of analysis of Gross Vehicle Weight (GVW) from the raw WIM dataset. The data currently obtained from MnDOT are from stations 26, 35, 36, 37, 39 and 40. Some important points to note are summarized as follows.

#### 1.4.1 Class 9 Trucks

GVW distribution is further divided into 3 groups as suggested by Dahlin (1992).

- Unloaded (GVW < 40 kips)
- partially loaded (GVW between 40 and 70 kips) and
- loaded (GVW > 70 kips)

#### 1.4.2 WIM Station 35

The measurements taken from Station 35 were inconsistent. Only lane 4 was calibrated and hence during the analysis, only Lane 4 data was analyzed.

Date range for data collection: 07/16/2009 to 05/15/2012
Calibration Date: 04/28/2011
Classes Analyzed: Class 2, 3 and 9
Lanes Considered: Lane 4

1.4.3 WIM Station 36

Date range for data collection: 04/01/2009 to 09/30/2009
Calibration Date: Not available
Classes Analyzed: Class 2, 3 and 9.
Lanes Considered: Lane 1, 2, 3, and 4

1.4.4 WIM Station 37

Date range for data collection: 07/14/2009 to 05/15/2012
The large dip in the plots refers to the failure of sensors in lane 1 on 03/09/2011 until 06/12/2011
Calibration Date: 02/10/2010, 12/01/2010(Lane 1 only), 12/10/2010, 01/05/2011, 01/24/2011, and 11/28/2011
Classes Analyzed: Class 2, 3 and 9.
Lanes Considered: Lane 1 and 2

1.4.5 WIM Station 39

Date range for data collection: 12/01/2010 to 05/15/2012
Calibration Date: Not available
Classes Analyzed: Class 2, 3 and 9.
Lanes Considered: Lane 1 and 2

1.4.6 WIM Station 40

Date range for data collection: 02/01/2011 to 05/15/2012
Calibration Date: 02/10/2010, 09/02/2010, 11/29/2010, 02/02/2011 (The only date within range)
Classes Analyzed: Class 2, 3 and 9.
Lanes Considered: Lane 1, 2, 3, and 4

## 1.5 Report Organization

This report is organized as follows. WIM data monitoring and modeling are presented in Chapter 2. Data quality assurance methodologies are discussed in Chapter 3. Data quality analysis is discussed in Chapter 4. In Chapter 5, a Matlab based graphical user's interface is presented. Finally, Chapter 6 discussed and summarized the findings.

A list of MnDOT WIM stations is included in Appendix A. Description of MnDOT WIM raw data is included in Appendix B. Processed results of selected WIM stations are included in Appendix C (WIM station #35 in Appendix C.1, #37 in Appendix C.2, #39 in Appendix C.3, and #40 in Appendix C.4). Appendix D includes the instructions to process the raw WIM data in Matlab. Data processing and analysis scripts are listed in Appendix E. And, finally, FHWA vehicle classification scheme is included in Appendix F.

# 2. WIM DATA MONITORING AND MODELING

## 2.1 Gross Vehicle Weight (GVW)

Nichols and Cetin (2007) proposed using a mixture modeling technique for fitting a statistical distribution that is weighted sum of multiple distributions. Dahlin (1992) proposed using the Gross Vehicle Weight (GVW) distribution of class 9 vehicles to monitor the WIM data quality. A sample GVW distribution of class 9 vehicles at MnDOT WIM station #37 is displayed in Figure 2-1. The GVW distribution is bimodal with a peak between 28and 32 kips for unloaded trucks and a second peak between 70 and 80 kips for fully loaded trucks.

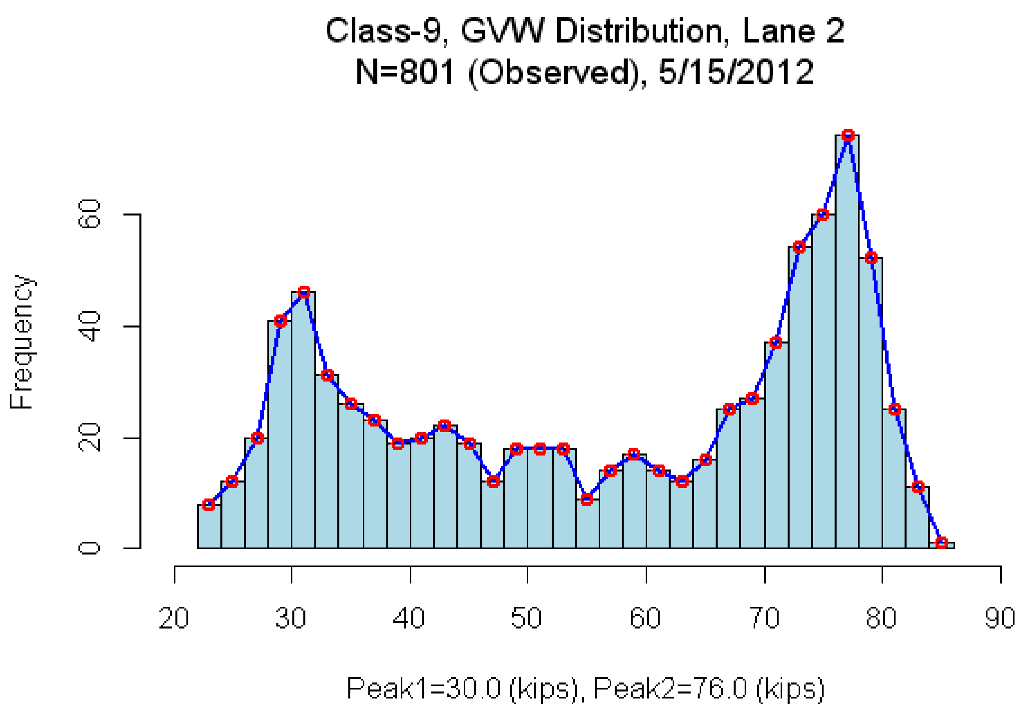


**Figure 2.1 Sample Class 9 GVW Histogram**

## 2.2 Mixture Models

In finite mixture modeling of normal densities, the unknown density of a multivariate random vector g(*x*) can be expressed using the following equation (McLachlan and Peel, 2000).

$$g(x) = \sum_{i=1}^{n} \lambda_i g_i(x) = \lambda_1 g_1(x) + \lambda_2 g_2(x) + \lambda_3 g_3(x) + \cdots \qquad (2\text{-}1)$$

Where,

$g_i(x)$ is the i^th^ component density with normal distribution,
$\lambda_i$ is the i^th^ non-negative component proportion, $\sum_{i=1}^{n} \lambda_i = 1$

The GVW of class 9 vehicles (GVW9) consists of unloaded, partially loaded and fully loaded components. A three-component mixture model, as described in equation 2-2, was formulated to estimate the parameters of the normal densities and corresponding mixture proportions using the Expectation Maximization (EM) algorithm (Dempster et al., 1997). The EM algorithm allows us to estimate the maximum likelihood of the model parameters. MATLAB (http://www.mathworks.com) scripts (see detail in Appendix E.2) were developed to process GVW9 mixture modeling using EM fitting technique.

$$GVW_9(x) = \lambda_1 g_1(x) + \lambda_2 g_2(x) + \lambda_3 g_3(x) \tag{2-2}$$

Where,

$GVW_9(x)$is the Class 9 Gross Vehicle Weight (GVW) distribution,
$g_1(x)$ is the empty class 9 truck normal GVW distribution,
$g_2(x)$ is the partially loaded class 9 truck normal GVW distribution,
$g_3(x)$ is the filly loaded class 9 truck normal GVW distribution,
$\lambda_i$ is the i$^{th}$ non-negative component proportion, $\lambda_1 + \lambda_2 + \lambda_3 = 1$.

### 2.3 EM Fitting Verification

EM fitting of a 3-component mixture model for vehicle class 9 GVW data on Aug. 3, 2010 at WIM station #37 was verified using. Parameters (mean and SD) and proportions of EM fitting were listed in Table 2-1 and 2-2 for lane 1 and 2, respectively, with approximate 95% confidence intervals for component means.

For lane 1, the estimated mean and standard deviation of unloaded trucks are 33.0 kips and 4.1 kips, respectively. The EM model estimated that 25% of the trucks are empty. The estimated mean and standard deviation of partially loaded trucks GVW are 55.8 kips and 13.5 kips, respectively. The EM model estimated that 47.5% of the trucks are partially loaded. The estimated mean and standard deviation of fully loaded trucks GVW are 76.0 kips and 3.8 kips, respectively. The EM model estimated that 27.5% of the trucks are fully loaded.

For lane 2, the estimated mean and standard deviation of unloaded trucks are 32.1 kips and 4.6 kips, respectively. The EM model estimated that 34% of the trucks are empty. The estimated mean and standard deviation of partially loaded trucks GVW are 54.9 kips and 12.8 kips, respectively. The EM model estimated that 32% of the trucks are partially loaded. The estimated mean and standard deviation of fully loaded trucks GVW are 78.0 kips and 4.3 kips, respectively. The EM model estimated that 34% of the trucks are fully loaded.

**Table 2.1 Mixture Model Parameters with 95% Confidence Intervals for Component Means (Lane 1)**

| Component | Lower Bound (kips) | Mean (kips) | Upper Bound (kips) | SD (kips) | Proportion |
|---|---|---|---|---|---|
| 1 – Unloaded | 32.6 | 33.0 | 33.5 | 4.1 | 0.25 |
| 2 – Partially loaded | 54.9 | 55.8 | 58.7 | 13.5 | 0.475 |
| 3 – Fully loaded | 75.6 | 76.0 | 76.4 | 3.8 | 0.275 |

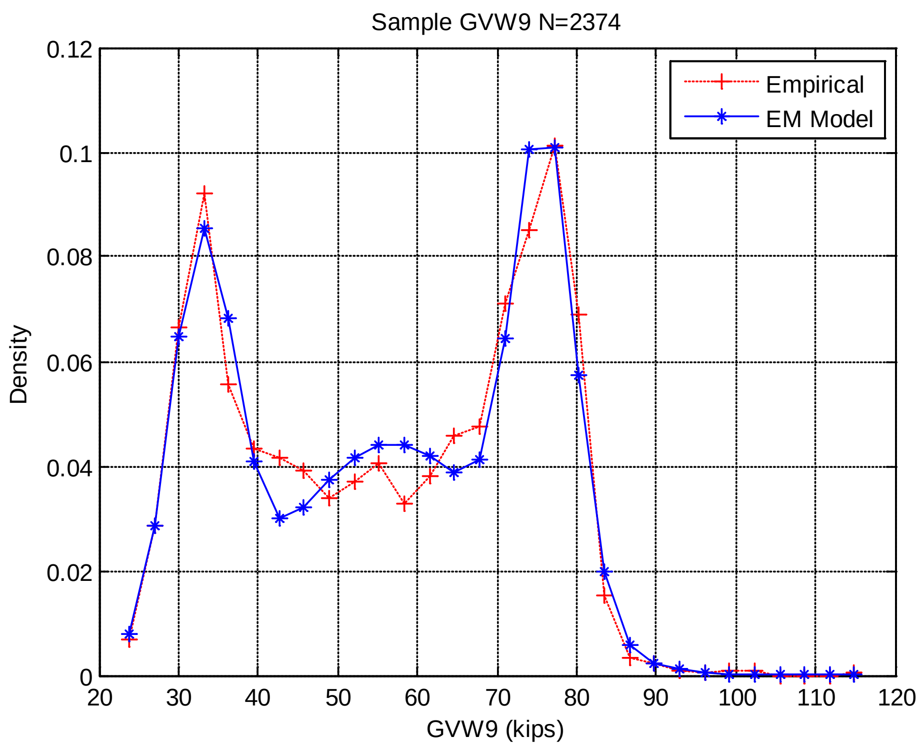


**Figure 2.2Compare Empirical Distribution to Mixture Model (WIM#37 Lane 1 GVW9)**

**Table 2.2 Mixture Model Parameters with 95% Confidence Intervals for Component Means (Lane 2)**

| Component | Lower Bound (kips) | Mean (kips) | Upper Bound (kips) | SD (kips) | Proportion |
|---|---|---|---|---|---|
| 1 – Unloaded | 31.4 | 32.1 | 32.9 | 4.6 | 0.34 |
| 2 – Partially loaded | 50.9 | 54.9 | 59.0 | 12.8 | 0.32 |
| 3 – Fully loaded | 77.3 | 78.0 | 78.7 | 4.3 | 0.34 |

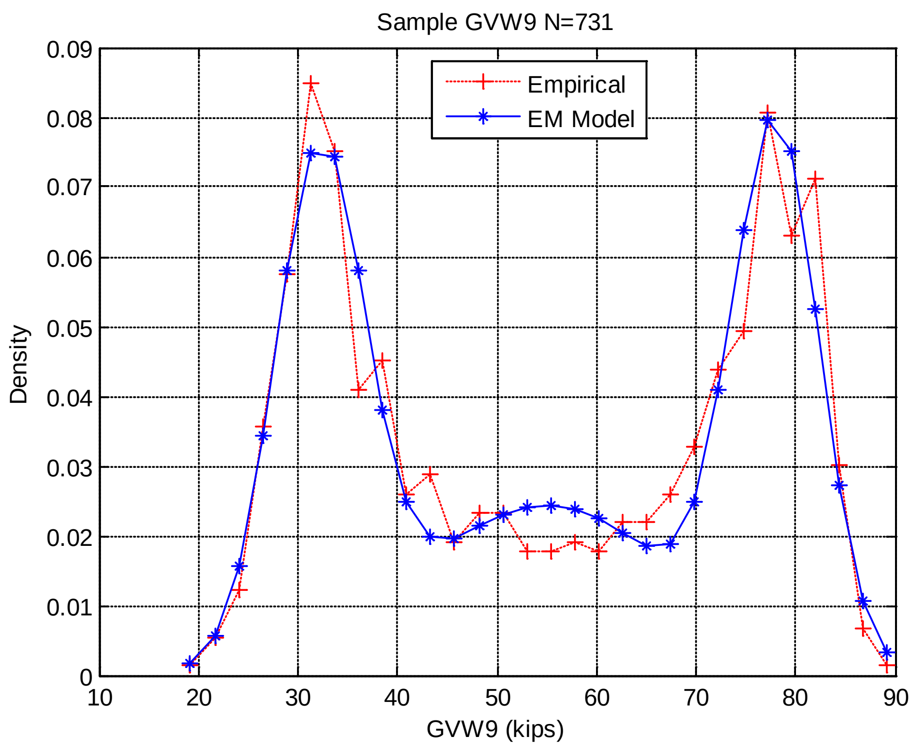


**Figure 2.3 Compare Empirical Distribution to Mixture Model (WIM#37 Lane 2 GVW9)**

## 2.4 Vehicle Class 9 Gross Vehicle Weight (GVW)

The fully loaded gross vehicle weights of vehicle class 9 at station 37 in lane #1 and #2 from Oct. 19, 2009 to May 15, 2012 were displayed respectively in Figure 2-4 and 2-5. The red vertical lines represent the dates when calibrations were performed.

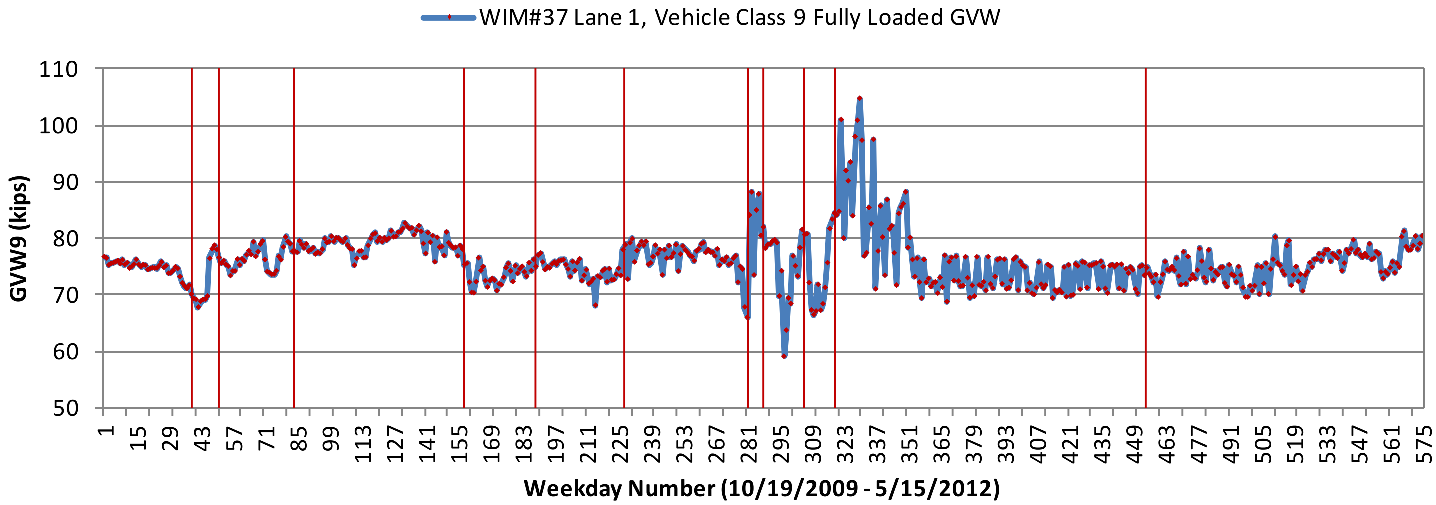


**Figure 2.4  WIM#37 Lane 1, Vehicle Class 9 Fully Loaded GVW**

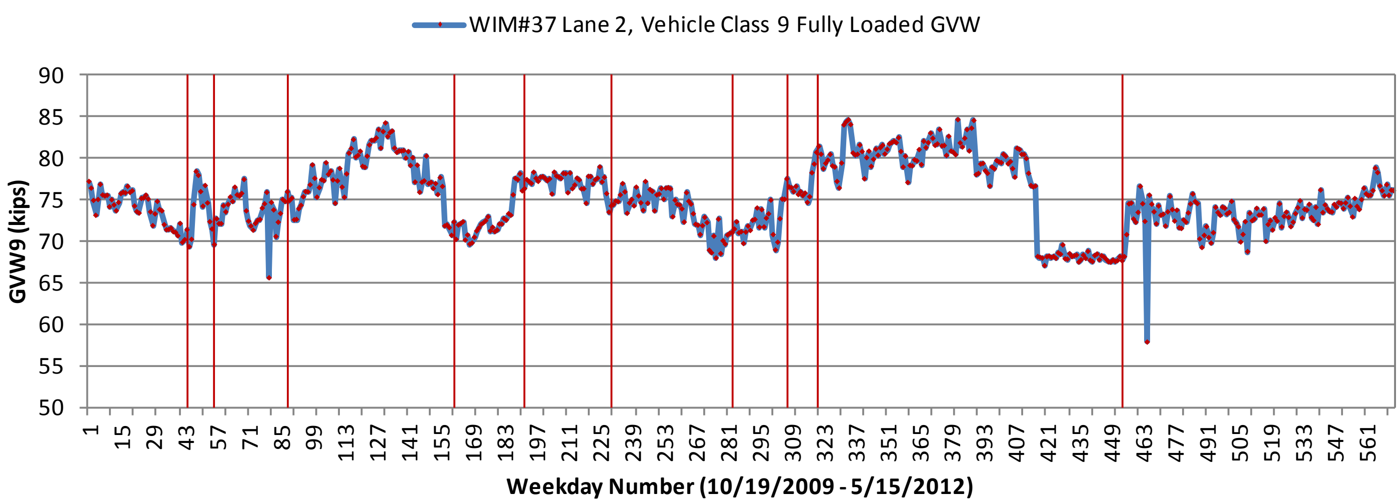


**Figure 2.5  WIM#37 Lane 2, Vehicle Class 9 Fully Loaded GVW**

Lane #1 data from 03/19/2011 to 06/10/2011 and lane #2 data from 07/16/2011 to 08/29/2011 are not available. Lane #1 calibration dates include 12/10/2009, 12/22/2009, 2/10/2010, 5/25/2010, 7/7/2010, 8/31/2010, 12/1/2010, 12/10/2010, 1/5/2011, 1/24/2011, and 11/28/2011. Lane #2 calibration dates include 12/10/2009, 12/22/2009, 2/10/2010, 5/25/2010, 7/7/2010, 8/31/2010, 12/10/2010, 1/5/2011, 1/24/2011, and 11/28/2011.

## 2.5 Front Axle Weight (FXW) or Steering Axle Weight (SXW)

According to a FHWA TechBrief (1998), using the average Front Axle Weight (FXW) of class 9 trucks is another key indicator to monitor the WIM sensor performance. The front axle weights for class 9 vehicles are fairly constant if a large enough sample is taken. Daily average FXW at WIM station 37 is used as an example to monitor the FXW variations corresponding to calibration dates as displayed in Figure 2-6 and 2-7, respectively.

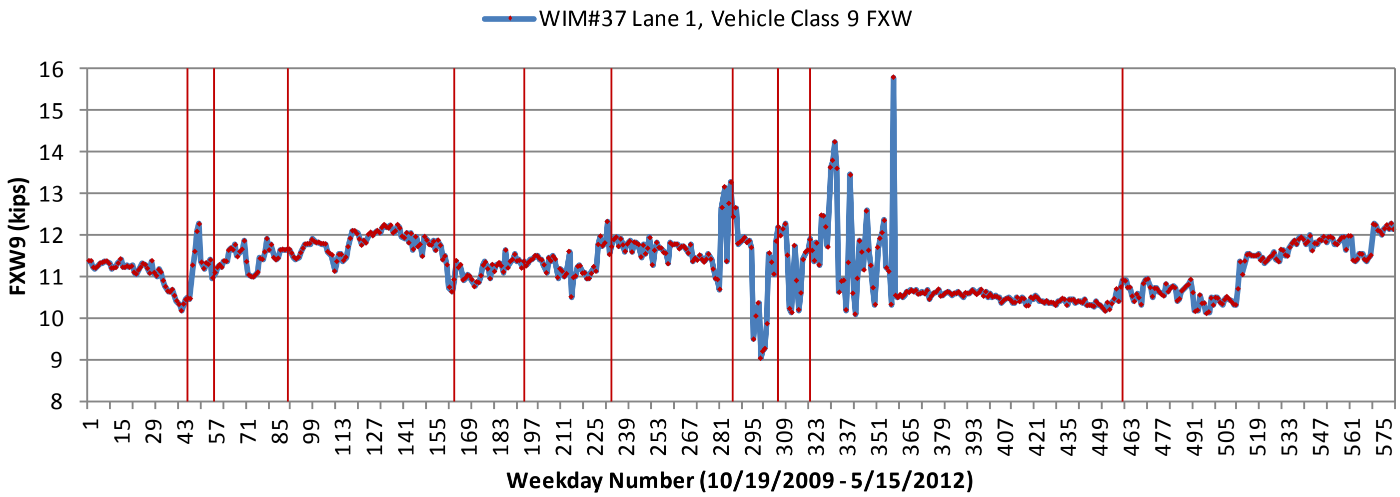


**Figure 2.6 Daily Average FXW of Class 9 Trucks at WIM Station #37 Lane 1**

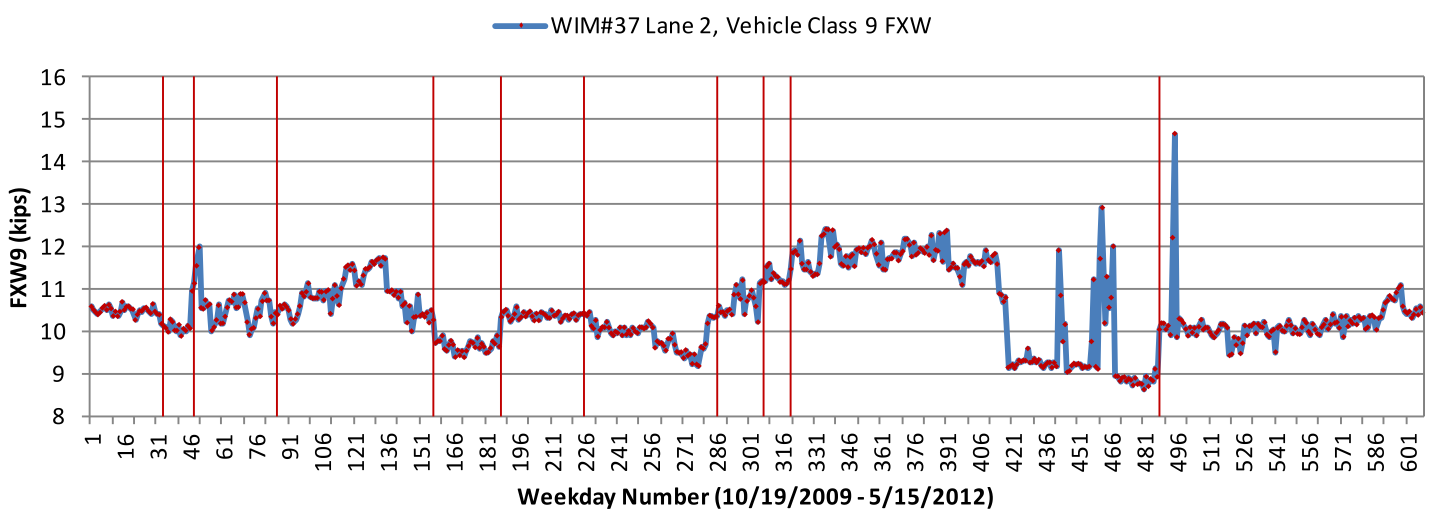


**Figure 2.7 Daily Average FXW of Class 9 Trucks at WIM Station#37 Lane 2**

Daily Average Steering Axle Weight by Group of Class 9 Trucks at WIM Station #37 for Lane 1 and Lane #2 were displayed in Figure 2-8 and 2-9, respectively. The WIM sensors at station #37 after 12/01/2010 was not function properly.

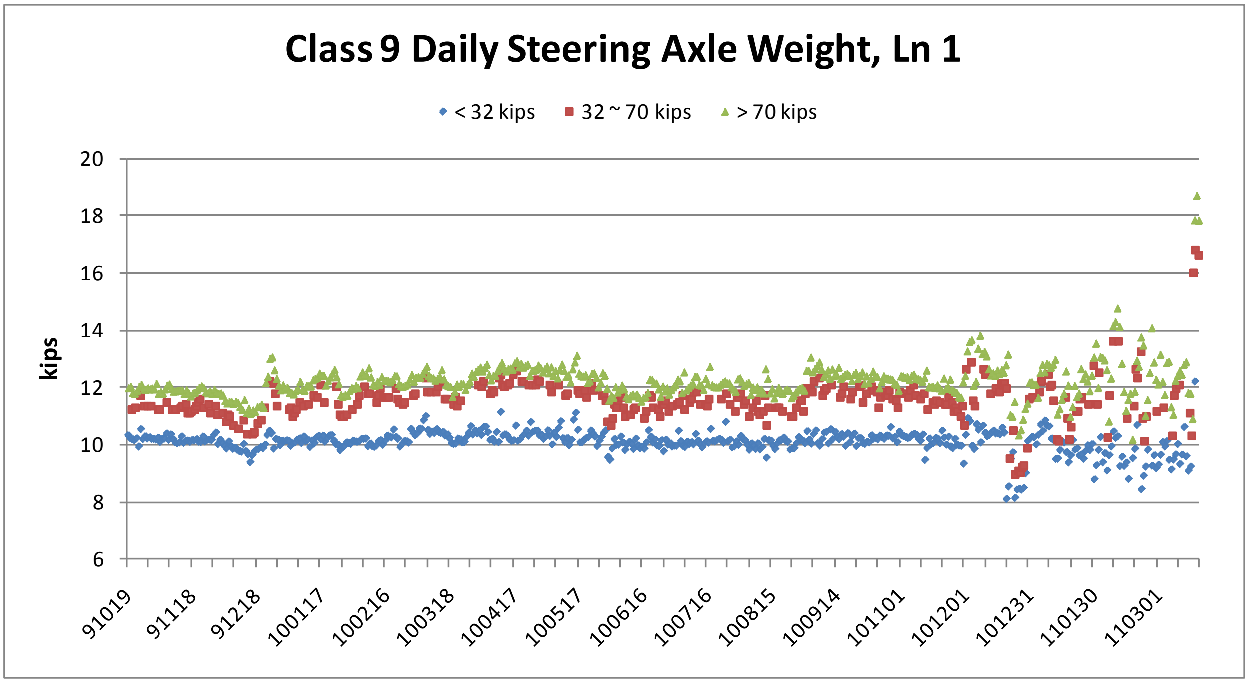


**Figure 2.8 Daily Average Steering Axle Weight by Group of Class 9 Trucks at WIM Station #37 Lane 1**

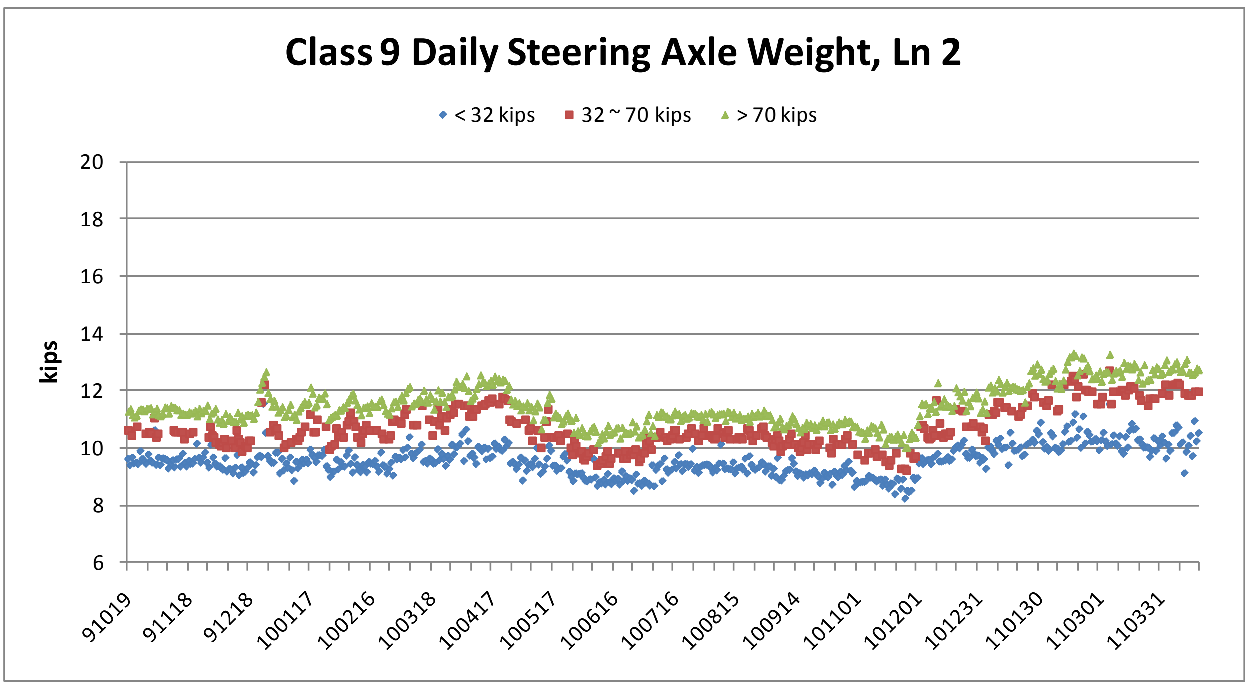


**Figure 2.9 Daily Average Steering Axle Weight by Group of Class 9 Trucks at WIM Station #37 Lane 2**

## 2.6 Equivalent Single Axle Load (ESAL)

The equivalent single axle load (ESAL) was developed by the American Association of State Highway Officials (AASHO) Road Test to establish a damage relationship for comparing the effects of axles carrying different loads. The reference axle load is an 18,000-lb. single axle with dual tires. Dahlin (1992) suggested using flexible ESAL factor to compare with properly calibrated system for WIM diagnosis.

The ESAL factor of Class 9 Trucks at WIM Station #37 for Lane 1 and Lane #2 were displayed in Figure 2-10 and 2-11, respectively. The WIM sensors at station #37 Lane 1 begins to drift after 12/01/2010 while the sensors in Lane #2 remain stable over the data analysis period.

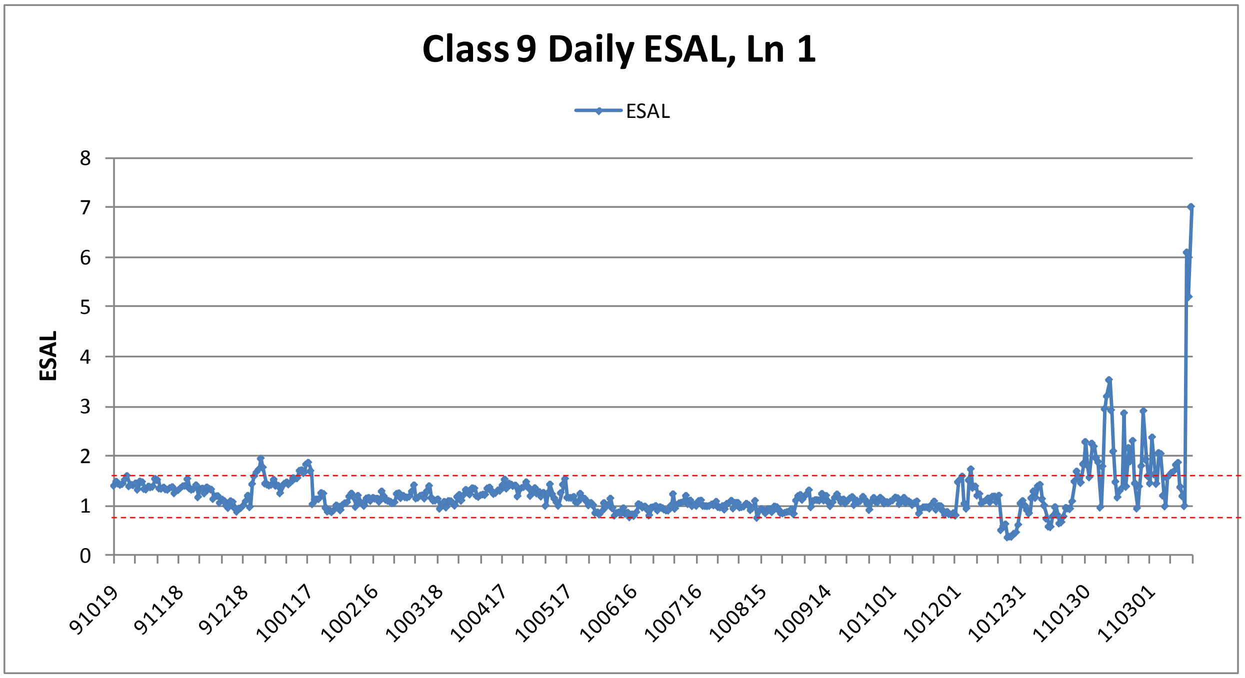


**Figure 2.10 ESAL of Class 9 Trucks at WIM Station #37 Lane 1**

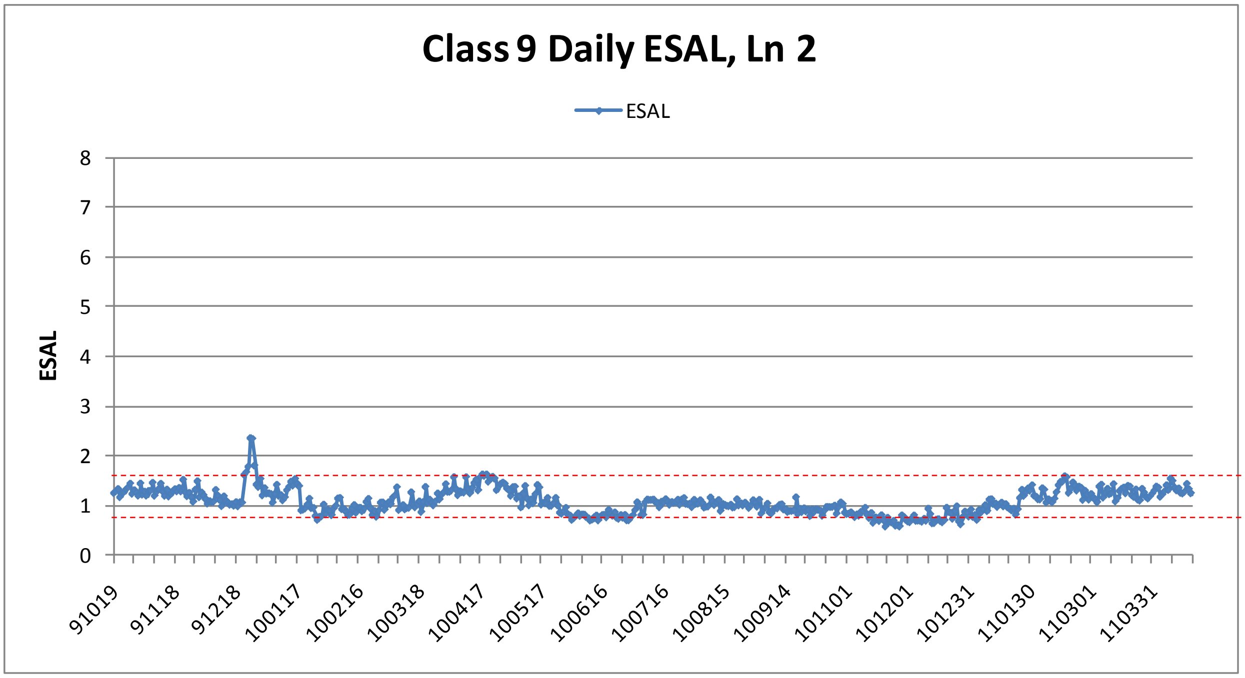


**Figure 2.11 ESAL of Class 9 Trucks at WIM Station #37 Lane 2**

# 3. WIM DATA QUALITY ASSURANCE

In addition to monitoring the performance of WIM sensors, data assurance algorithms can be helpful to the WIM system managers and operators in determining when the systems require calibration.

## 3.1 Loadometer Scale Methodology

Southgate (2001) proposed a regression model (Eq. 3-1) using the ratio of steering axle load to axle space number 1 (i.e., loadometer scale) to evaluate the quality of WIM data.

$$log_{10}(Y) = a + b \times log_{10}(X) \qquad (3\text{-}1)$$

Where,

$Y = \frac{steering\ axle\ load}{axle\ space\ \#1}$, and
$X$ is the axle space #1 in feet

One day WIM FXW and FXS data (May 15, 2012) was used as a sample to evaluate the model as expressed in equation (3-1). The resulting log-log regression model has an intercept a = 3.7179, slope b = -0.7002, and $R^2 = 0.5347$ as shown in Figure 3-1.

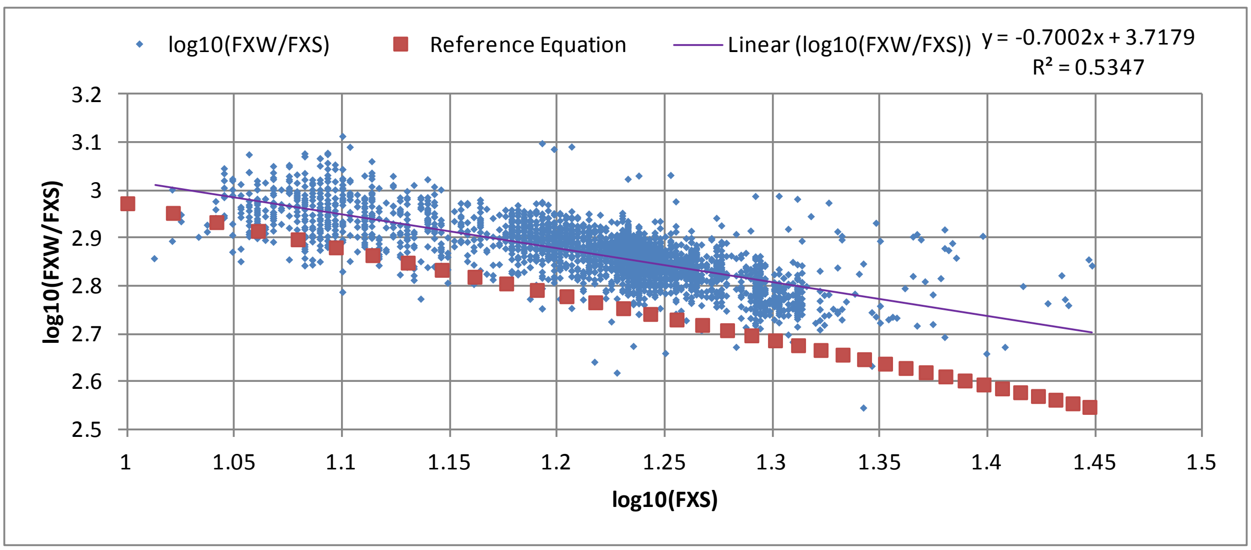


**Figure 3.1 Log-Log Regression Model of Class 9 Trucks at WIM Station #37 Lane 1 (May 15, 2012)**

WIM data quality was calibrated against a reference model (Eq. 3-2) derived based on a linear log-log regression model fitted to the 1984 Kentucky static scale data for pavement stations. Scale adjustment factor was derived by comparing the observed ratio of steering axle load to axle space number 1with the reference equation (Eq. 3-2).

$$log_{10}(Y) = 3.925361 - 0.952182 \times log_{10}(X) \qquad (3\text{-}2)$$

Figure 3-2 and 3-3 display the intercept (a) and slope (b) parameters of log-log linear regression of WIM station #37 class 9 trucks in lane #1 in weekdays from 10/19/2009 to 5/15/2012. The vertical red lines represent the calibration dates. Overall, the average intercept value is about 3.7 and the average slope is about -0.7. From both graphs, there is no detectable pattern of sensor drifts or system malfunction prior to the calibrations. Figure 3-4 displays the adjustment factor derived using Southgate's (2001) methodology. The adjusted factor plot is somewhat similar to the gross vehicle weight (Figure 2-4) and steering axle weight (Figure 2-6) that there is no detectable pattern of sensor drifts or system malfunction prior to the calibrations except at day 38 (12/10/2009), 46 (12/22/2009), and 280 (12/1/2010).

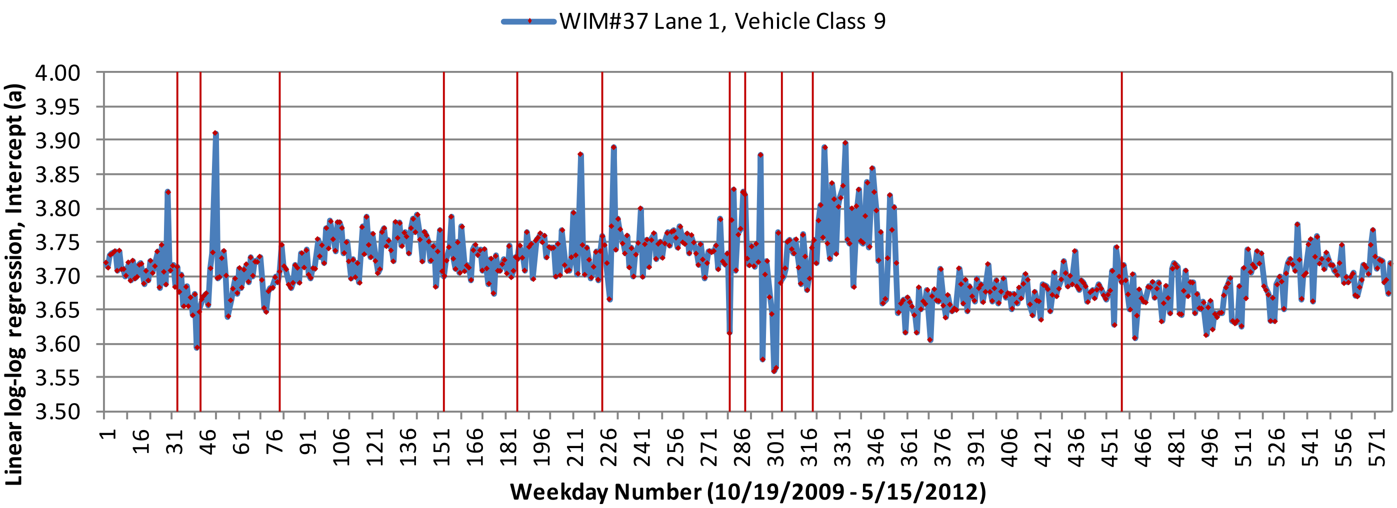


**Figure 3.2 Log-Log Linear Regression Intercepts of Class 9 Trucks at WIM Station #37 Lane 1**

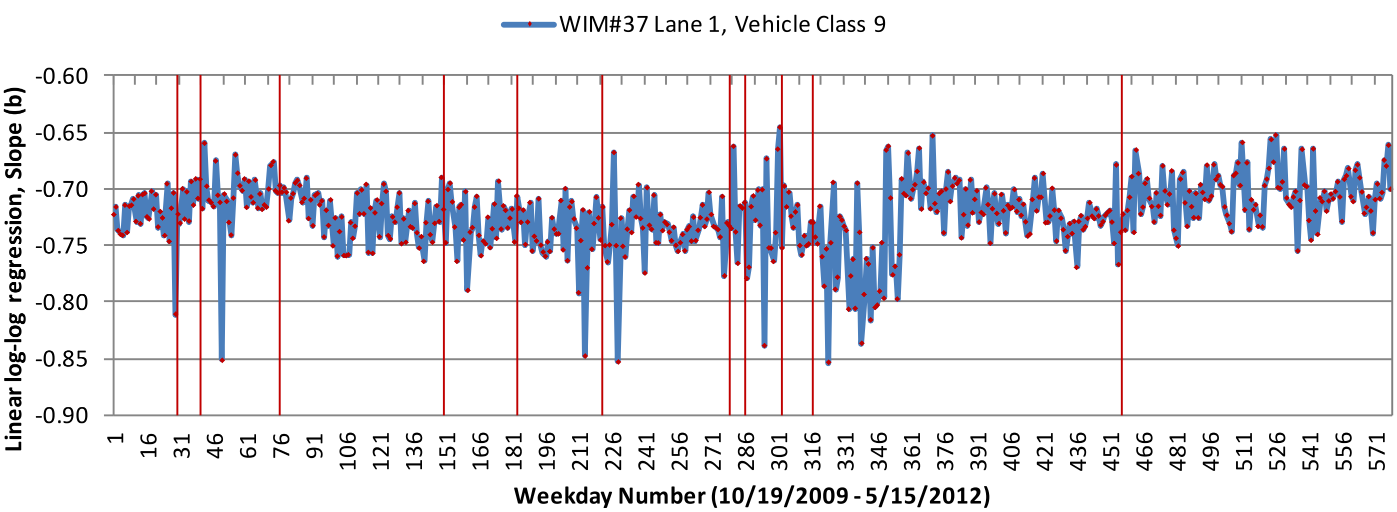


**Figure 3.3 Log-Log Linear Regression Slopes of Class 9 Trucks at WIM Station #37 Lane 1**

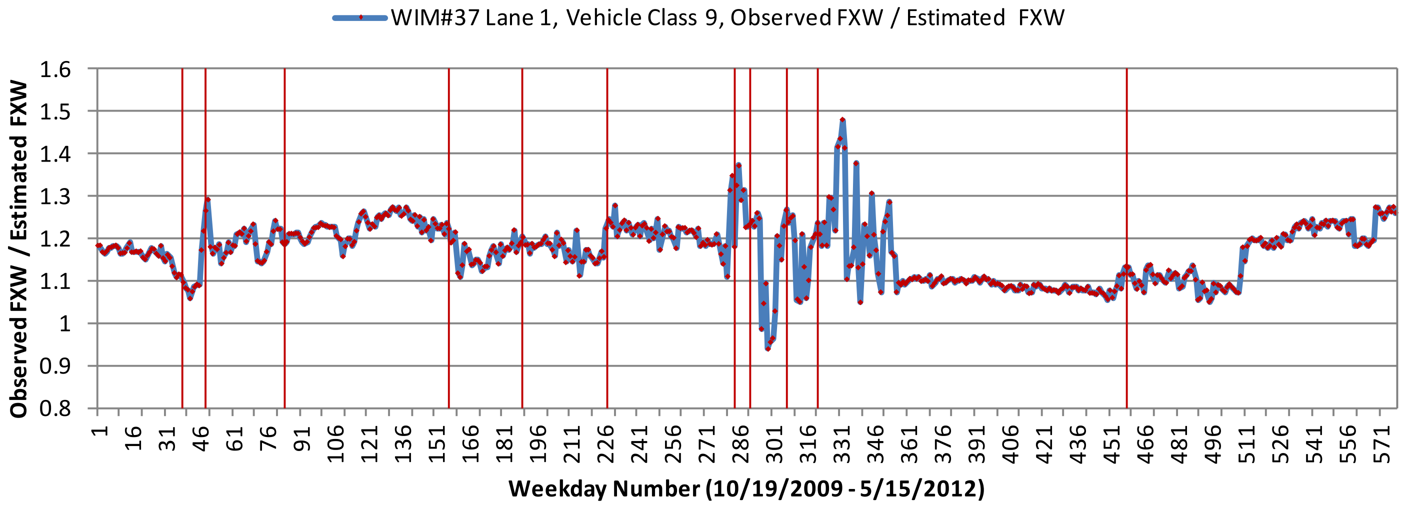


**Figure 3.4 Estimated Adjustment Factors of Class 9 Trucks at WIM Station #37 Lane 1**

Similarly, Figure 3-5 and 3-6 display the intercept (a) and slope (b) parameters of log-log linear regression of WIM station #37 class 9 trucks in lane #2 in weekdays from 10/19/2009 to 5/15/2012. The vertical red lines represent the calibration dates. Overall, the average intercept value is about 3.7 and the average slope is about -0.7. From both graphs, there is no detectable pattern of sensor drifts or system malfunction prior to the calibrations. Figure 3-7 displays the adjustment factor derived using Southgate's (2001) methodology. The adjusted factor plot is somewhat similar to the gross vehicle weight (Figure 2-5) and steering axle weight (Figure 2-7) that there is no detectable pattern of sensor drifts or system malfunction prior to the calibrations except at day 46 (12/22/2009) and 485 (11/28/2011). The adjustment factor spikes from 1.0 to around 1.7 on day 492(12/7/2011).

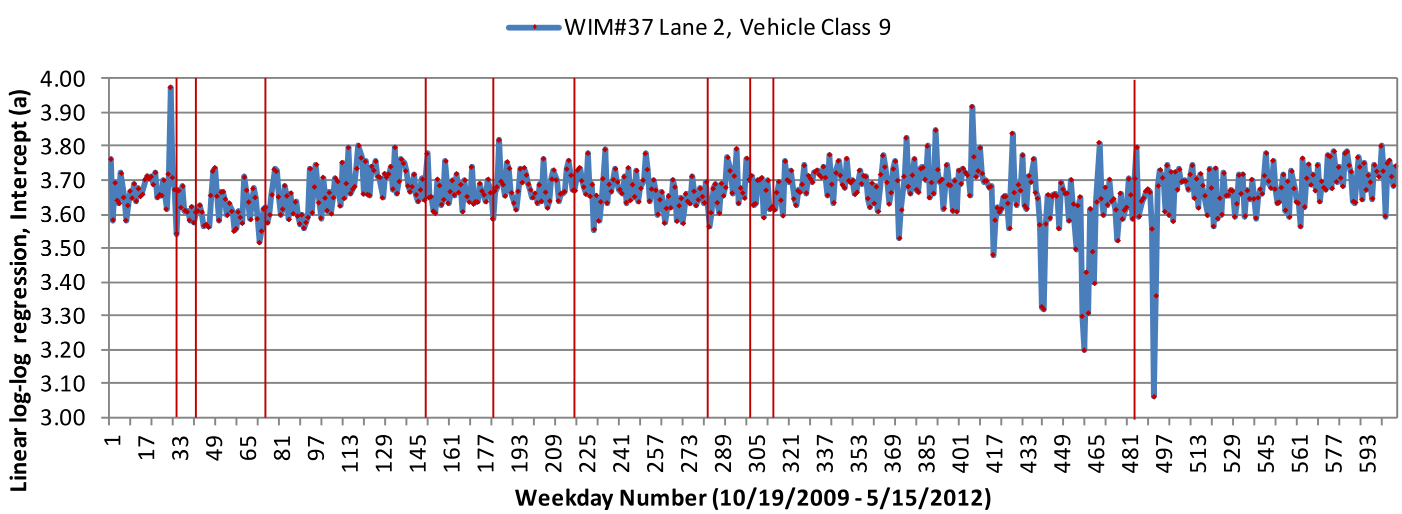


**Figure 3.5 Log-Log Linear Regression Intercepts of Class 9 Trucks at WIM Station #37 Lane 2**

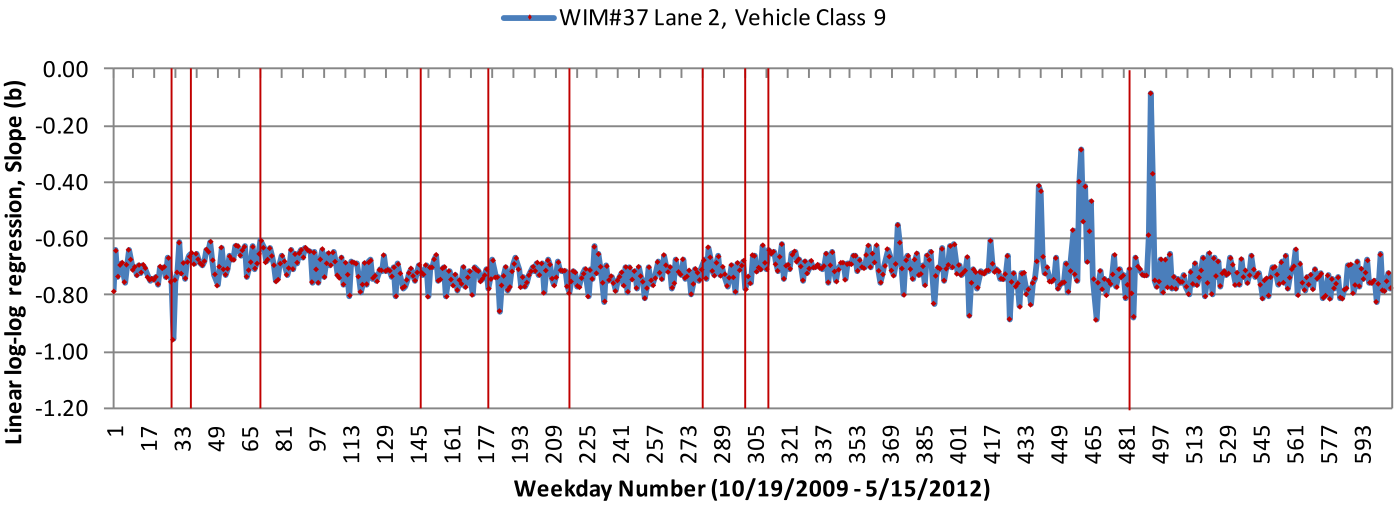


**Figure 3.6 Log-Log Linear Regression Slopes of Class 9 Trucks at WIM Station #37 Lane 2**

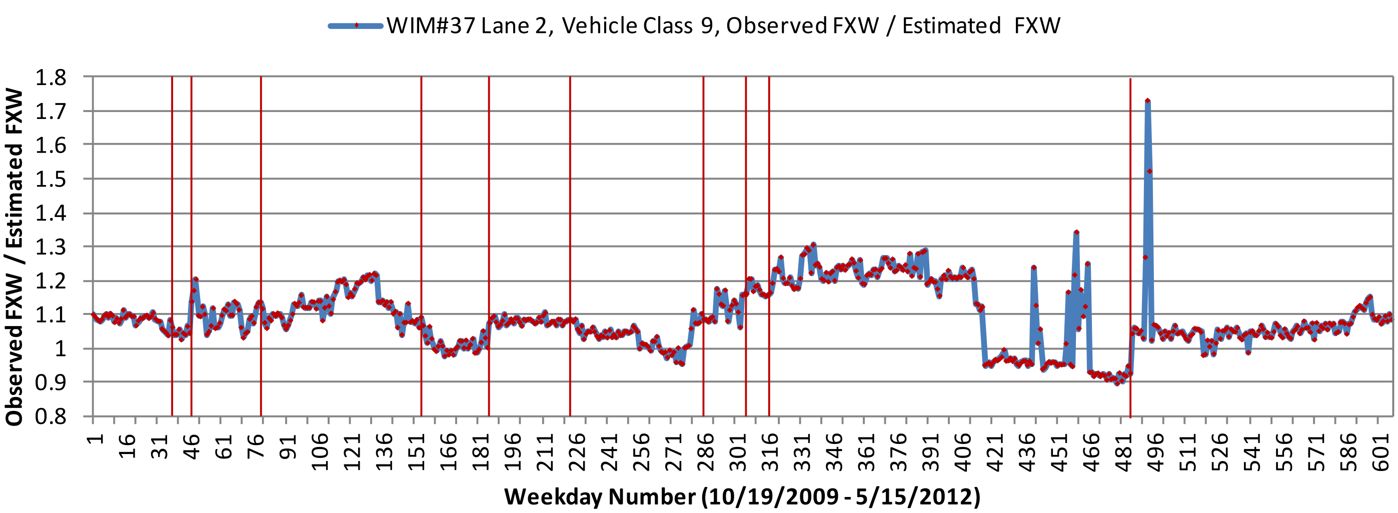


**Figure 3.7 Estimated Adjustment Factors of Class 9 Trucks at WIM Station #37 Lane 2**

## 3.2 WIM Sensor Drifts Detection

Cumulative sum (CUSUM) charts are often used to detect persistent deviations of a process mean from a known target value. The CUSUM methodology is explored to detect drifts of WIM sensors.

### 3.2.1 Cumulative Sum (CUSUM) Methodology

The CUSUM chart is a commonly used quality control method to detect deviations from benchmark values. Hawkins & Olwell (1998) used CUSUM charts and charting as Statistical

Process Control (SPC) tools for quality improvement. Luceño (2004) used generalized CUSUM charts to detect level shifts in auto correlated noise. Lin et al. (2007) developed an adaptive CUSUM algorithm to robustly detect anomaly. The cumulative sum of difference between each measurement and the benchmark value is calculated as the CUSUM value. Cumulative Sum (CUSUM) is expressed as follows.

$$C_n = \sum_{i=1}^{n} (X_i - \mu) \qquad (3\text{-}3)$$

Or in recursive form,

$$C_n = C_{n-1} + (X_i - \mu) \qquad (3\text{-}4)$$

Where,

$X_i$ is the i$^{th}$ data reading
$\mu$ is the data mean
$C_n$ is the sum of independent normal $N(0, \sigma^2)$ quantities

The CUSUM charts of GVW9 (group 1 – unloaded, group 2 - partially loaded, group 3 – fully loaded) for both lane #1 and #2 are displayed in Figure 3-8 and 3-9, respectively. Figure 3-8 displays the changes of CUSUM charts of WIM #37 lane #1 at several calibration dates 2/10/2010 (A), 5/25/2010 (B), 8/31/2010 (C, unloaded and fully loaded groups only) and 1/24/2011(D). After the calibration adjustment on 1/24/2011, the CUSUM values continue to increase until 3/15/2011 when the CUSUM values begin to decrease.

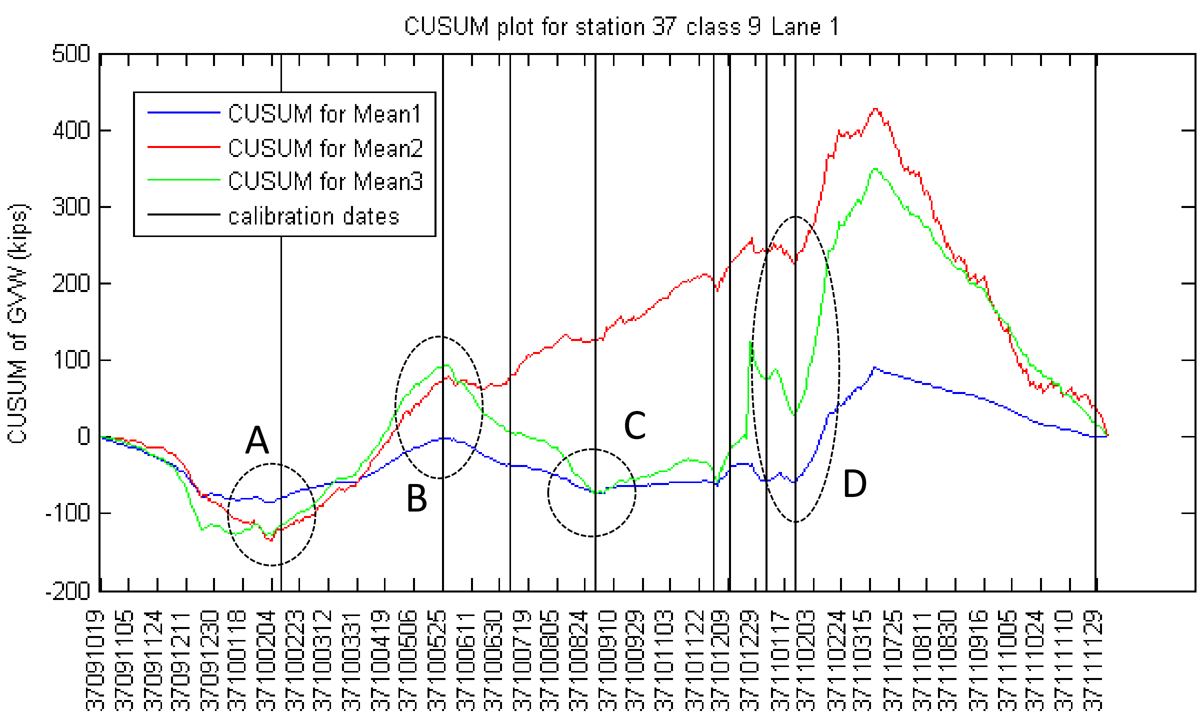


**Figure 3.8 CUSUM Plot of WIM #37 GVW9 Lane 1 (10/19/2009 – 11/29/2011)**

Similarly, Figure 3-9 displays the changes of CUSUM charts of WIM #37 lane #2 at several calibration dates, 5/25/2010 (B), 8/31/2010 (C) and 1/24/2011(D). The calibration adjustment on 2/10/2010 apparent did not affect the sensor outputs until about one month later on 3/15/2010 in lane #2. After the calibration adjustment on 1/24/2011, the CUSUM values continue to increase until 7/11/2011 when the CUSUM values of lane #2 begin to decrease. Additional plots of FXW and FXS for other stations are included in Appendix C.

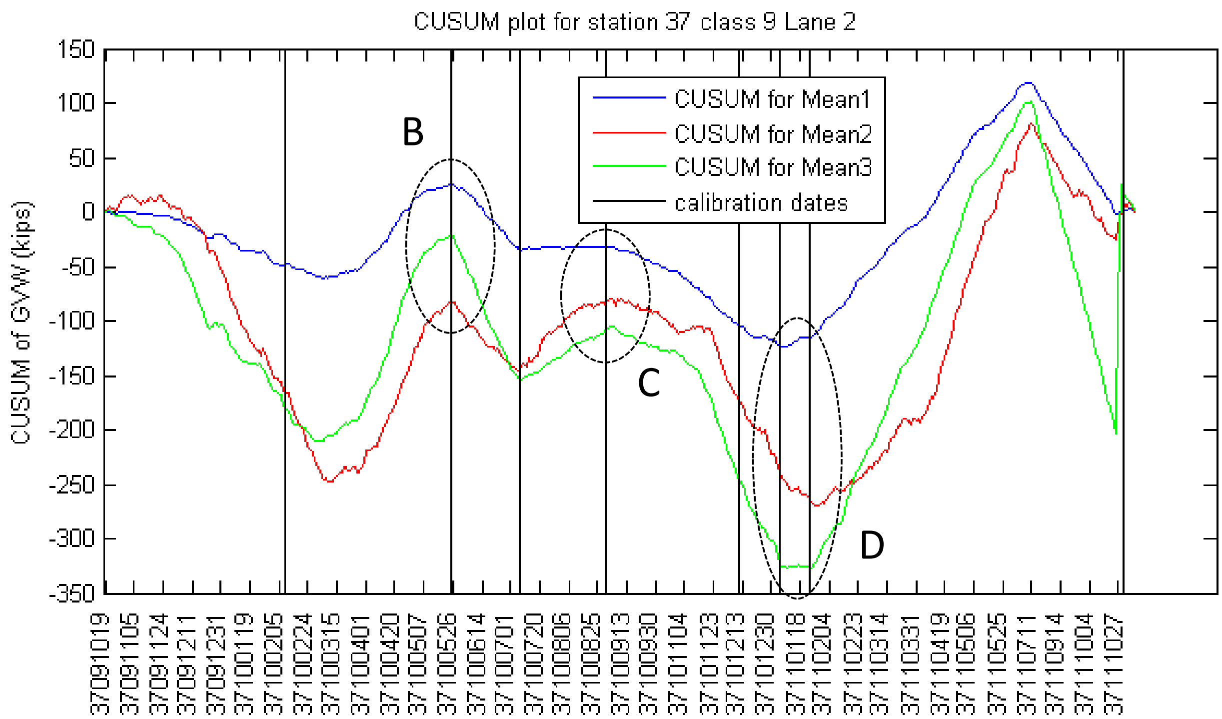


**Figure 3.9 CUSUM Plot of WIM #37 GVW9 Lane 2 (10/19/2009 – 11/29/2011)**

3.2.2 Adjusting CUSUM Methodology

The CUSUM equations (3-3 and 3-4) can also be standardized to have zero mean and unit standard deviation as follows.

$$U_i = (X_i - \mu)/\sigma \tag{3-5}$$

$$S_n = \sum_{i=1}^{n} U_i \tag{3-6}$$

Or in recursive form,

$$S_n = S_{n-1} + U_n \tag{3-7}$$

Where,

$U_i$ is the difference of measurement from mean in unit of standard deviation
$S_n$ is the cumulative difference in unit of standard deviation
$\sigma$ is the standard deviation of a data set

Cumulative distribution function and normal inverse cumulative distribution function (illustrated in Figure 3-10) were used before calculating CUSUM. This gives the adjusting CUSUM values. The following equations are used to calculate the adjusting CUSUM. Adjusting CUSUM plots for GVW9 at station #37 Lane #1 & #2 are plotted in Figure 3-11 & 3-12, respectively.

$$\bar{x}_1 = \frac{\sum_{i=1}^{n_0} \mu_i}{n_0} \tag{3-8}$$

$$w_1 = \sum_{i=1}^{n_0} (\mu_i - \bar{x}_1)^2 \tag{3-9}$$

$$\bar{x}_{j+1} = \bar{x}_j + \left[\frac{(\mu_{j+n_0} - \bar{x}_j)}{j+n_0}\right] \tag{3-10}$$

$$w_{j+1} = w_j + (j + n_0 - 1)\left[\frac{(\mu_{j+n_0} - \bar{x}_j)^2}{j+n_0}\right] \tag{3-11}$$

$$\sigma_j^2 = \frac{w_j}{j+n_0-1} \tag{3-12}$$

$$T_j = \frac{\mu_j - \bar{x}_j}{\sigma_j} \tag{3-13}$$

$$p_j = tcdf\left(T_j . \sqrt{\frac{j+n_0-1}{j+n_0}}, j + n_0 - 2\right) \tag{3-14}$$

$$U_j = norminv(p_j, 0, 1) \tag{3-15}$$

$$adj.cusum_j = \sum_{k=1}^{j} U_k \tag{3-16}$$

Where,

n = number of days,
$n_0 = 3$, initial number of days
$w_j$ is sum of squared difference between individual data and mean,
$\sigma_j^2$, is the variance,
$m = n - n_0$,
$\mu$ is an array of daily GVW average,
$p = tcdf(x, v)$ is the student's t cumulative distribution function (CDF) in Matlab. The result, p, is the probability that a single observation from the t distribution with ν degrees of freedom will fall in the interval [–∞, x), and
$U = norminv(p, \mu = 0, \sigma = 1)$ is the normal inverse cumulative distribution function in Matlab. It computes the inverse of the normal CDF with parameters ☐ (mean) and ☐ (star
probabilities in p.

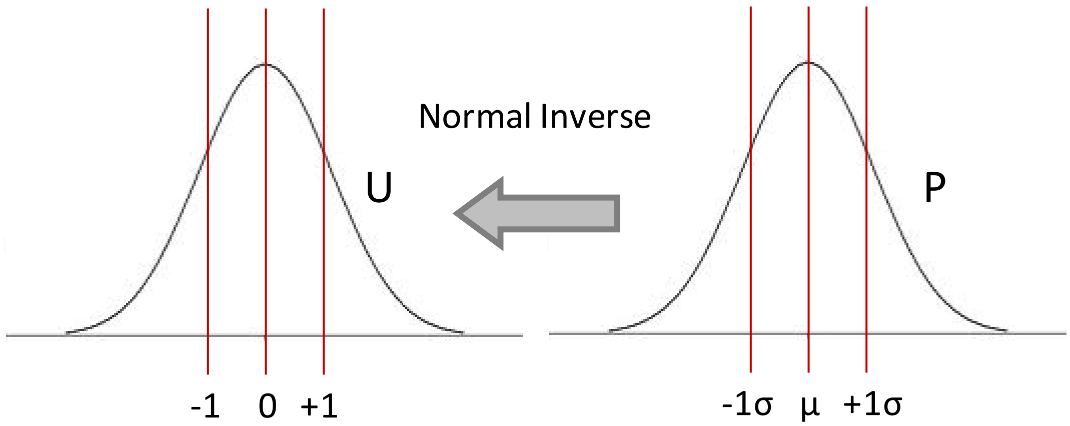


**Figure 3.10 Illustration of Normal Inverse Cumulative Distribution Function**

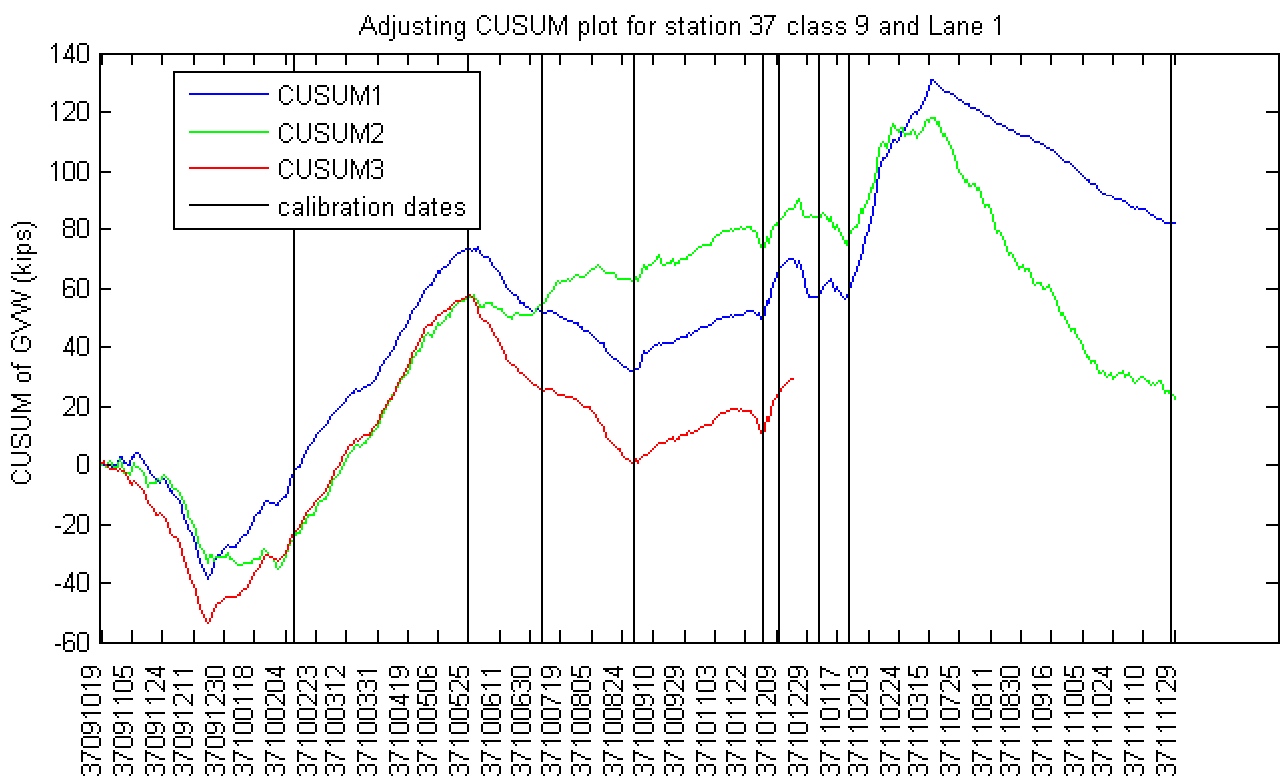


**Figure 3.11 Adjusting CUSUM Plot of WIM #37 GVW9 Lane 1**

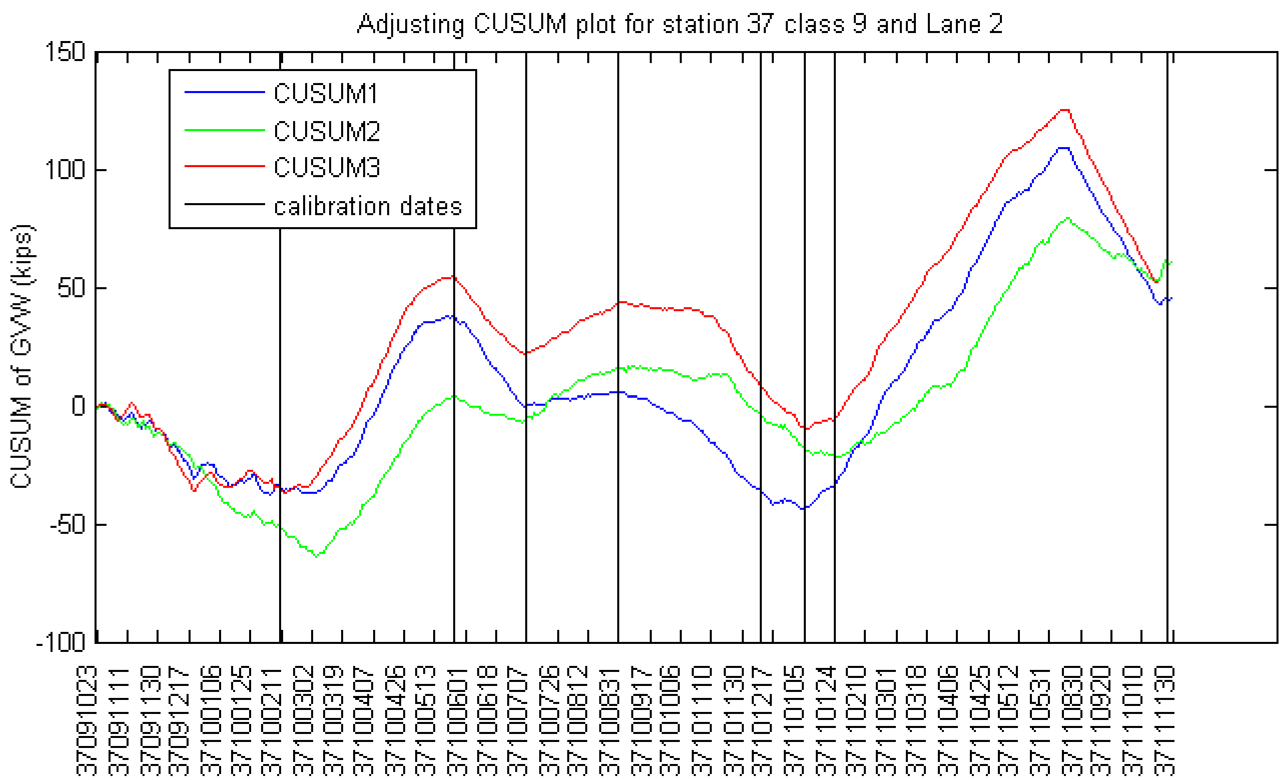


**Figure 3.12 Adjusting CUSUM Plot of WIM #37 GVW9 Lane 2**

3.2.3 Decision Interval (DI)

The standardized CUSUM form, $S_n$ (Eq. 3-6), can be used to directly interpret random walks and linear drifts of a process mean. The Decision Interval (DI) of CUSUM is proposed by Hawkins & Olwell (1998) to detect a process shift in mean that changes from general horizontal motion to a non horizontal linear drift. For example, a particular slope k and leg height h can be specified to test a shift. The sequence to monitor an upward shift in mean is defined in equation (3-17 & 3-18) as follows.

$$S_0^+ = 0 \tag{3-17}$$

$$S_n^+ = \max(0,\ S_{n-1}^+ + U_n - \mathrm{k}) \tag{3-18}$$

It signals an upward shift in mean if $S_0^+ > h$. Similarly, the sequence to monitor a downward shift in mean is defined in equation (3-19 & 3-20) as follows.

$$S_0^- = 0 \tag{3-19}$$

$$S_n^- = \min\left(0,\ S_{n-1}^- + U_n + \mathrm{k}\right) \tag{3-20}$$

It signals a downward shift in mean if $S_0^- < -h$. The constant k represents a reference value or allowance, and constant h is the decision interval. Hawkins & Olwell (1998) described in detail on how to choose an appropriate reference value k for the shift in mean of a normal distribution. The k value is chosen for optimal response that the CUSUM process will detect a shift of 2×k standard deviations.

For example, Figure 3-13 illustrates a decision interval form of a CUSUM of a process. The CUSUM graph shows the upper CUSUM $S_n^+$ and the lower CUSUM $S_n^-$ along with the decision intervals at h = 4 and h = - 4. The lower CUSUM drops after point 15, breaking out of the decision interval after point 29. This signals the presence of the shift of mean and the estimated shift in mean can be calculated as
$\hat{\delta} = 0.5 + \frac{4}{29-15} =$ 0.79 standard deviations.

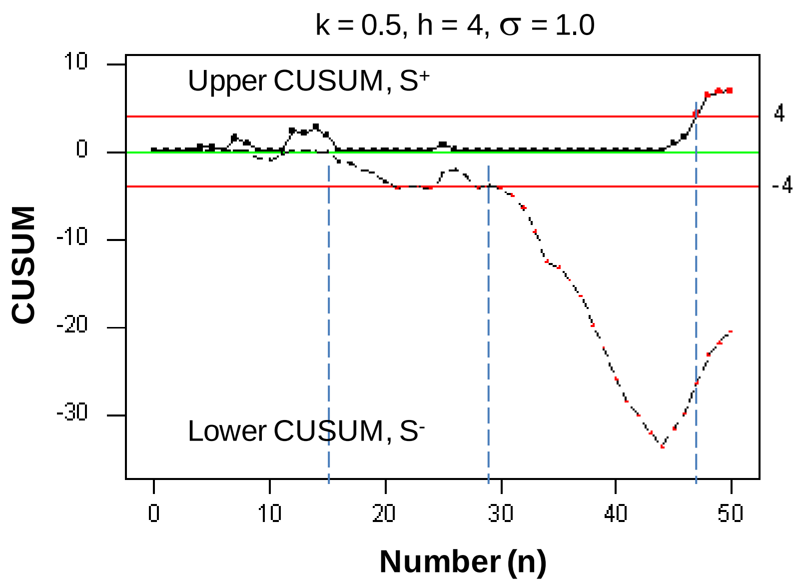


**Figure 3.13 Example of CUSUM Decision Interval**

The run length of a CUSUM process is the number of observations from the starting point to the point where CUSUM crossing the decision interval. The run length is a random variable with a mean, a variance, and a distribution. The Average Run Length (ARL) represents the mean of CUSUM run length. It is a performance of a CUSUM process. The ARL depends on the values of k and h. Larger values of either k or h will lead to larger ARL. More detailed information about the relationship among k, h, and ARL is described in Hawkins & Olwell (1998).

### 3.2.4 Analysis of Reference Value (k)

During the period from 1/8/2010 to 3/10/2010, the WIM station #37 functions properly without sensor drifts. The GVW9 values of unloaded and fully loaded trucks were analyzed to compute the reference value k by using 5% of average GVW as reference value or allowance. The estimated k value can be calculated using equation (3-21) as follows.

$$k = \frac{(5\% \text{ of Average GVW})}{2 \times \sigma} \qquad (3\text{-}21)$$

The analyzed results for both lane #1 and #2 were listed in Table 3-1 as follows. Therefore, k = 1.04 and h = ± 4 were chosen for adjusting CUSUM analysis.

**Table 3.1 Reference Value Analysis**

| WIM #37 | Group 1 GVW (kips) unloaded | | | | Group 3 GVW (kips), fully loaded | | | |
|---|---|---|---|---|---|---|---|---|
| Lane 1 | AVG | 33.80 | 5% AVG = | 1.69 | AVG | 77.72 | 5% AVG = | 3.89 |
| | SD | 0.96 | Estimated k= | 0.88 | SD | 1.86 | Estimated k= | 1.04 |
| Lane 2 | AVG | 31.12 | 5% AVG = | 1.56 | AVG | 74.29 | 5% AVG = | 3.71 |
| | SD | 0.99 | Estimated k= | 0.78 | SD | 2.25 | Estimated k= | 0.83 |

# 4. CUSUM ANALYSIS

## 4.1 Fully Loaded Truck (WIM #37 Lane #1)

The adjusting CUSUM plots of fully loaded trucks at WIM#37 Lane #1 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 10/19/2009 to 1/4/2010 with k = 1.04 and h = ± 4 are displayed in Figure 4-1. The sensor was calibrated using a test truck prior to 10/19/2009. The upper CUSUM stays in-control throughout the entire analysis period. However, the lower CUSUM plunges below the boundary of decision interval (-4) on 12/4/2009. The WIM system was calibrated on 12/22/2009 with adjustment of +10% to the calibration factor according to MnDOT WIM monthly report. The lower CUSUM curve recovers from its minimum value (-17.5) on 12/21/2009 after the calibration as illustrated in Figure 4-1. The estimated shift in mean can be calculated as $\hat{\delta} = 1.04 + \frac{4}{8\ days} = \ 1.54$ standard deviations.

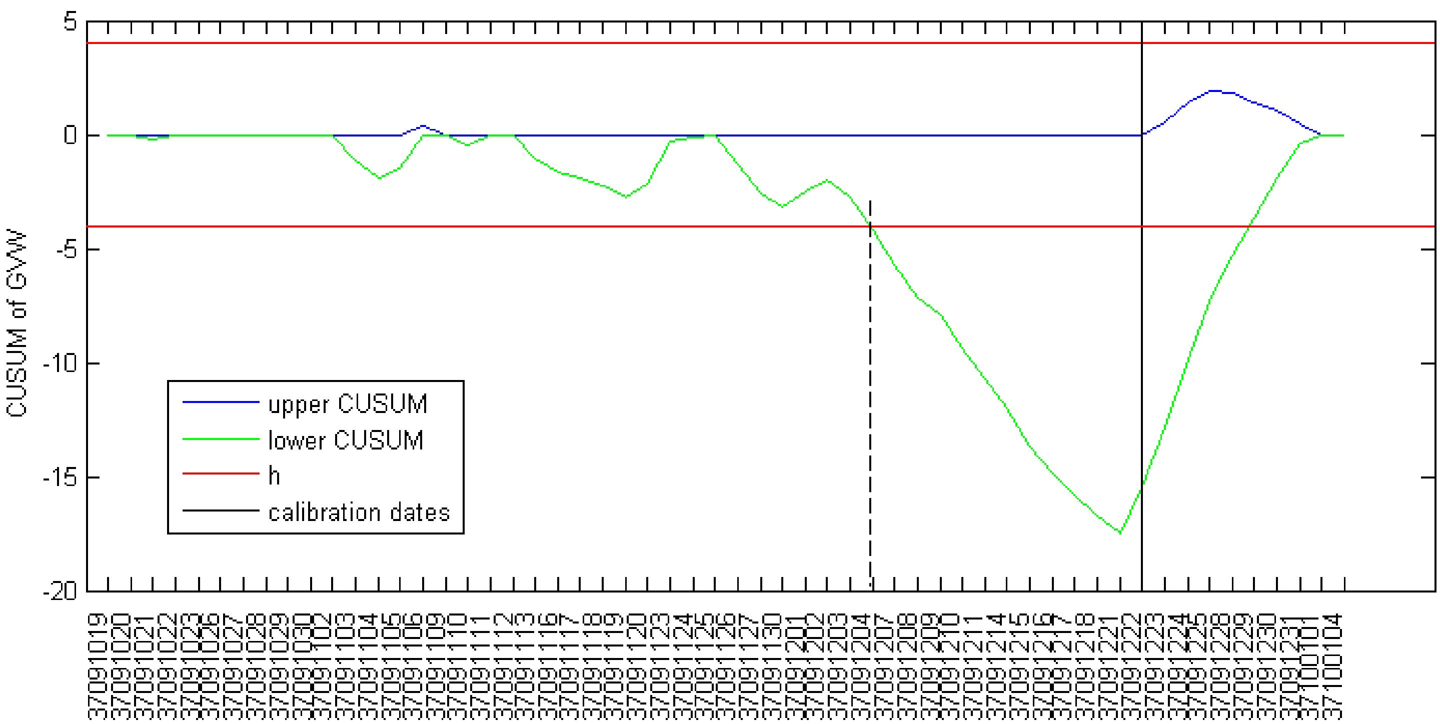


**Figure 4.1 Decision Interval CUSUM plot for Fully Loaded GVW9 Lane 1 (10/19/2009 – 1/4/2010)**

The adjusting CUSUM plots of fully loaded trucks at WIM#37 Lane #1 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 1/6/2011 to 3/14/2011 with k = 1.04 and h = ± 4 are shown in Figure 4-2. The sensor was calibrated using a test truck on 1/5/2011. The lower CUSUM stays in-control throughout the entire analysis period. However, the upper CUSUM increases above the boundary of decision interval (+4) on 1/25/2011 to its peak value (12) on 2/11/11 and then decreases below the boundary of decision interval (+4) on 2/24/12. The WIM system was not calibrated during this analysis period. The reason for the upper CUSUM curve drifts and then recovers during the one month period is unknown. Possible speculation might relate to the weather in Minnesota.

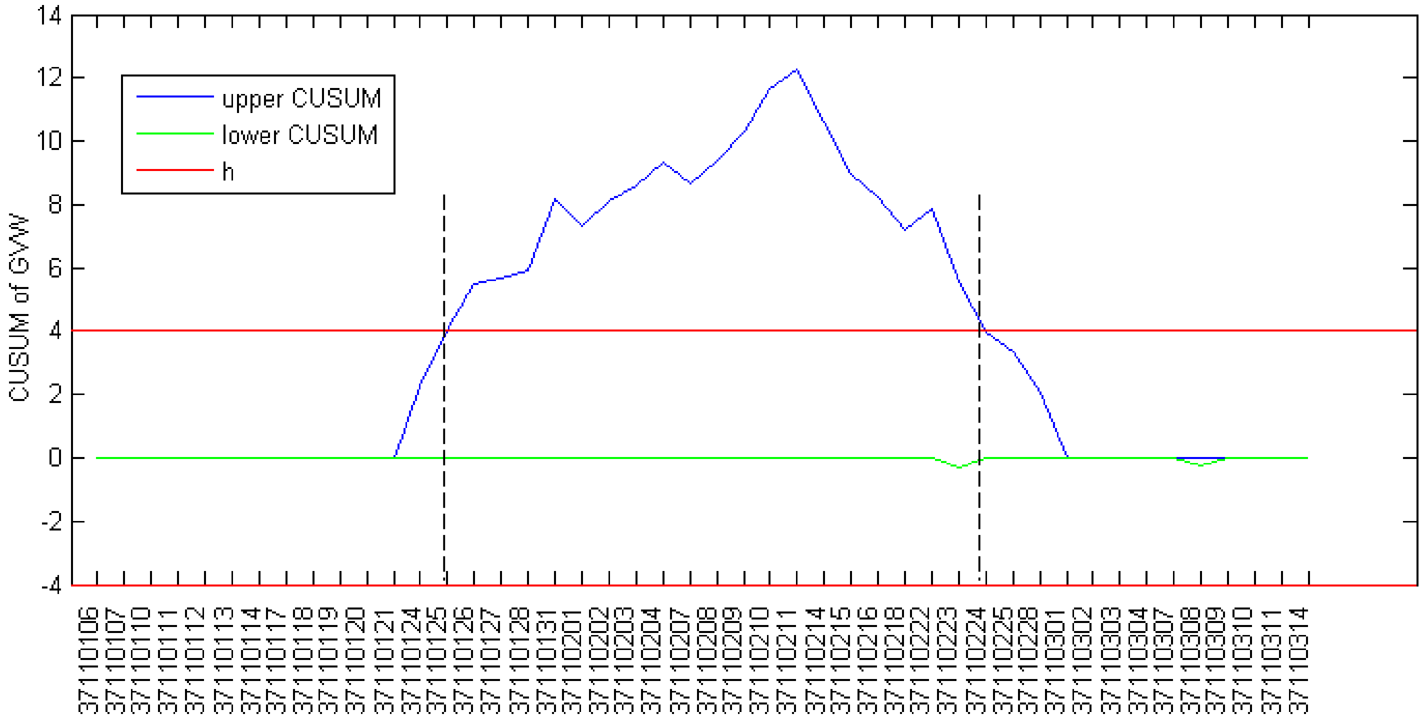


**Figure 4.2 Decision Interval CUSUM plot for Fully Loaded GVW9 Lane 1 (1/6/2011 – 3/14/2011)**

The adjusting CUSUM plots of fully loaded trucks at WIM#37 Lane #1 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 7/11/2011 to 12/5/2011 with k = 1.04 and h = ± 4 are shown in Figure 4-3. The sensor was calibrated using a test truck on 7/10/2011. Both upper and lower CUSUM curves stay in-control throughout the entire analysis period. The WIM system was calibrated on 11/28/2011, but no adjustment were made according to MnDOT monthly WIM report.

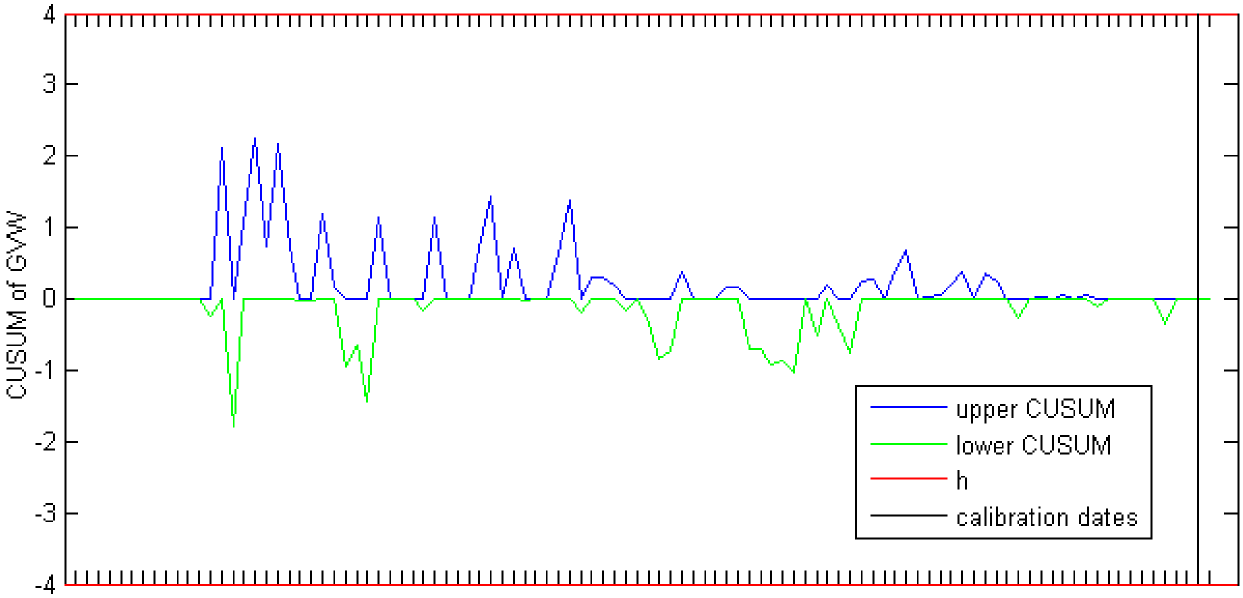


**Figure 4.3 Decision Interval CUSUM plot for Fully Loaded GVW9 Lane 1 (7/11/2011 – 12/5/2011)**

### 4.2 Unloaded Truck (WIM #37 Lane #1)

The adjusting CUSUM plots of unloaded trucks at WIM#37 Lane #1 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 10/19/2009 to 1/4/2010 with k = 1.04 and h = ± 4 are displayed in Figure 4-4. The sensor was calibrated using a test truck prior to 10/19/2009. Similar to the fully loaded trucks, the upper CUSUM stays in-control throughout the entire analysis period. However, the lower CUSUM plunges below the boundary of decision interval (-4) on 12/6/2009. The WIM system was calibrated using a loaded testing truck on 12/22/2009 with adjustment of +10% to the calibration factor according to MnDOT WIM monthly report. The lower CUSUM curve recovers from its minimum value (-15.5) on 12/21/2009 after the calibration and returns within the boundary of decision interval (-4) on 2/25/2009 as illustrated in Figure 4-4. The estimated shift in mean can be calculated as $\hat{\delta} = 1.04 + \frac{4}{8\ days} = \ 1.54$ standard deviations.

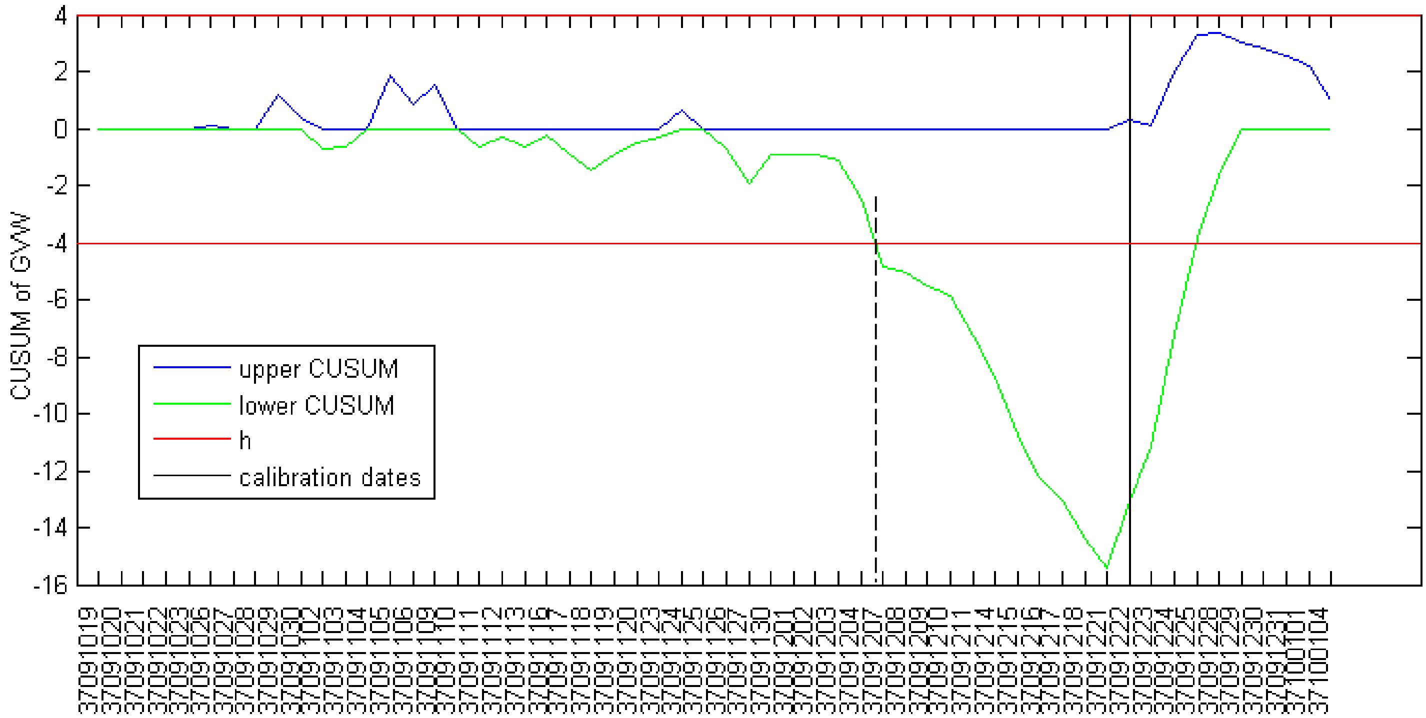


**Figure 4.4 Decision Interval CUSUM plot for Unloaded GVW9 Lane 1 (10/19/2009 – 1/4/2010)**

The adjusting CUSUM plots of unloaded trucks at WIM#37 Lane #1 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 12/2/2010 to 1/20/2011 with k = 1.04 and h = ± 4 are shown in Figure 4-5. The sensor was calibrated using a test truck on 12/1/2010. Both upper and lower CUSUM curves stay in-control throughout the entire analysis period. The WIM system was calibrated on 1/5/2011, but no adjustment were made according to MnDOT monthly WIM report. Both CUSUM curves remain in-control with minimal variations after the calibration on 1/5/2011.

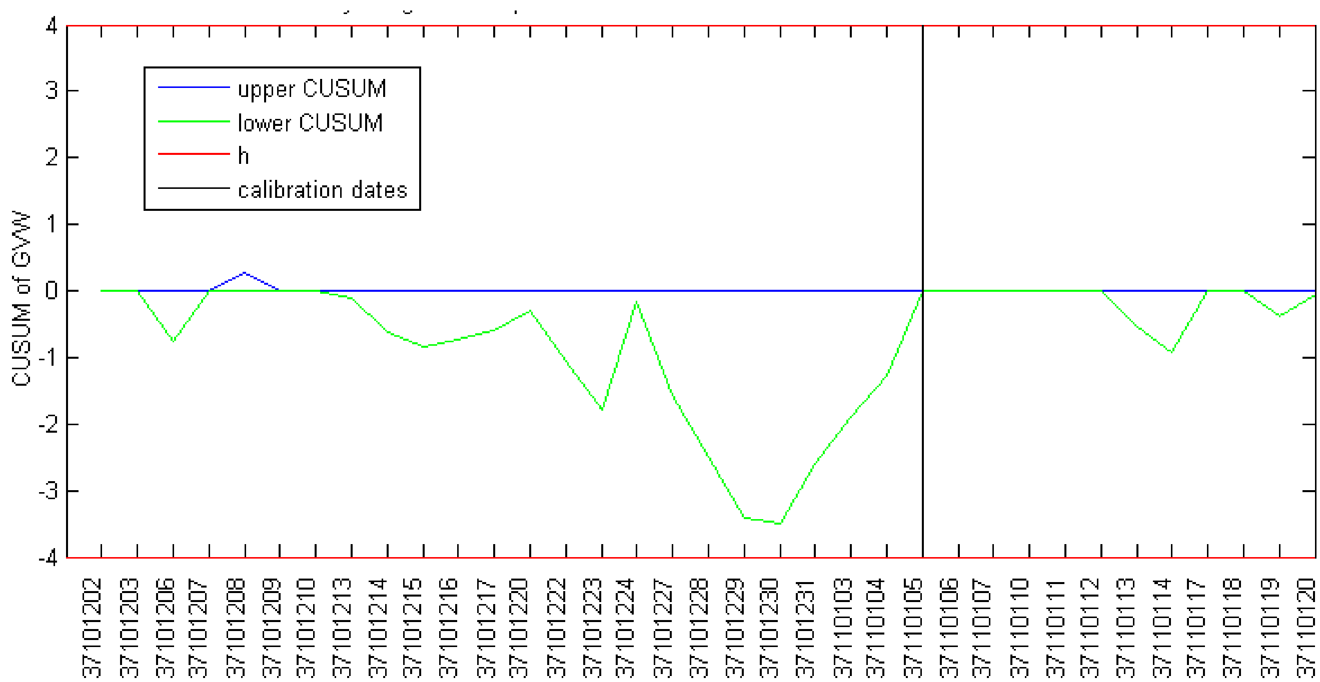


**Figure 4.5 Decision Interval CUSUM plot for Unloaded GVW9 Lane 1 (12/2/2010 – 1/20/2011)**

### 4.3 Fully Loaded Truck (WIM #37 Lane #2)

The adjusting CUSUM plots of fully loaded trucks at WIM#37 Lane #2 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 10/19/2009 to 1/4/2010 with k = 1.04 and h = ± 4 are displayed in Figure 4-6. The sensor was calibrated using a test truck prior to 10/19/2009. The upper CUSUM crosses over the upper boundary of decision interval (+4) on 11/11/2009 and then returns back in-control and stays in-control after 12/17/2009. However, the lower CUSUM plunges below the boundary of decision interval (-4) on 12/2/2009. The WIM system was calibrated on 12/22/2009 with adjustment of +10% to the calibration factor according to MnDOT WIM monthly report. The lower CUSUM curve recovers from its minimum value (-16) on 12/21/2009 after the calibration as illustrated in Figure 4-6. The estimated shift in mean can be calculated as $\hat{\delta} = 1.04 + \frac{4}{6\ days} = 1.7$ standard deviations. The CUSUM deviation slope between 12/2/2009 and 12/21/2009 is $\frac{-16-(-4)}{12\ days} = -1.0$ standard deviation per weekday.

The adjusting CUSUM plots of fully loaded trucks at WIM#37 Lane #2 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 3/10/2010 to 7/27/2010 with k = 1.04 and h = ± 4 are displayed in Figure 4-7. The sensor was calibrated using a test truck prior to 3/9/2010. The upper CUSUM crosses over the upper boundary of decision interval (+4) on 4/12/2010 and then returns back in-control and stays in-control after 5/5/2010. A calibration using loaded testing truck was conducted on 5/17/2010 with an adjustment of -9% to the sensor calibration factor. After the calibration on 5/17/2010, the upper CUSUM stays in-control afterward. However, the lower CUSUM plunges below the boundary of decision interval (-4) on 5/27/2010 after 10 days. The WIM system was again calibrated on 6/17/2010 with adjustment of -9% to the calibration factor according to MnDOT WIM monthly report. A third calibration was performed on 7/7/2010 with adjustment of -9% to the calibration factor. The lower CUSUM curve later recovers from its minimum value (-21) on 7/2/2010 after the calibrations as illustrated in Figure 4-7. The estimated shift in mean can be calculated as $\hat{\delta} = 1.04 + \frac{4}{8\ days} = \ 1.54$ standard deviations. The CUSUM deviation slope between 5/27/2010 and 6/17/2010 is about $\frac{-19-(-4)}{15\ days} = -1.0$ standard deviation per weekday.

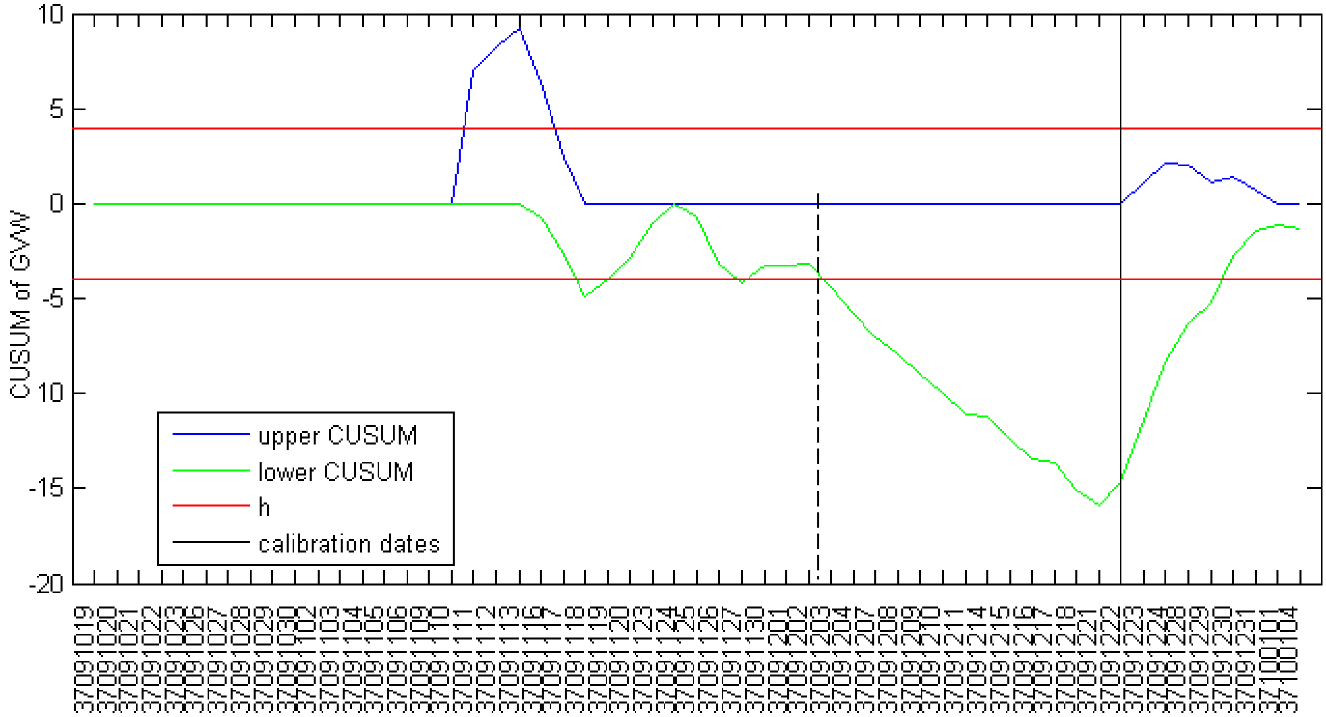


**Figure 4.6 Decision Interval CUSUM plot for Fully Loaded GVW9 Lane 2 (10/19/2009 – 1/4/2010)**

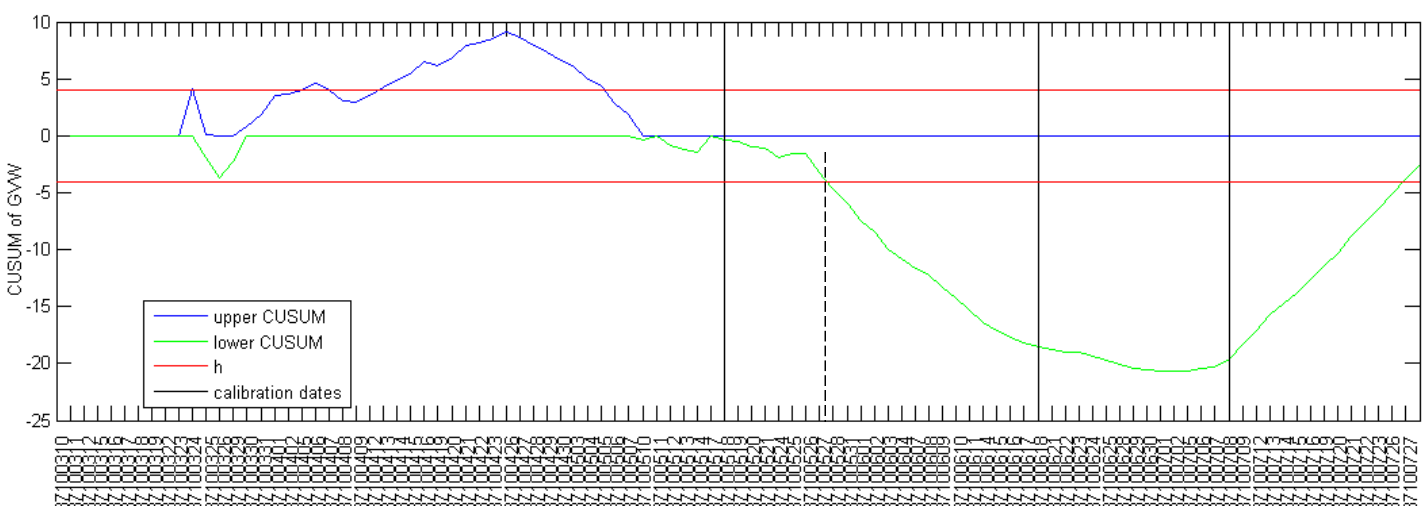


**Figure 4.7 Decision Interval CUSUM plot for Fully Loaded GVW9 Lane 2 (3/10/2010 – 7/27/2010)**

### 4.4 Unloaded Truck (WIM #37 Lane #2)

The adjusting CUSUM plots of unloaded trucks at WIM#37 Lane #2 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 10/19/2009 to 1/4/2010 with k = 1.04 and h = ± 4 are displayed in Figure 4-8. The sensor was calibrated using a test truck prior to 10/19/2009. Similar to the fully loaded trucks, the upper CUSUM stays in-control throughout the entire analysis period. However, the lower CUSUM plunges below the boundary of decision interval (-4) on 12/17/2009. The WIM system was calibrated using a loaded testing truck on 12/22/2009 with adjustment of +10% to the calibration factor according to MnDOT WIM monthly report. The lower CUSUM curve recovers from its minimum value (-6.5) on 12/21/2009 after the calibration and returns within the boundary of decision interval (-4) on 2/22/2009 as illustrated in Figure 4-8. The estimated shift in mean can be calculated as $\hat{\delta} = 1.04 + \frac{4}{10\ days} =\ 1.44$ standard deviations.

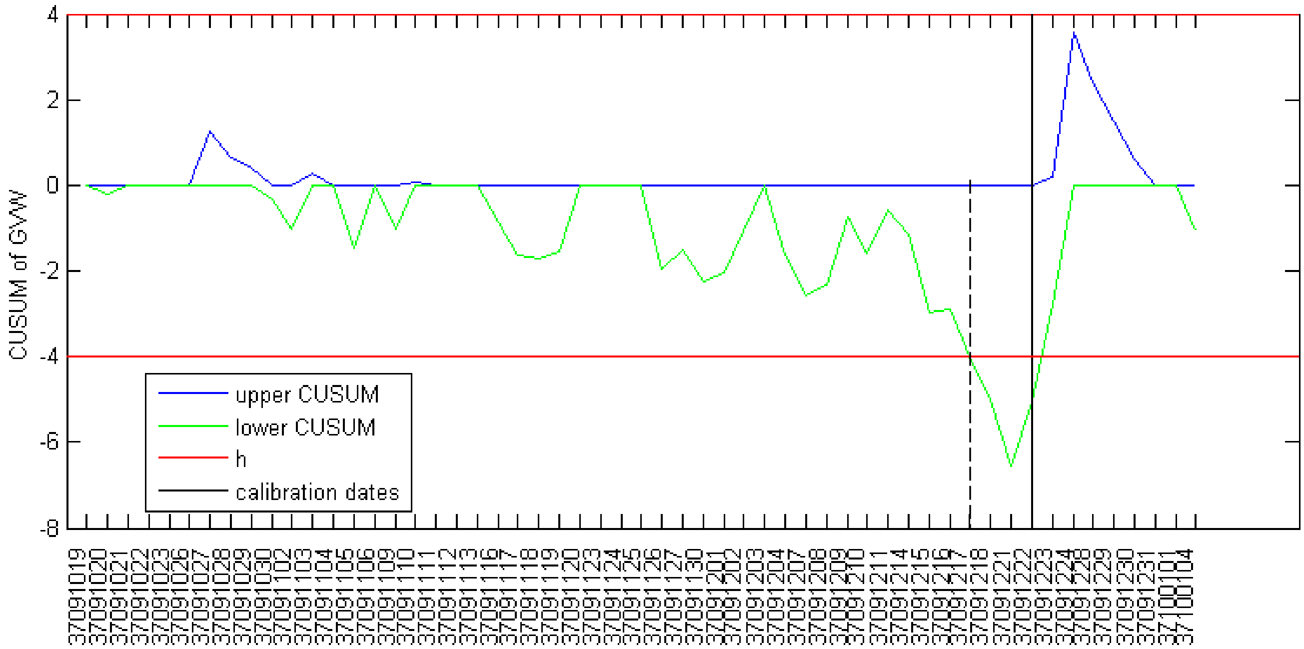


**Figure 4.8 Decision Interval CUSUM plot for Unloaded GVW9 Lane 2 (10/19/2009 – 1/4/2010)**

The adjusting CUSUM plots of unloaded trucks at WIM#37 Lane #2 including both upper ($S_n^+$) and lower ($S_n^-$) CUSUM on weekdays from 3/10/2010 to 7/27/2010 with k = 1.04 and h = ± 4 are displayed in Figure 4-9. The sensor was calibrated using a test truck prior to 3/9/2010. The upper CUSUM crosses over the upper boundary of decision interval (+4) on 4/14/2010 and then returns back in-control and stays in-control after 4/27/2010. A calibration using loaded testing truck was conducted on 5/17/2010 with an adjustment of -9% to the sensor calibration factor. After the calibration on 5/17/2010, the upper CUSUM stays in-control afterward. However, the lower CUSUM plunges below the boundary of decision interval (-4) on 6/1/2010. The WIM system was again calibrated on 6/17/2010 with adjustment of -9% to the calibration factor according to MnDOT WIM monthly report. A third calibration was performed on 7/7/2010 with adjustment of -9% to the calibration factor.  The lower CUSUM curve later recovers from its minimum value (-19) on 7/5/2010 after the calibrations as illustrated in Figure 4-9. The estimated shift in mean can be calculated as $\hat{\delta} = 1.04 + \frac{4}{11\,days} =$ 1.4 standard deviations. The CUSUM deviation slope between 6/1/2010 and 6/17/2010 is about $\frac{-19-(-4)}{12\,days} = -1.25$ standard deviation per weekday.

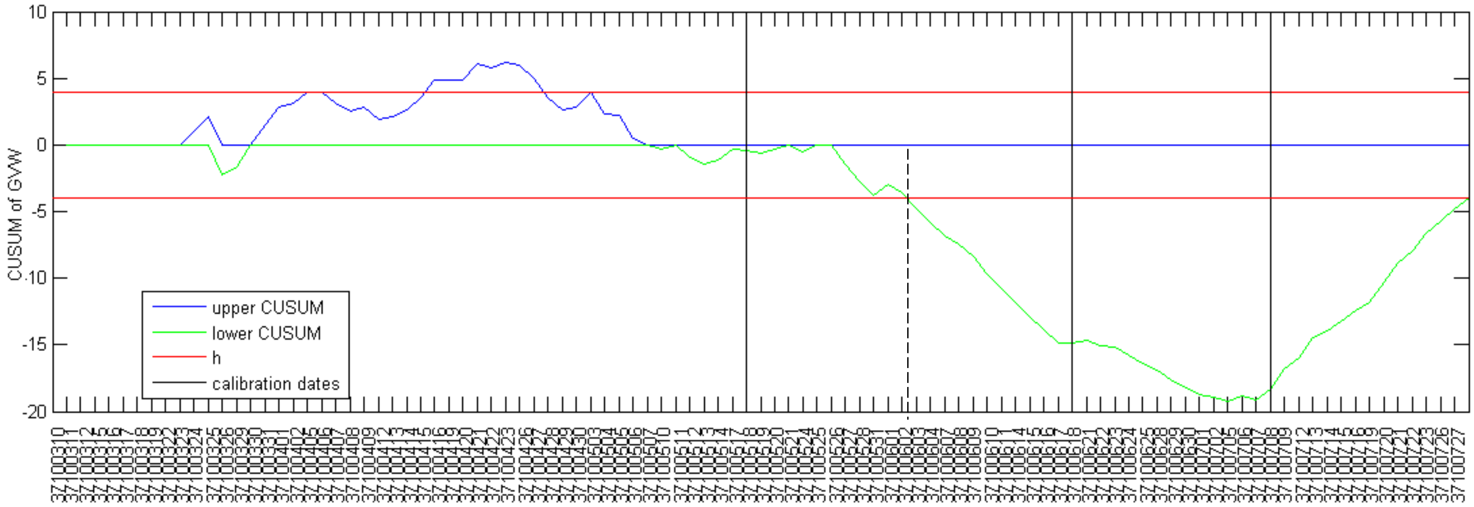


**Figure 4.9 Decision Interval CUSUM plot for Unloaded GVW9 Lane 2 (3/10/2010 – 7/27/2010)**

### 4.5 Adjusting CUSUM Deviation and Calibration Adjustment

The adjusting CUSUM deviations computed from the CUSUM charts when the process is out of control were compared with the actual calibration adjustment at WIM station #37 as listed in Table 4-1. The graph displayed in Figure 4-10 indicated that the computed deviations from adjusting CUSUM methodology did not necessarily reflect the actual calibration adjustments in the field ($R^2 = 0.01$). Figure 4-1, 4-4, and 4-6 to 4-9 indicated that the adjusting CUSUM methodology detects the sensor output drifts 1 to 2 weeks in average before the actual calibration was performed. Sometimes, the WIM sensors may shift outside the decision interval boundary for a few days (5 days in Figure 4-6, and 19 days in Figure 4-2) and then return back in control.

**Table 4.1 CUSUM Deviation versus Calibration Adjustment**

| Lane | k | h | In-control Days | Deviation (# SD) | Calibration Adjustment (%) |
|---|---|---|---|---|---|
| 1 | 1.04 | 4 | 7 | -1.61 | 10.0% |
| 2 | 1.04 | 4 | 7 | -1.61 | 10.0% |
| 2 | 1.04 | 4 | 9 | -1.48 | -9.0% |
| 2 | 1.04 | 4 | 3 | -2.37 | -9.0% |
| 2 | 1.04 | 4 | 6 | 1.71 | -2.3% |
| 2 | 1.04 | 4 | 4 | -2.04 | 9.6% |
| 2 | 1.04 | 4 | 2 | 3.04 | 9.6% |
| 2 | 1.04 | 4 | 9 | -1.48 | -9.0% |
| 2 | 1.04 | 4 | 4 | -2.04 | 9.6% |

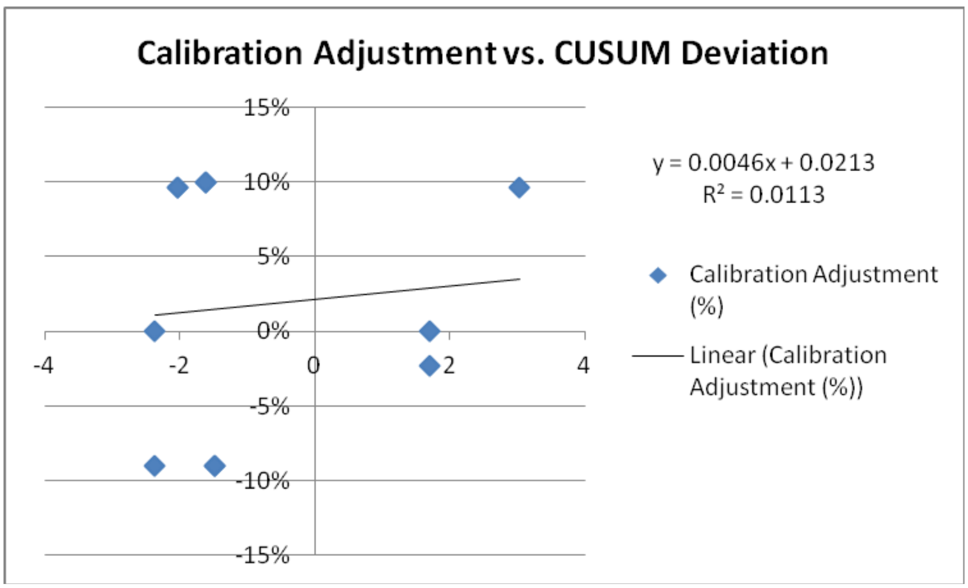


Figure 4.10 Calibration Adjustment vs. Adjusting CUSUM Deviation

# 5. GRAPHICAL USER INTERFACE (GUI)

A Matlab based Graphical user's Interface (GUI) prototype, as illustrated in Figure 5-1, was developed to automate the data processing and analysis. The raw data (*.asc) files first need to be copied to the ~\data\station_ID\ sub directory under the user selectable project directory (e.g., C:\production\ data\station_ID\). Secondly, select the starting and ending dates of the WIM data to be processed. Finally select the station ID for the data to be processed before clicking on the OK button to begin the data processing.

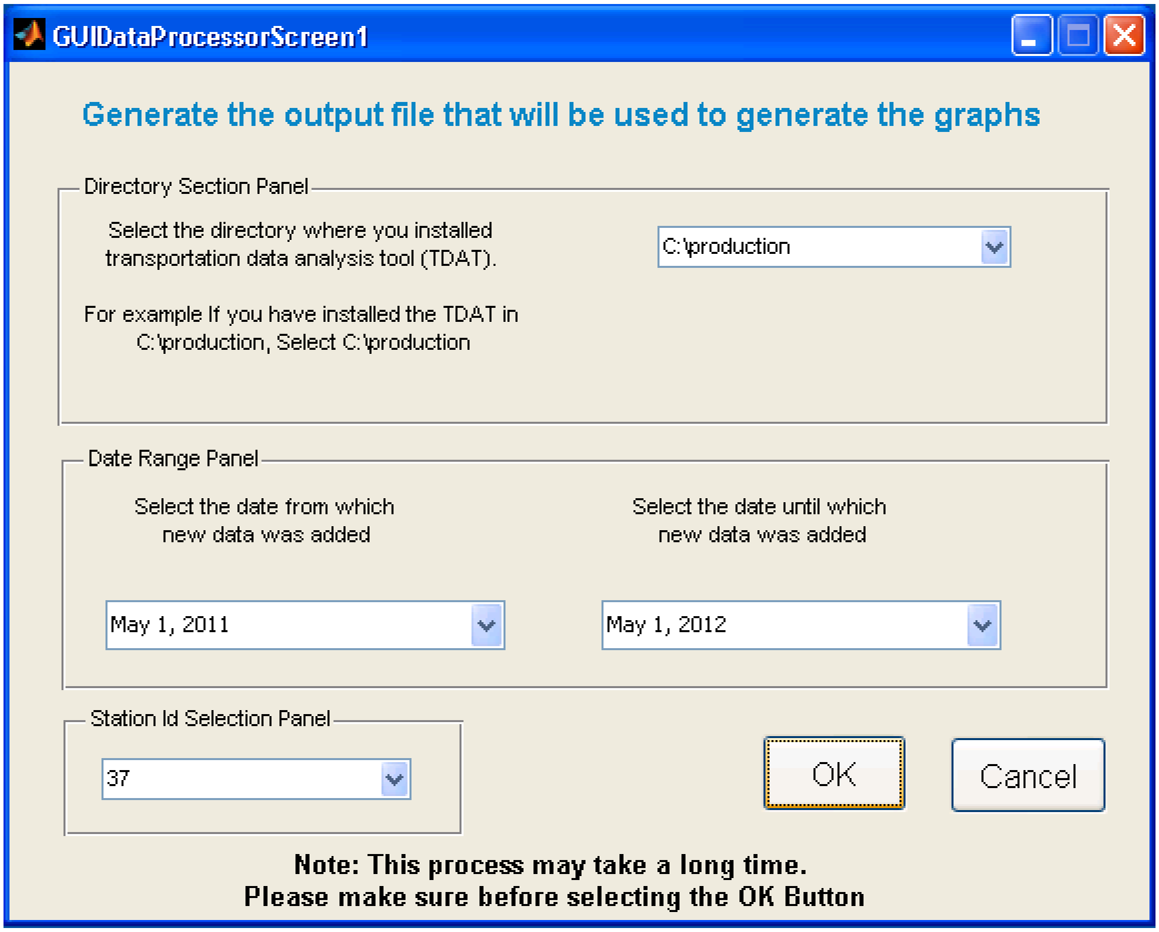


**Figure 5.1 Matlab GUI**

Processed data output will be stored in two different sub directories (~\output\processedOutput\ and ~\output\processDays) under the user selectable project directory (e.g., C:\production\ output\processedOutput\). The processDays sub directory stores the date string and day of week number for Matlab scripts to process the WIM raw data. The processedOutput sub directory contains the mean and standard deviation of daily WIM data by vehicle class. Results for vehicle class 9 GVW are separated in three different groups (unloaded, partially loaded, and fully loaded). Table 5-1 lists a sample of processed data for WIM station #40 Lane #1.

**Table 5.1** **Sample Processed GVW9 Output**

| Date | 40110103 | 40110104 | 40110105 | 40110106 | 40110107 | 40110110 | 40110111 | 40110112 |
|---|---|---|---|---|---|---|---|---|
| **N** | 485 | 523 | 680 | 713 | 530 | 599 | 307 | 541 |
| **$\mu_1$_L** | 31.45512 | 31.40467 | 32.29371 | 32.22286 | 32.34293 | 31.78292 | 31.60483 | 31.70611 |
| **$\mu_1$** | 32.1315 | 32.02516 | 32.89237 | 32.90315 | 33.03477 | 32.55503 | 32.44615 | 32.43569 |
| **$\mu_1$_U** | 32.80789 | 32.64565 | 33.49103 | 33.58344 | 33.72662 | 33.32713 | 33.28747 | 33.16526 |
| **$\mu_2$_L** | 47.16194 | 46.87011 | 51.44323 | 49.79332 | 49.88923 | 45.73054 | 43.06264 | 42.68303 |
| **$\mu_2$** | 51.39558 | 50.15445 | 55.70946 | 53.2237 | 54.59149 | 49.02175 | 46.33989 | 45.7651 |
| **$\mu_2$_U** | 55.62921 | 53.43879 | 59.97569 | 56.65408 | 59.29375 | 52.31296 | 49.61714 | 48.84717 |
| **$\mu_3$_L** | 76.77881 | 77.45932 | 77.90576 | 77.90173 | 77.32389 | 76.48528 | 76.65423 | 70.99342 |
| **$\mu_3$** | 77.69006 | 78.16559 | 78.60884 | 78.45472 | 78.06504 | 77.18262 | 77.49993 | 73.8601 |
| **$\mu_3$_U** | 78.60132 | 78.87186 | 79.31191 | 79.00771 | 78.80618 | 77.87996 | 78.34564 | 76.72678 |
| **σ1** | 3.994313 | 3.350424 | 3.971757 | 4.142557 | 3.847611 | 4.485624 | 2.986409 | 4.075372 |
| **σ2** | 11.31829 | 11.78512 | 13.0639 | 14.72755 | 14.24627 | 10.13171 | 10.87521 | 5.074658 |
| **σ3** | 4.747737 | 4.069484 | 4.234475 | 3.387672 | 3.992227 | 4.784342 | 4.214498 | 12.35094 |
| **p1** | 0.406042 | 0.337638 | 0.373398 | 0.332435 | 0.338201 | 0.358489 | 0.292028 | 0.399737 |
| **p2** | 0.255826 | 0.320714 | 0.291404 | 0.352963 | 0.330814 | 0.231338 | 0.326452 | 0.114766 |
| **p3** | 0.338131 | 0.341648 | 0.335198 | 0.314602 | 0.330985 | 0.410173 | 0.381519 | 0.485497 |

Where,

Date: date in [station ID][yy][mm][dd] format,
N: number of vehicles,
$\mu_1$_L: lower bound of 95% confidence interval of group 1 average,
$\mu_1$: group 1 average,
$\mu_1$_U: upper bound of 95% confidence interval of group 1 average,
$\mu_2$_L: lower bound of 95% confidence interval of group 2 average,
$\mu_2$: group 2 average,
$\mu_2$_U: upper bound of 95% confidence interval of group 2 average,
$\mu_3$_L: lower bound of 95% confidence interval of group 3 average,
$\mu_3$: group 3 average,
$\mu_3$_U: upper bound of 95% confidence interval of group 3 average,
$\sigma 1$, $\sigma 2$, $\sigma 3$: standard deviation of group 1, 2, and 3, and
p1, p2, p3: standard deviation of group 1, 2, and 3.

Detailed information regarding the data processing descriptions is included in Appendix D.

# 6. SUMMARY AND CONCLUSION

This study explored several statistical data analysis methodologies to detect WIM sensor drifts and support WIM calibration. A mixture modeling technique using EM algorithm was developed to divide the vehicle class 9 GVW into three normally distributed components, unloaded, partially loaded, and fully loaded trucks. In addition to the GVW for vehicle class 9, steering axle weight for vehicle class 2, 3, and 9 were also analyzed to examine potential trend of data drifting by comparing the variation with calibration dates.

CUSUM charts are often used to detect persistent deviations of a process mean from a known target value. The CUSUM methodology was explored to detect drifts of WIM sensors. An adjusting CUSUM methodology was formulated and implemented to detect anomaly on weekdays. The adjusting CUSUM was reset back to zero whenever a WIM calibration is performed. The DIs and allowance reference of adjusting CUSUM were also implemented to detect a process shift in mean that changes from general horizontal motion to a non-horizontal linear drift. A known period of WIM data set with no sensor drifts was used to develope the corresponding reference allowance (k) and DI (h) for anomaly detection.

The results indicated that the adjusting CUSUM methodology was able to detect the sensor drifts prior to the actual calibration. The CUSUM curves can trigger an alert to the WIM manager or operator that the WIM sensor may drift further from normal operation if the CUSUM curves do not fall back inside the DI band with a time period (1-2 weeks). Further investigation was performed to compare the CUSUM deviation and the calibration adjustment. However, the analysis results did not indicate any relationship between the derived CUSUM deviation and the calibration adjustment.

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# APPENDIX A: WIM SITES IN MINNESOTA

### A.1 List of Minnesota WIM Sites

- WIM 26: I-35, Owatonna
- WIM 27: MN 60, St. James
- WIM 29: US 53, Cotton
- WIM 30: MN 61, Two Harbors
- WIM 31: US 2, Fisher
- WIM 33: US 212, Olivia
- WIM 34: MN 23, Clara City
- WIM 35: US 2, Bagley
- WIM 36: MN 36, Lake Elmo
- WIM 37: I-94, Albertville
- WIM 38: I-535, Duluth
- WIM 39: MN 43, Winona
- WIM 40: US 52, South St. Paul
- WIM 41: CSAH 14, Crookston
- WIM 42: US 61, Cottage Grove
- WIM 43: US 10, Glyndon

# APPENDIX B: WEIGH-IN-MOTION (WIM) DATA

**B.1 Raw WIM Data (IRD Software Operator's Manual)**

A listing ASCII vehicle data records as collected and stored by the system, including diagnostic and calibration records. A file in this format may be used as input to other data processing programs. Each record ends with a carriage return (ASCII code 013); fields are delimited by commas. Each record will contain between 47 and 67 fields. Fields without data are filled with zeros, with the exception of the external data tag and external information fields, which have a null entry if there is no data (the field delimiting commas will still be present). The external data tag and external information fields are optional; if present they always appear as a pair. There may be between 0 and 10 pairs of external data/information fields; the number of pairs used will be determined by the requirements of the data collection site, but will be a fixed number for that site.

The data fields are:

- year,
- month,
- day,
- hour,
- minute,
- second,
- error number,
- status code
- record type,
- lane,
- speed,
- class,
- length,
- GVW,
- ESAL,
- weight axle 1,
- axle spacing 1-2,
- weight axle 2,
- axle spacing 2-3,
- weight axle 3,
- axle spacing 3-4,

- weight axle 13,
- axle spacing 13-14,
- weight 14,
- External data tag 1 (optional),
- External information 1 (optional),
- External data tag n (optional),

- External information n (optional),
- temperature

The status code field is a bitmap which indicates the state of the various errors and warnings. When the status is set for an error or warning, the corresponding bit in the bitmap will be set. The following list displays the bitmap (in hexadecimal characters) for each error or warning:

**Table B-1 WIM Data Status Code**

| Error or Warning Displayed | Hexadecimal Bitmap |
|---|---|
| None | 0x00000000 |
| Offscale Hit | 0x00000001 |
| Overheight | 0x00000002 |
| Onscale Missed | 0x00000004 |
| Significant Speed Change | 0x00000008 |
| Significant Weight Difference | 0x00000010 |
| Vehicle Headway Too Short | 0x00000020 |
| Unequal Axle Count on Sensors | 0x00000040 |
| Tailgating | 0x00000080 |
| Wrong Lane | 0x00000100 |
| Running Scale | 0x00000200 |
| Truck Not In WIM Lane | 0x00000400 |
| Overlength | 0x00000800 |
| Overweight | 0x00001000 |
| OverGVW | 0x00002000 |
| Safety (Random) | 0x00004000 |
| Speeding | 0x00008000 |
| Truck is Late to Station | 0x00010000 |
| Truck is unexpected | 0x00020000 |
| Truck is overdue | 0x00040000 |
| Vehicle Not Matched | 0x00080000 |
| Lateral Position Error | 0x00100000 |
| No Compliance Information | 0x00200000 |
| Sort Override Failed | 0x00400000 |
| Failed Credential Check | 0x00800000 |

If more than one error or warning status has been set, the bitmap will display as the hexadecimal sum of the set bits. For example, if the warnings are:

UNEQUAL_AXLE_COUNT = 0x00000040

TAILGATING = 0x00000080

The status field bitmap will be: 0x000000C0

### B.2 Sample of Raw WIM Data

The sample below is a report listing raw ASCII records of vehicle data for a 3 minute period starting at 12:00 PM on May 15, 2012 at WIM station #39:

```
12,5,15,12, 0, 8,0,00000000,12,1,54,9,61,74.4,1.7040,12.0,14.5,16.8,4.4,15.7,29.8,14.2,4.7,15.8,0.0,. . . ,,,91

12,5,15,12, 0,13,0,00000000,12,1,50,2,15,3.0,0.0004,1.6,8.7,1.4,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 0,21,0,00000000,12,1,48,3,18,5.5,0.0013,3.2,11.6,2.4,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 0,58,0,00000000,12,1,47,2,15,4.2,0.0013,3.0,9.0,1.2,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1, 9,0,00000000,12,1,17,2,12,4.2,0.0004,2.1,8.9,2.1,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,22,0,00000000,12,2,45,9,57,71.9,1.6885,10.5,12.8,14.1,4.2,14.7,28.2,16.6,4.2,15.9,0.0,. . . ,,,91

12,5,15,12, 1,25,0,00000000,12,2,43,2,14,3.5,0.0004,2.0,8.6,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,27,0,00000000,12,2,45,2,18,3.2,0.0004,2.1,9.6,1.2,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,31,0,00000000,12,2,48,3,27,5.3,0.0013,3.0,12.0,2.3,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,33,0,00000000,12,2,47,2,16,3.0,0.0004,1.9,8.7,1.1,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,35,0,00000000,12,2,46,3,17,5.3,0.0013,3.3,9.9,2.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,39,0,00000000,12,2,48,5,15,7.4,0.0062,5.3,8.9,2.1,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,39,0,00000000,12,1,46,9,72,49.1,0.3365,10.8,16.4,9.3,4.3,9.0,36.4,9.9,4.2,10.0,0.0,. . . ,,,91

12,5,15,12, 1,41,0,00000010,12,1,44,5,15,10.0,0.0612,8.5,9.6,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,48,0,00000000,12,1,51,2,15,3.5,0.0004,2.0,8.6,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,54,0,00000000,12,2,47,2,20,2.8,0.0004,1.9,8.7,0.9,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 1,57,0,00000000,12,1,52,2,16,3.9,0.0004,2.3,9.3,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,19,0,00000000,12,2,51,5,21,11.2,0.0160,5.4,13.0,5.9,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,23,0,00000000,12,1,60,3,17,3.5,0.0004,2.3,10.7,1.2,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,26,0,00000000,12,2,57,3,18,3.8,0.0004,2.3,10.0,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,27,0,00000000,12,2,58,3,13,3.8,0.0004,2.2,9.9,1.6,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,35,0,00000000,12,1,53,9,63,25.7,0.0992,10.0,18.5,5.8,4.3,5.1,29.9,2.1,4.1,2.6,0.0,. . . ,,,91

12,5,15,12, 2,38,0,00000000,12,1,52,5,24,11.0,0.0240,3.6,14.7,7.4,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,48,0,00000000,12,1,59,3,17,4.5,0.0013,2.6,10.0,1.9,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 2,58,0,00000000,12,1,52,2,5,2.0,0.0004,0.8,5.3,1.2,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91

12,5,15,12, 3,19,0,00000000,12,1,48,2,16,3.3,0.0004,2.0,9.2,1.3,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
```

```
12,5,15,12, 3,20,0,00000000,12,1,50,3,18,4.7,0.0013,2.8,11.3,1.8,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,21,0,00000000,12,2,48,2,14,3.6,0.0004,2.1,8.8,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,23,0,00000000,12,2,48,2,17,3.7,0.0004,2.4,9.3,1.3,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,25,0,00000000,12,2,45,3,20,4.8,0.0013,2.2,11.2,2.6,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,28,0,00000000,12,2,48,3,18,4.0,0.0004,2.4,9.9,1.7,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,30,0,00000000,12,2,46,2,15,3.8,0.0004,2.2,8.6,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,31,0,00000000,12,2,46,3,19,5.6,0.0013,3.3,12.5,2.3,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,39,0,00000000,12,2,47,2,11,3.2,0.0004,1.7,6.7,1.5,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,43,0,00000000,12,1,58,2,17,3.6,0.0004,2.2,9.0,1.4,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 3,52,0,00000000,12,2,55,2,16,4.0,0.0004,2.0,8.7,2.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,14,0,00000000,12,2,46,6,38,24.2,0.0810,8.5,18.2,7.8,4.2,7.9,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,15,0,00000000,12,1,41,2,16,3.3,0.0004,2.1,9.3,1.2,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,17,0,00000000,12,2,44,2,15,2.7,0.0004,1.7,8.8,1.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,18,0,00000000,12,2,43,2,13,2.1,0.0004,1.4,8.7,0.8,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,19,0,00000000,12,2,42,2,16,3.4,0.0004,2.1,9.3,1.3,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,19,0,00000000,12,1,48,5,23,15.5,0.0710,6.3,14.3,9.2,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,22,0,00000000,12,1,50,3,18,4.3,0.0004,2.5,11.2,1.8,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,31,0,00000000,12,1,47,9,50,26.0,0.0700,9.3,15.2,4.3,4.2,5.4,21.3,3.8,4.2,3.2,0.0,. . . ,,,91
12,5,15,12, 4,49,0,00001000,12,1,48,9,61,73.0,1.9270,7.7,18.0,17.5,4.3,17.6,28.9,14.2,4.1,16.1,0.0,. . . ,,,91
12,5,15,12, 4,52,0,00000000,12,1,45,2,17,3.8,0.0004,2.3,9.7,1.4,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,54,0,00000000,12,1,44,3,18,5.0,0.0013,3.3,10.5,1.7,0.0,0.0,0.0,0.0,0.0,0.0,0.0,. . . ,,,91
12,5,15,12, 4,58,0,00000000,12,1,45,9,56,27.9,0.0745,9.4,13.7,6.0,4.7,4.8,27.9,2.5,4.0,5.3,0.0,. . . ,,,91
```

### B.3 Summary of Missing Data

The following table gives the number of values missed in each case, so that the cumulative distribution function could be applied.

| Type | station id, Class id, lane id, type | Number of values missed | station id, Class id, lane id, type | Number of values missed |
|---|---|---|---|---|
| *GVW* | *35,2,4* | *All* | *39,2,1* | *65* |
| | *36,9,all* | *All* | *39,3,2* | *45* |
| | *39,9,all* | *All* | *40,2,1* | *55* |
| | *35,9,4* | *3* | *40,2,2* | *10* |
| | *35,3,4* | *5* | *40,3,2* | *5* |
| | *36,2,4* | *75* | *40,3,4* | *5* |
| | *36,3,1* | *35* | *40,9,2* | *55* |
| | *36,3,3* | *30* | *40,9,3* | *65* |
| | *37,2,2* | *5* | *40,9,4* | *5* |
| | *37,9,2* | *5* | | |

| Type | station id, Class id, lane id, type | Number of values missed | station id, Class id, lane id, type | Number of values missed |
|---|---|---|---|---|
| *FXW* | *37,3,2* | *all* | *37,3,2* | *85* |
| | *35,2,4* | *55* | *37,9,1* | *5* |
| | *35,3,4* | *55* | *37,9,2* | *5* |
| | *35,9,4* | *5* | *39,2,1* | *40* |
| | *36,2,4* | *75* | *39,3,1* | *40* |
| | *36,3,1* | *5* | *39,3,2* | *65* |
| | *36,3,3* | *30* | *39,9,1* | *95* |
| | *36,9,1* | *30* | *40,2,1* | *70* |
| | *37,2,2* | *5* | *40,2,2* | *10* |
| | *40,3,1* | *20* | *40,3,2* | *60* |
| | *40,3,3* | *80* | *40,3,4* | *80* |
| | *40,9,1* | *50* | *40,9,4* | *10* |

| Type | station id, Class id, lane id, type | Number of values missed | station id, Class id, lane id, type | Number of values missed |
|---|---|---|---|---|
| *FXS* | | | *37,3,1* | *55* |
| | *35,2,4* | *5* | *37,9,1* | *5* |
| | *35,3,4* | *55* | | |
| | *36,2,1* | *25* | *39,2,2* | *35* |
| | *36,2,4* | *5* | *39,3,1* | *75* |
| | *36,3,1* | *35* | *39,3,2* | *65* |
| | *36,3,2* | *5* | *39,9,1* | *10* |
| | *36,3,2* | *5* | *39,9,2* | *10* |
| | *36,3,3* | *5* | *40,2,1* | *5* |
| | *36,3,4* | *15* | *40,2,2* | *5* |
| | *36,9,1* | *5* | *40,9,1* | *80* |
| | *36,9,4* | *60* | *40,9,3* | *5* |
| | | | *40,9,4* | *40* |

*Note:* NaN values in between data can cause the dates value to be incorrectly comprehended causing the calibration lines to be skewed. For most stations this isn't a problem as NaN values appear only at the end. However, for station 37 there are a lot of NaN values in between the data.

### B.4 Sample Data of EM Fitting Output

The sample below is a report listing EM fitting output of vehicle class 9 GVW for 28 weekdays starting on April 3, 2012 at WIM station #37:

| Date | N | µ1_L | µ1 | µ1_U | µ2_L | µ2 | µ2_U | µ3_L | µ3 | µ3_U | SD1 | SD2 | SD3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 37120403 | 627 | 29.01 | 29.62 | 30.24 | 45.46 | 48.46 | 51.45 | 72.91 | 73.53 | 74.15 | 2.59 | 12.88 | 3.99 | 0.20 | 0.42 | 0.38 |
| 37120404 | 583 | 29.85 | 30.38 | 30.91 | 49.54 | 52.29 | 55.05 | 73.78 | 74.44 | 75.10 | 2.13 | 12.85 | 3.98 | 0.16 | 0.45 | 0.38 |
| 37120405 | 663 | 29.32 | 29.85 | 30.37 | 45.80 | 48.33 | 50.86 | 73.51 | 74.12 | 74.73 | 2.24 | 11.82 | 4.47 | 0.18 | 0.38 | 0.44 |
| 37120406 | 486 | 30.63 | 31.36 | 32.08 | 49.81 | 53.69 | 57.57 | 73.92 | 74.65 | 75.38 | 2.84 | 13.35 | 3.90 | 0.21 | 0.42 | 0.37 |
| 37120409 | 563 | 29.76 | 30.87 | 31.98 | 48.68 | 52.00 | 55.32 | 73.95 | 74.58 | 75.20 | 4.55 | 11.80 | 3.53 | 0.24 | 0.41 | 0.34 |
| 37120410 | 640 | 29.80 | 30.63 | 31.47 | 49.30 | 52.55 | 55.80 | 73.37 | 73.94 | 74.51 | 4.16 | 11.40 | 3.73 | 0.27 | 0.35 | 0.38 |
| 37120411 | 675 | 31.24 | 32.20 | 33.15 | 50.97 | 54.67 | 58.38 | 74.06 | 74.62 | 75.18 | 4.59 | 12.56 | 3.63 | 0.26 | 0.38 | 0.37 |
| 37120412 | 715 | 31.28 | 32.17 | 33.06 | 53.64 | 56.44 | 59.24 | 74.73 | 75.26 | 75.79 | 4.70 | 11.17 | 3.38 | 0.28 | 0.38 | 0.34 |
| 37120413 | 611 | 29.71 | 30.50 | 31.28 | 47.38 | 49.90 | 52.41 | 73.65 | 74.22 | 74.78 | 3.29 | 11.39 | 3.56 | 0.21 | 0.43 | 0.35 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 37120416 | 514 | 29.65 | 30.78 | 31.90 | 48.82 | 52.90 | 56.98 | 72.29 | 72.92 | 73.56 | 4.59 | 12.38 | 3.47 | 0.25 | 0.39 | 0.36 |
| 37120417 | 630 | 30.64 | 31.50 | 32.36 | 50.29 | 53.37 | 56.46 | 74.59 | 75.15 | 75.72 | 4.03 | 12.07 | 3.44 | 0.25 | 0.40 | 0.35 |
| 37120418 | 742 | 30.93 | 31.88 | 32.82 | 48.82 | 52.51 | 56.21 | 73.61 | 74.20 | 74.80 | 4.21 | 13.16 | 4.13 | 0.22 | 0.38 | 0.40 |
| 37120419 | 680 | 30.10 | 30.92 | 31.73 | 48.04 | 51.68 | 55.32 | 73.22 | 73.83 | 74.43 | 3.88 | 12.42 | 4.08 | 0.24 | 0.37 | 0.39 |
| 37120420 | 675 | 30.03 | 30.49 | 30.94 | 45.28 | 47.56 | 49.85 | 74.45 | 75.02 | 75.59 | 1.95 | 12.60 | 3.96 | 0.18 | 0.43 | 0.39 |
| 37120423 | 528 | 33.01 | 34.18 | 35.36 | 55.77 | 59.02 | 62.28 | 75.85 | 76.39 | 76.93 | 5.73 | 10.60 | 2.88 | 0.33 | 0.35 | 0.32 |
| 37120424 | 643 | 31.33 | 32.25 | 33.18 | 48.01 | 51.01 | 54.01 | 75.05 | 75.71 | 76.38 | 4.02 | 11.23 | 4.27 | 0.22 | 0.38 | 0.39 |
| 37120425 | 704 | 30.45 | 31.12 | 31.78 | 48.87 | 51.54 | 54.21 | 75.05 | 75.51 | 75.97 | 2.96 | 12.49 | 3.43 | 0.19 | 0.40 | 0.41 |
| 37120426 | 764 | 30.59 | 31.16 | 31.74 | 51.52 | 54.01 | 56.49 | 75.08 | 75.57 | 76.05 | 2.73 | 14.23 | 3.15 | 0.20 | 0.47 | 0.33 |
| 37120427 | 677 | 31.13 | 31.70 | 32.28 | 48.53 | 51.32 | 54.10 | 75.56 | 76.11 | 76.65 | 2.81 | 12.58 | 3.70 | 0.23 | 0.40 | 0.37 |
| 37120430 | 577 | 31.85 | 32.71 | 33.57 | 50.87 | 54.05 | 57.22 | 78.35 | 78.81 | 79.28 | 4.00 | 12.59 | 3.02 | 0.25 | 0.39 | 0.37 |
| 37120501 | 738 | 32.01 | 32.86 | 33.70 | 52.55 | 55.20 | 57.84 | 77.85 | 78.28 | 78.70 | 3.95 | 12.25 | 3.10 | 0.21 | 0.40 | 0.39 |
| 37120502 | 742 | 31.21 | 31.98 | 32.75 | 52.60 | 55.62 | 58.64 | 76.13 | 76.67 | 77.21 | 3.59 | 13.11 | 3.66 | 0.21 | 0.41 | 0.38 |
| 37120503 | 814 | 31.13 | 31.94 | 32.76 | 51.90 | 54.73 | 57.56 | 75.64 | 76.09 | 76.53 | 4.18 | 12.05 | 3.43 | 0.23 | 0.37 | 0.40 |
| 37120504 | 665 | 30.37 | 31.06 | 31.76 | 46.37 | 48.90 | 51.44 | 74.82 | 75.49 | 76.15 | 3.00 | 11.76 | 4.38 | 0.21 | 0.42 | 0.37 |
| 37120507 | 529 | 31.91 | 33.03 | 34.16 | 56.84 | 60.13 | 63.41 | 76.11 | 76.82 | 77.53 | 5.35 | 11.10 | 3.51 | 0.30 | 0.38 | 0.32 |
| 37120508 | 736 | 29.77 | 30.40 | 31.04 | 49.72 | 52.44 | 55.17 | 75.04 | 75.53 | 76.03 | 3.28 | 12.17 | 3.51 | 0.23 | 0.39 | 0.38 |
| 37120509 | 718 | 30.17 | 31.09 | 32.01 | 51.70 | 54.48 | 57.26 | 75.65 | 76.16 | 76.67 | 3.96 | 12.42 | 3.40 | 0.20 | 0.43 | 0.36 |
| 37120510 | 760 | 31.92 | 32.67 | 33.42 | 49.60 | 52.58 | 55.56 | 75.52 | 76.10 | 76.69 | 3.58 | 12.47 | 3.98 | 0.23 | 0.41 | 0.37 |

Where,

N: Data size

$\mu_i$_L: Lower bound mean of EM class i (95% confidence interval)

$\mu_i$: Mean of EM group i

$\mu_i$_U: Upper bound mean of EM class i (95% confidence interval)

SDi: Standard deviation of EM class i

$p_i$: Proportion of $i^{th}$ component

**B.5 Lane Correlations**

Correlation among different lanes of station 40 class 9:

Correlation coefficient varies from -1 to +1. A coefficient value of 1(-1) indicates a linear relationship and a value of 0 indicates that the values are not correlated. The correlation coefficient of lane 1 with respect to lane 2, 3, 4 of station 40, class 9 GVW can be tabularized as follows:

| Lane 1 vs. Lane 2 | Mean 1 (unloaded) | Mean 2 (partially loaded) | Mean 3 (fully loaded) |
|---|---|---|---|
| Correlation | 0.2733 | -0.03831 | -0.07389 |

| Lane 1 vs. Lane 3 | Mean 1 (unloaded) | Mean 2 (partially loaded) | Mean 3 (fully loaded) |
|---|---|---|---|
| Correlation | **-0.00199** | **-0.07245** | **-0.20304** |

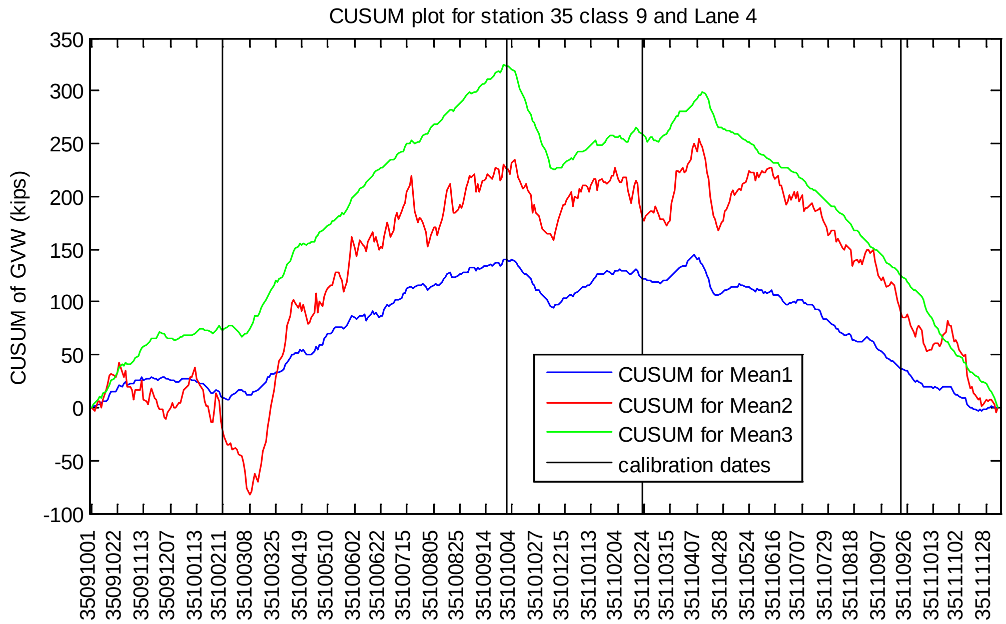
| Lane 1 vs. Lane 4 | Mean 1 (unloaded) | Mean 2 (partially loaded) | Mean 3 (fully loaded) |
|---|---|---|---|
| Correlation | **0.35849** | **-0.06993** | **-0.19611** |

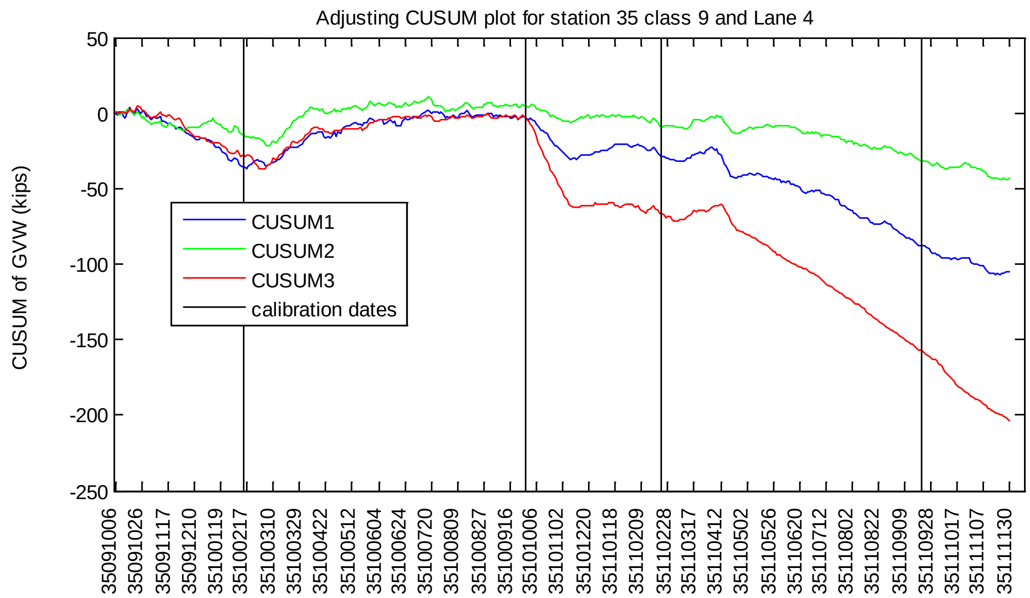
# APPENDIX C: PROCESSED DATA OF SELECTED WIM STATIONS

### C.1 WIM Station #35

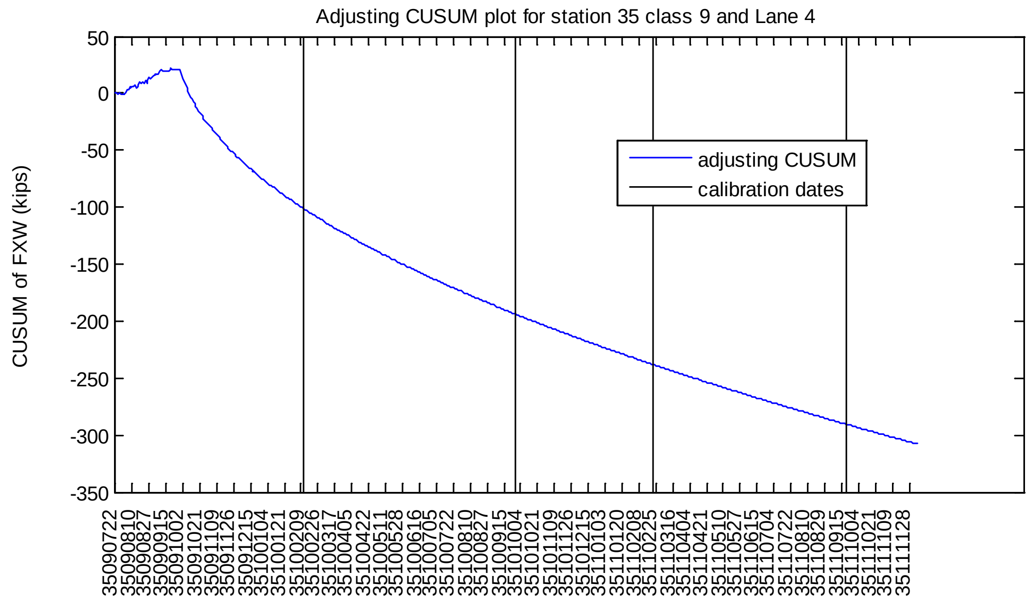
Calibration dates: 9/28/2010, 2/11/2010, 2/23/2011, and 9/21/2011

C.1.1 GVW9

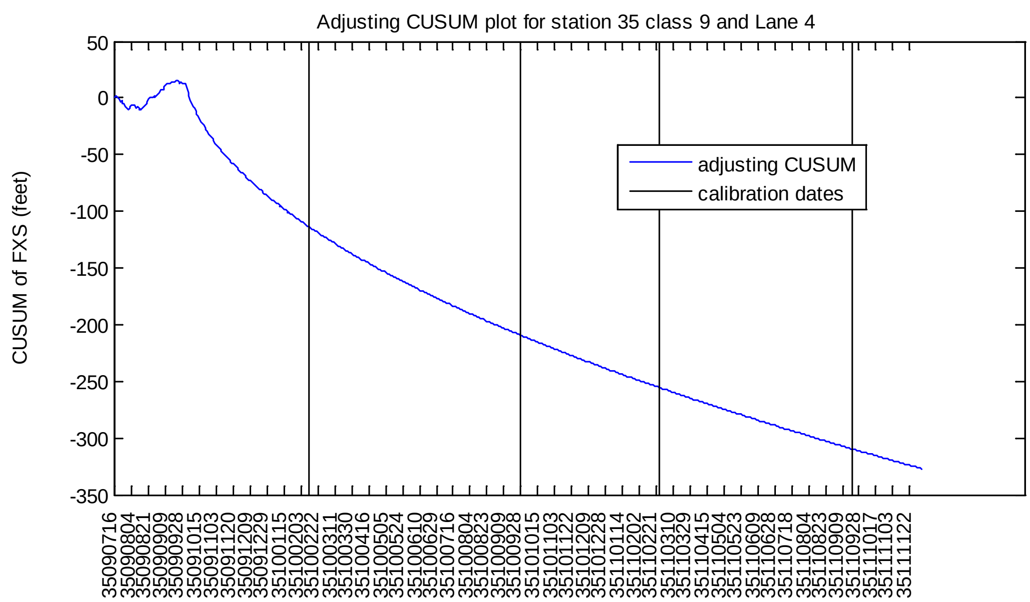


C.1.2 Front Axle Weight (FXW)




C.1.3 Front Axle Spacing (FXS)

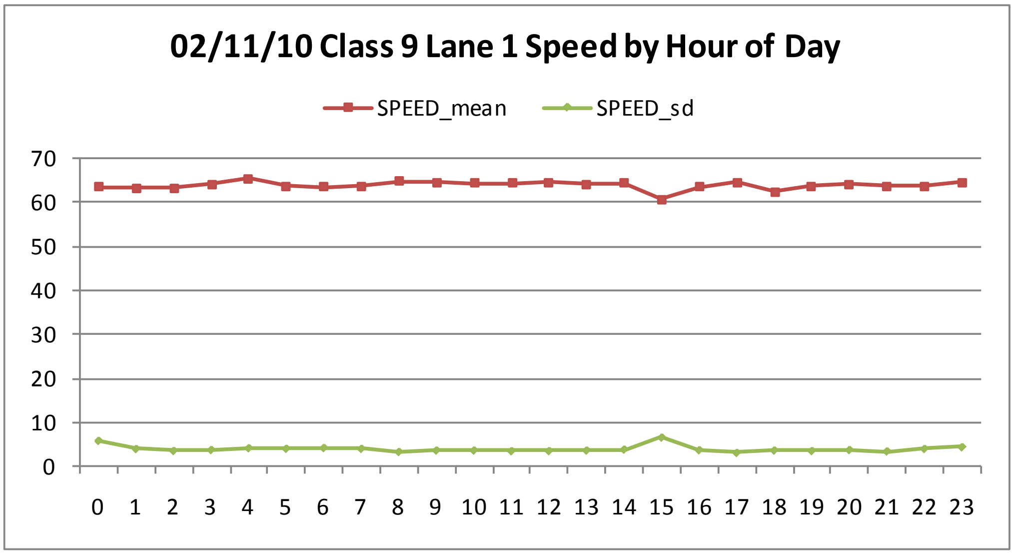


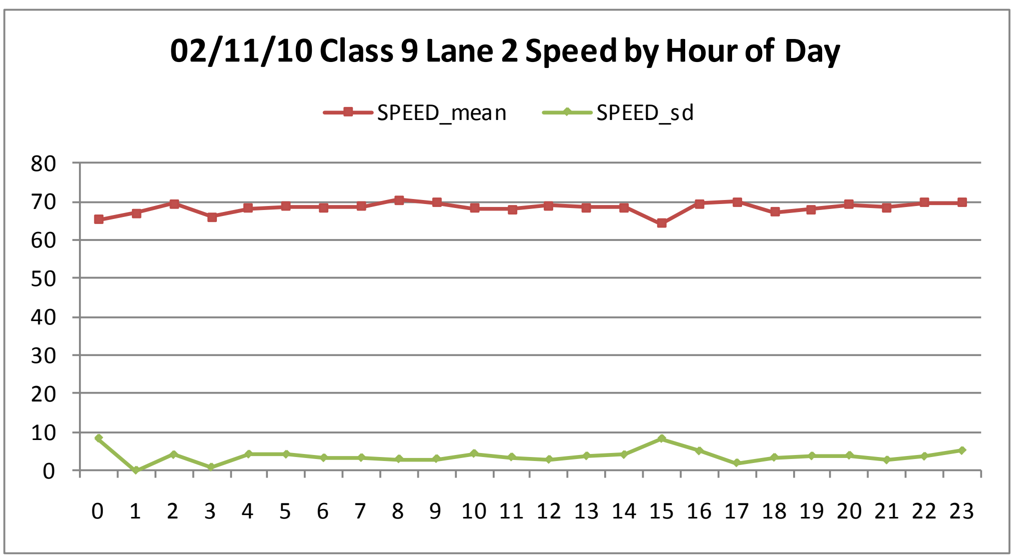

## C.2 WIM Station #37

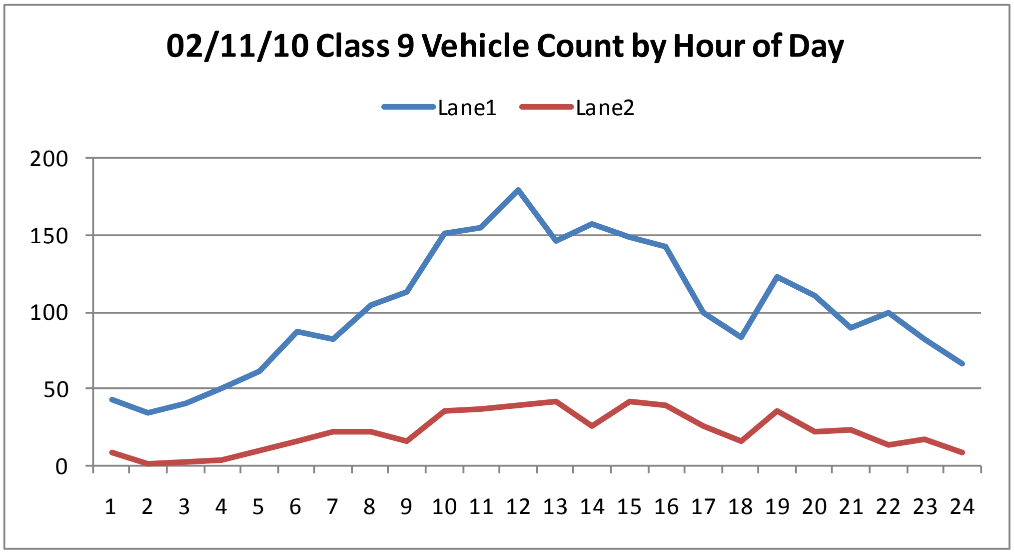
Lane #1 calibration dates: 12/10/2009, 12/22/2009, 2/10/2010, 5/25/2010, 7/7/2010, 8/31/2010, 12/1/2010, 12/10/2010, 1/5/2011, 1/24/2011, and 11/28/2011.

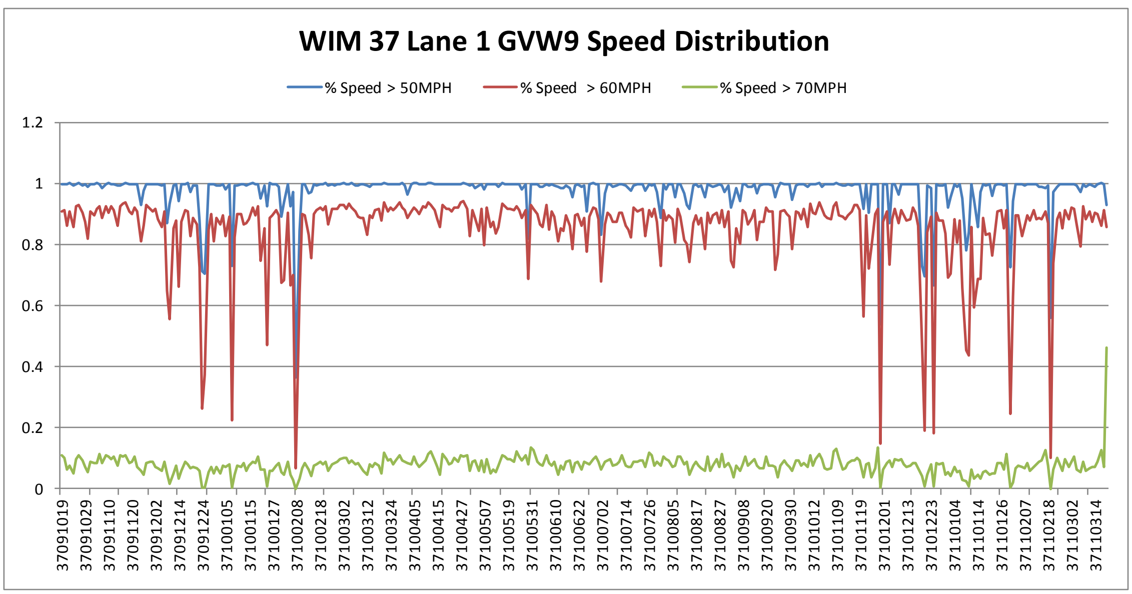
Lane #2 calibration dates include 12/10/2009, 12/22/2009, 2/10/2010, 5/25/2010, 7/7/2010, 8/31/2010, 12/10/2010, 1/5/2011, 1/24/2011, and 11/28/2011.

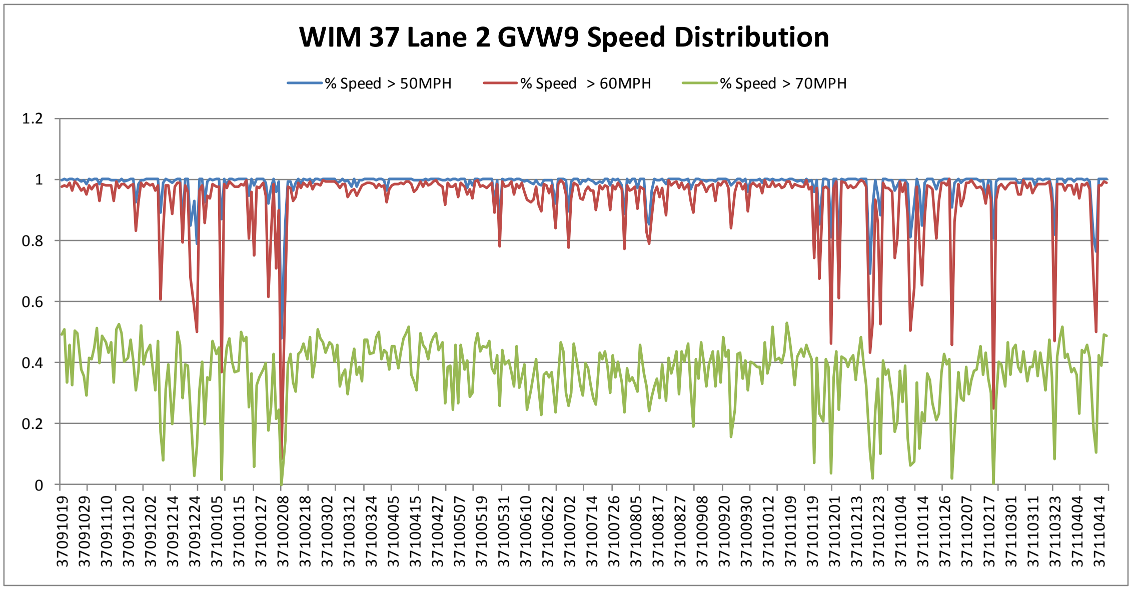
C.2.1 Speed and Vehicle Count

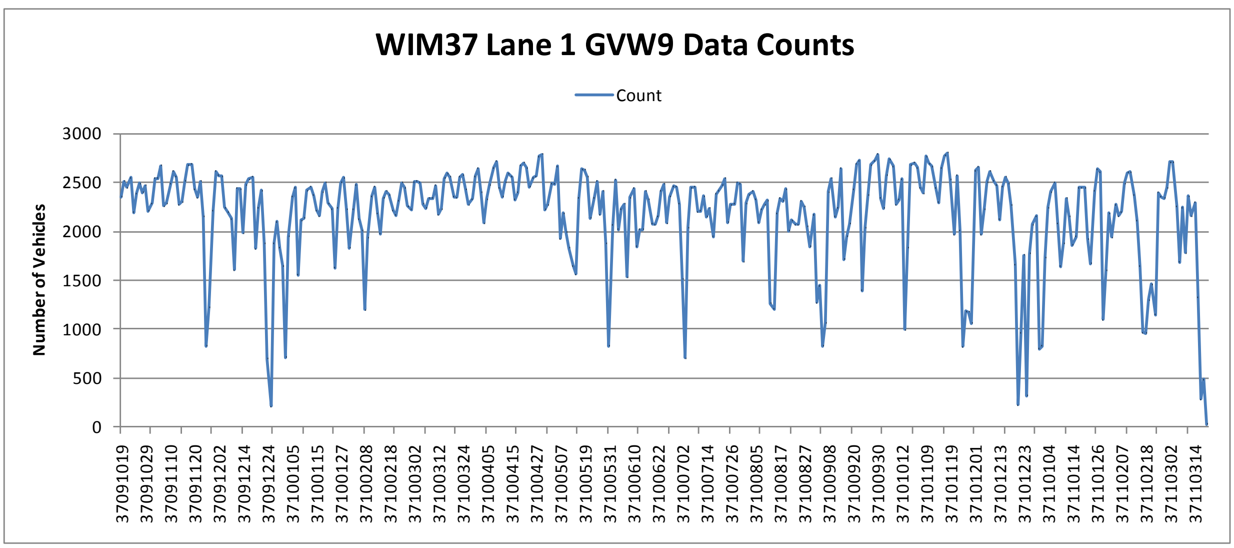


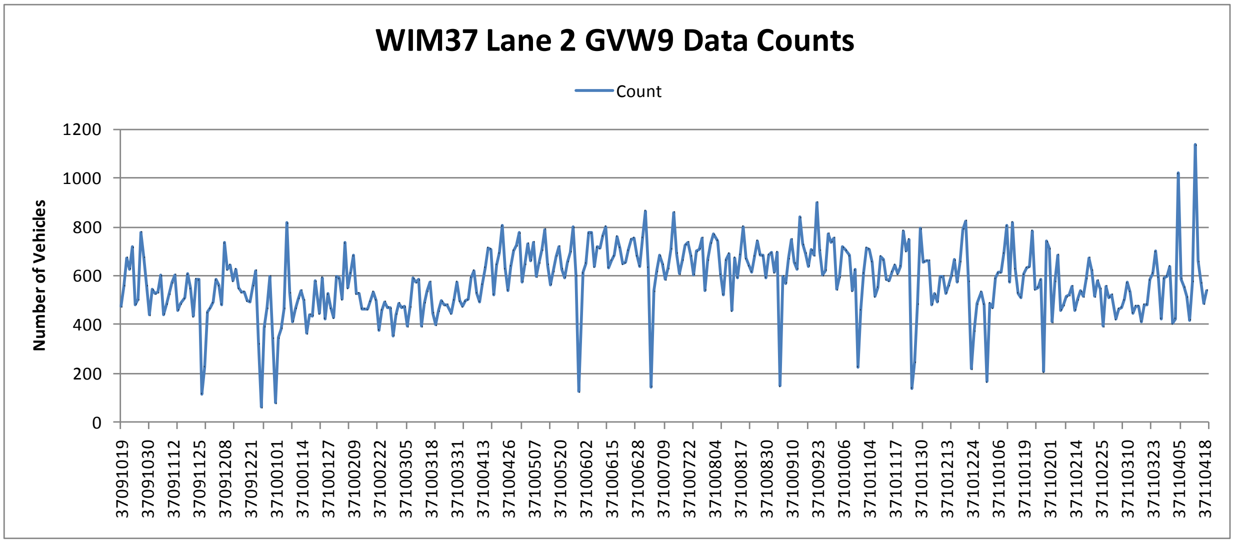




02/11/10 Class 9 Vehicle Count by Hour of Day
Lane1
Lane2
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

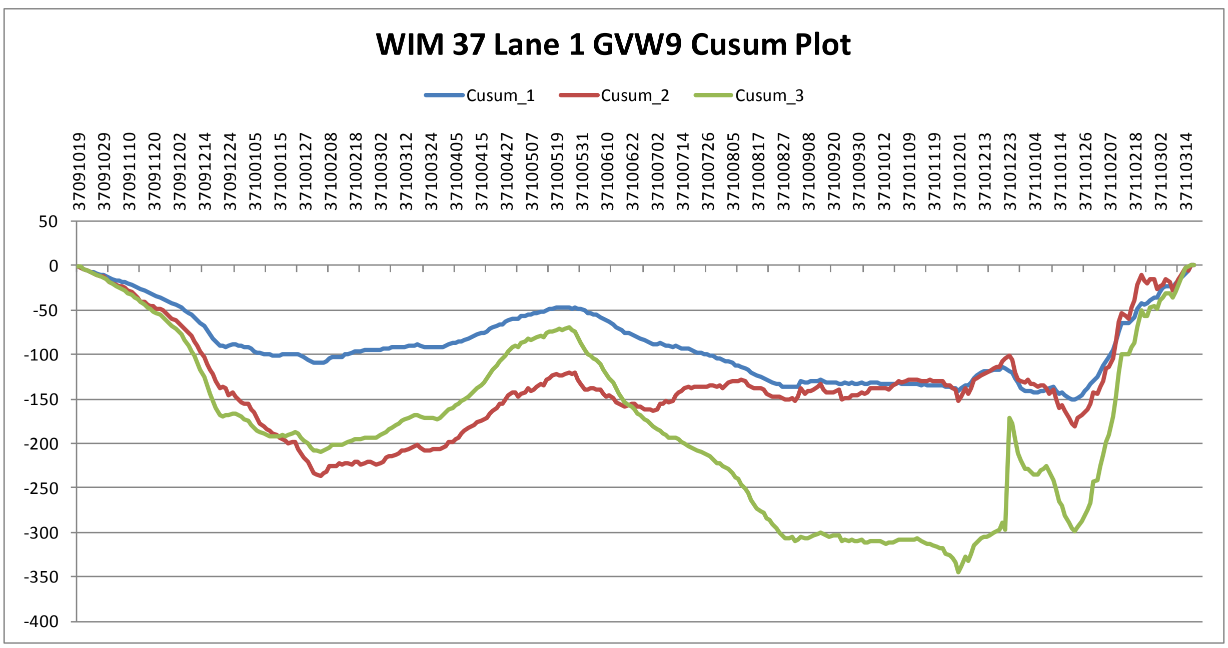

WIM 37 Lane 1 GVW9 Speed Distribution
% Speed > 50MPH
% Speed > 60MPH
% Speed > 70MPH
1.2
1
0.8
0.6
0.4
0.2
0

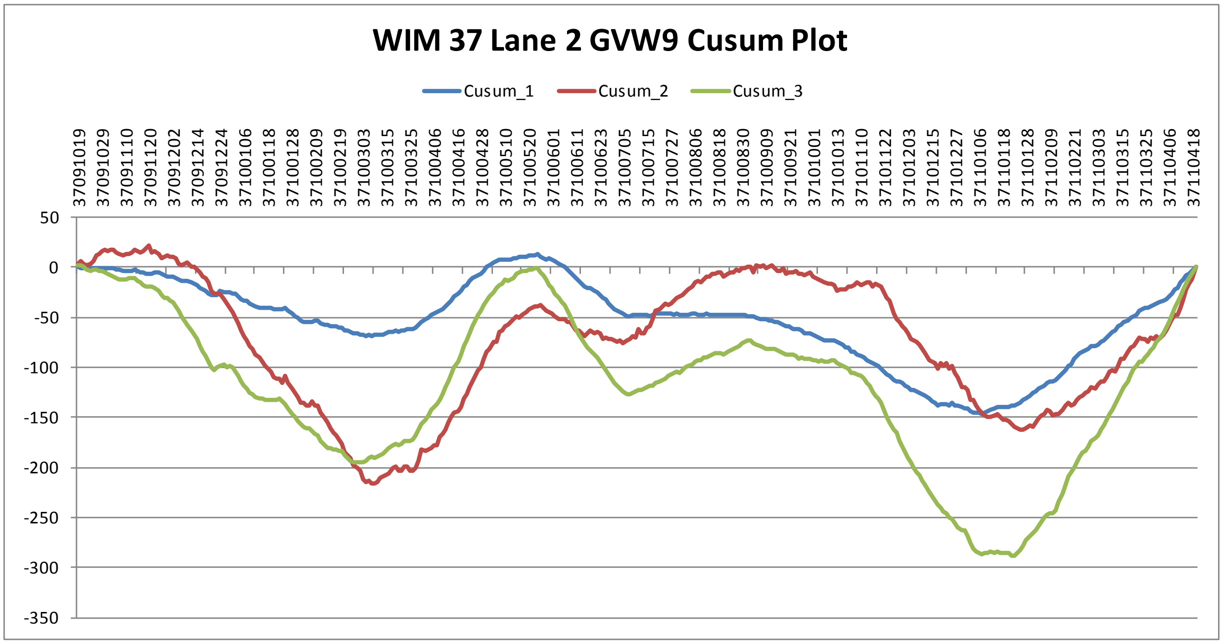

WIM 37 Lane 2 GVW9 Speed Distribution
% Speed > 50MPH
% Speed > 60MPH
% Speed > 70MPH
1.2
1
0.8
0.6
0.4
0.2
0
37091019
37091029
37091110
37091120
37091202
37091214
37091224
37100105
37100115
37100127
37100208
37100218
37100302
37100312
37100324
37100405
37100415
37100427
37100507
37100519
37100531
37100610
37100622
37100702
37100714
37100726
37100805
37100817
37100827
37100908
37100920
37100930
37101012
37101109
37101119
37101201
37101213
37101223
37110104
37110114
37110126
37110207
37110217
37110301
37110311
37110323
37110404
37110414

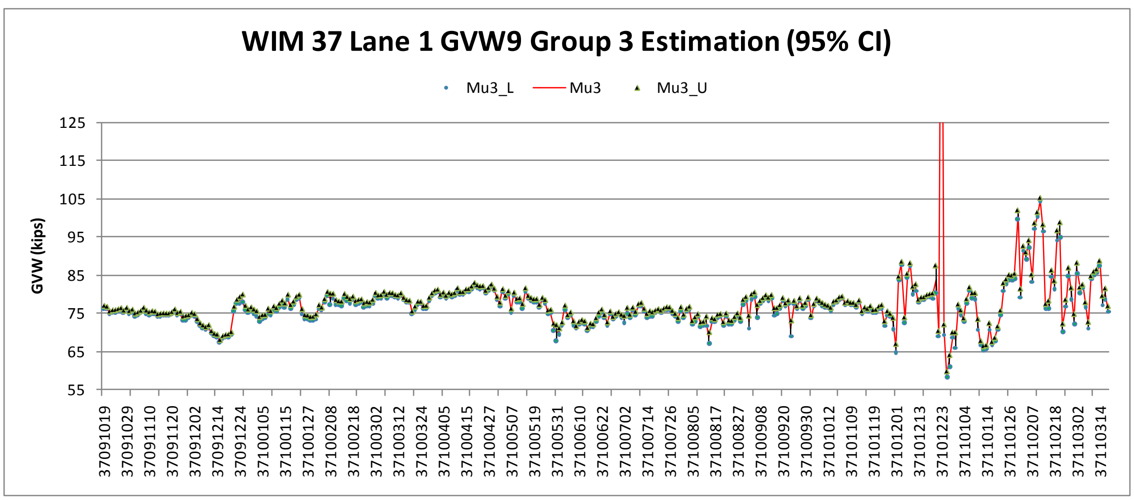

WIM37 Lane 1 GVW9 Data Counts
Count
Number of Vehicles
3000
2500
2000
1500
1000
500
0
37091019
37091029
37091110
37091120
37091202
37091214
37091224
37100105
37100115
37100127
37100208
37100218
37100302
37100312
37100324
37100405
37100415
37100427
37100507
37100519
37100531
37100610
37100622
37100702
37100714
37100726
37100805
37100817
37100827
37100908
37100920
37100930
37101012
37101109
37101119
37101201
37101213
37101223
37110104
37110114
37110126
37110207
37110218
37110302
37110314

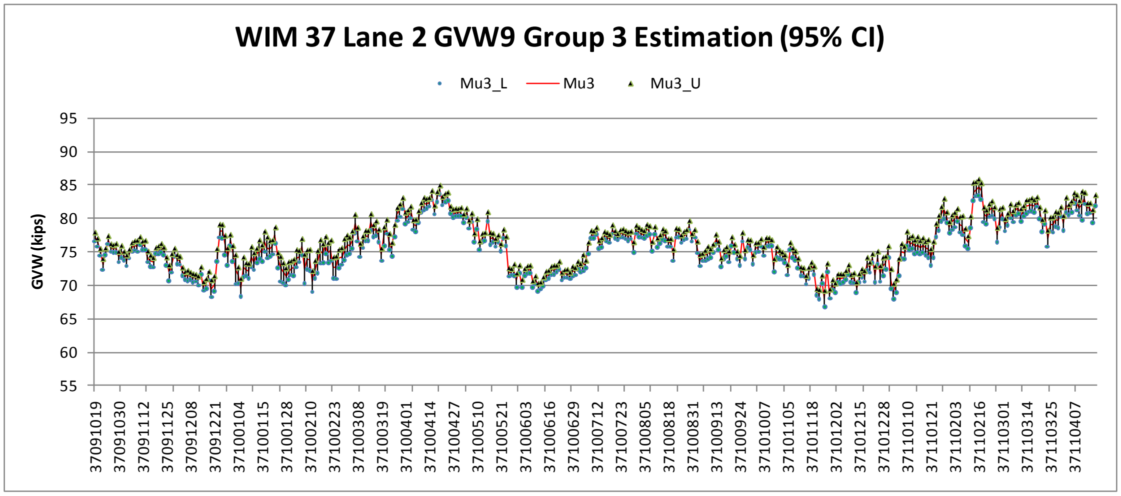


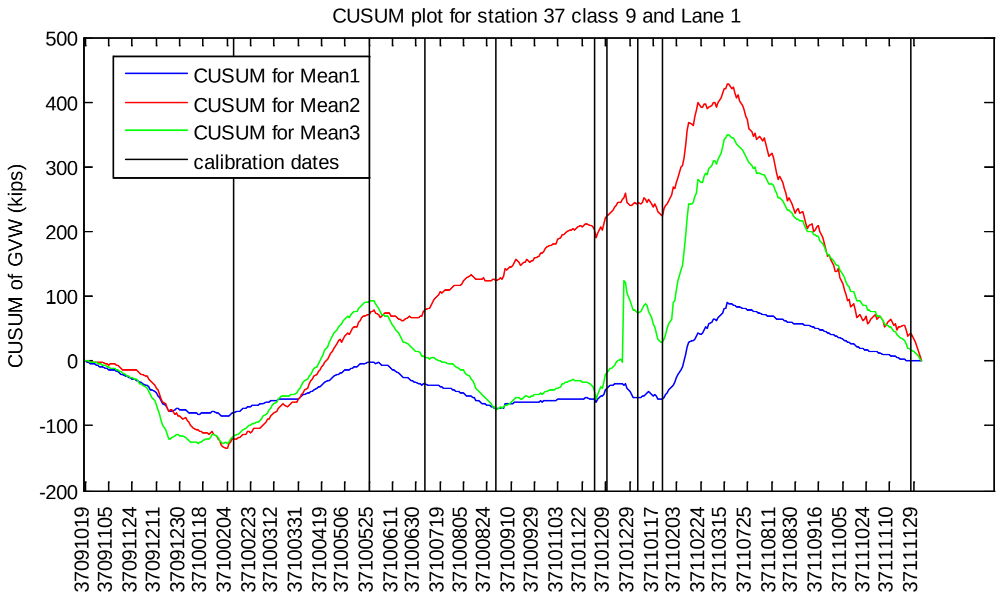

C.2.2 GVW9 and CUSUM Plots

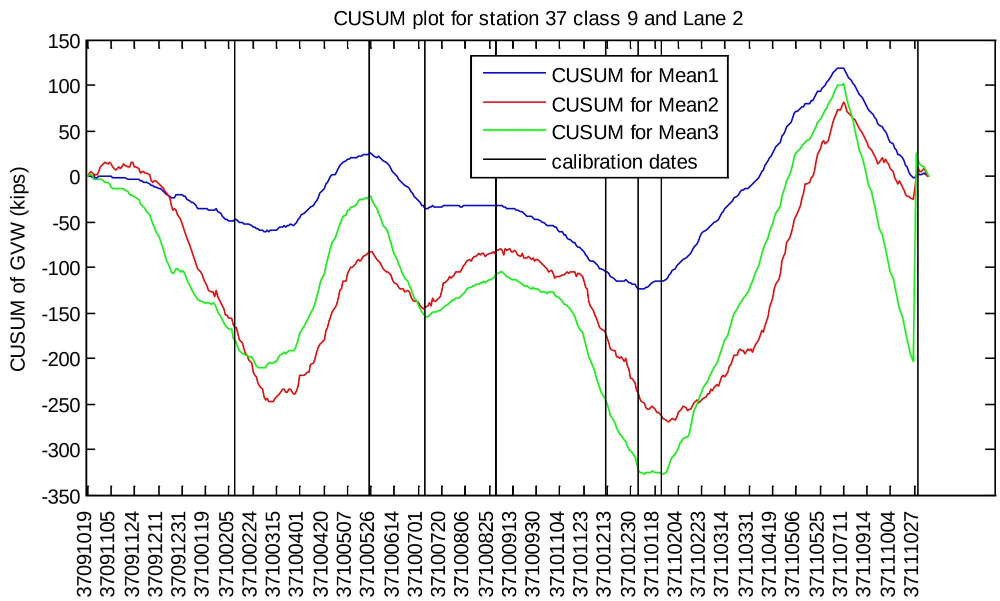


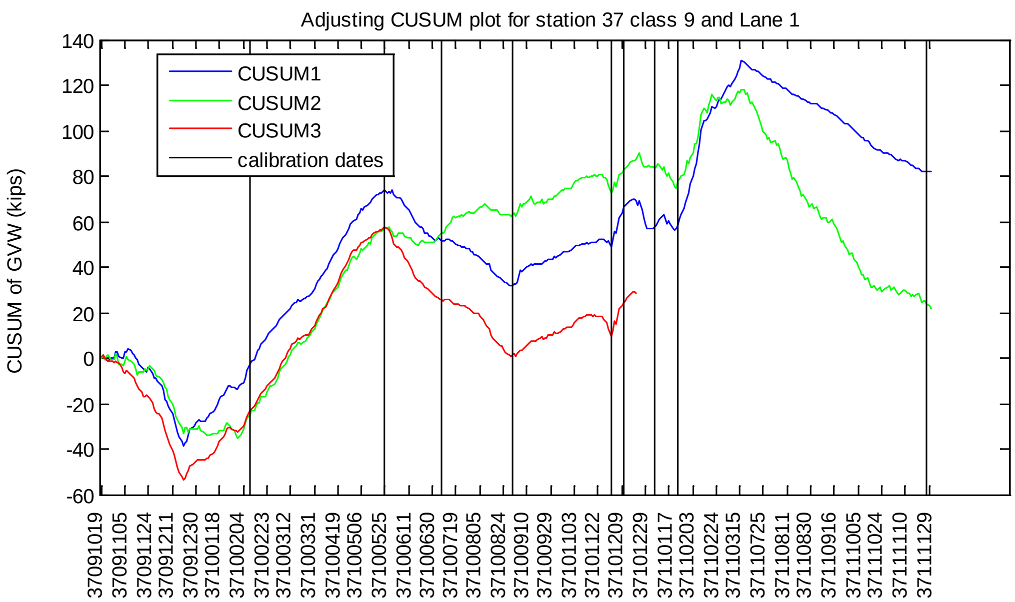

WIM 37 Lane 2 GVW9 Cusum Plot
Cusum_1
Cusum_2
Cusum_3
50
0
-50
-100
-150
-200
-250
-300
-350

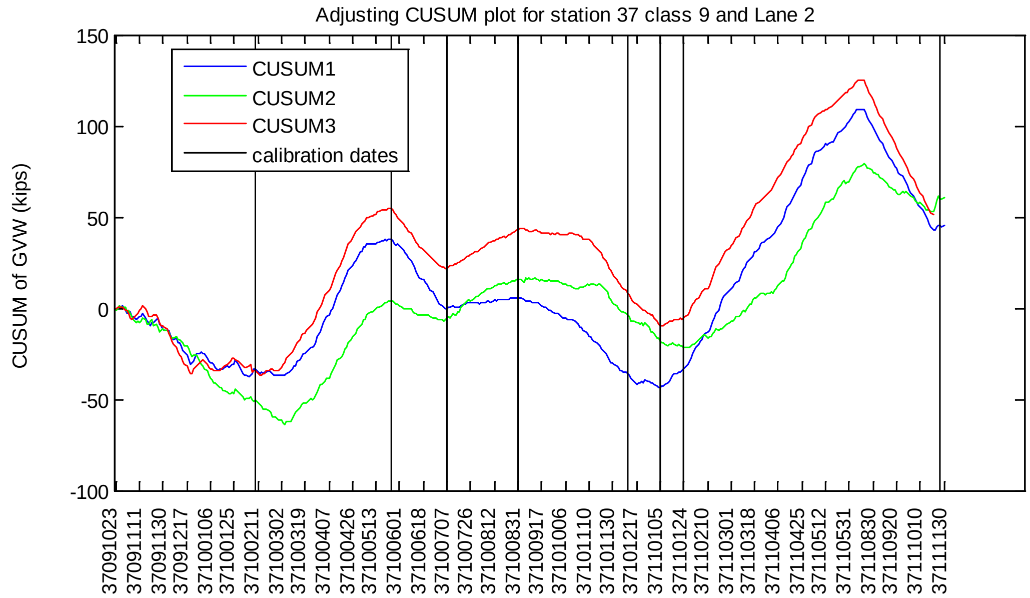

WIM 37 Lane 1 GVW9 Group 3 Estimation (95% CI)
Mu3_L
Mu3
Mu3_U
GVW (kips)
125
115
105
95
85
75
65
55


WIM 37 Lane 2 GVW9 Group 3 Estimation (95% CI)
Mu3_L
Mu3
Mu3_U
GVW (kips)
95
90
85
80
75
70
65
60
55
37091019
37091030
37091112
37091125
37091208
37091221
37100104
37100115
37100128
37100210
37100223
37100308
37100319
37100401
37100414
37100427
37100510
37100521
37100603
37100616
37100629
37100712
37100723
37100805
37100818
37100831
37100913
37100924
37101007
37101105
37101118
37101202
37101215
37101228
37110110
37110121
37110203
37110216
37110301
37110314
37110325
37110407

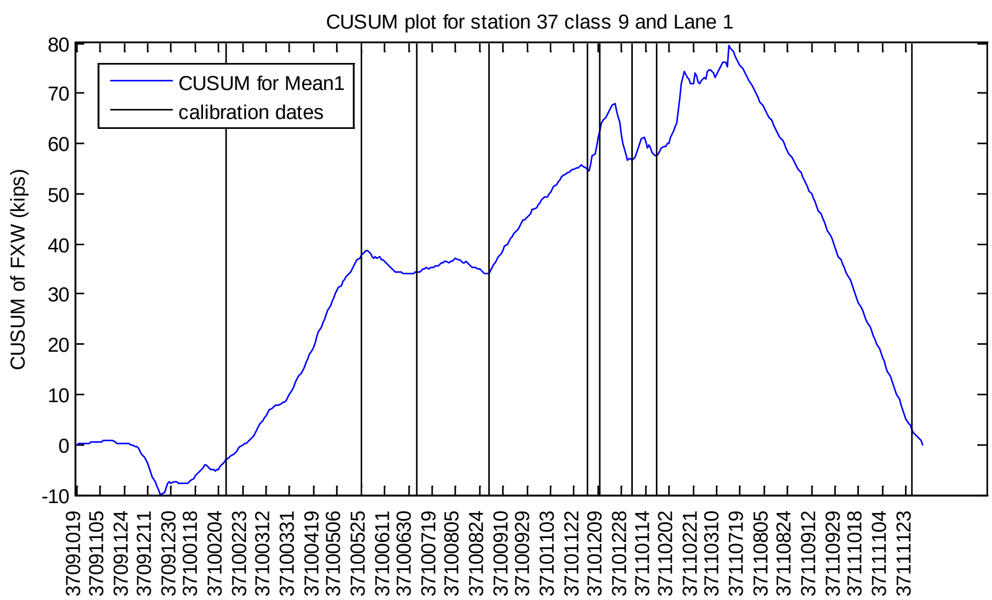

CUSUM plot for station 37 class 9 and Lane 1
CUSUM for Mean1
CUSUM for Mean2
CUSUM for Mean3
calibration dates
CUSUM of GVW (kips)
500
400
300
200
100
0
-100
-200
37091019
37091105
37091124
37091211
37091230
37100118
37100204
37100223
37100312
37100331
37100419
37100506
37100525
37100611
37100630
37100719
37100805
37100824
37100910
37100929
37101103
37101122
37101209
37101229
37110117
37110203
37110224
37110315
37110725
37110811
37110830
37110916
37111005
37111024
37111110
37111129

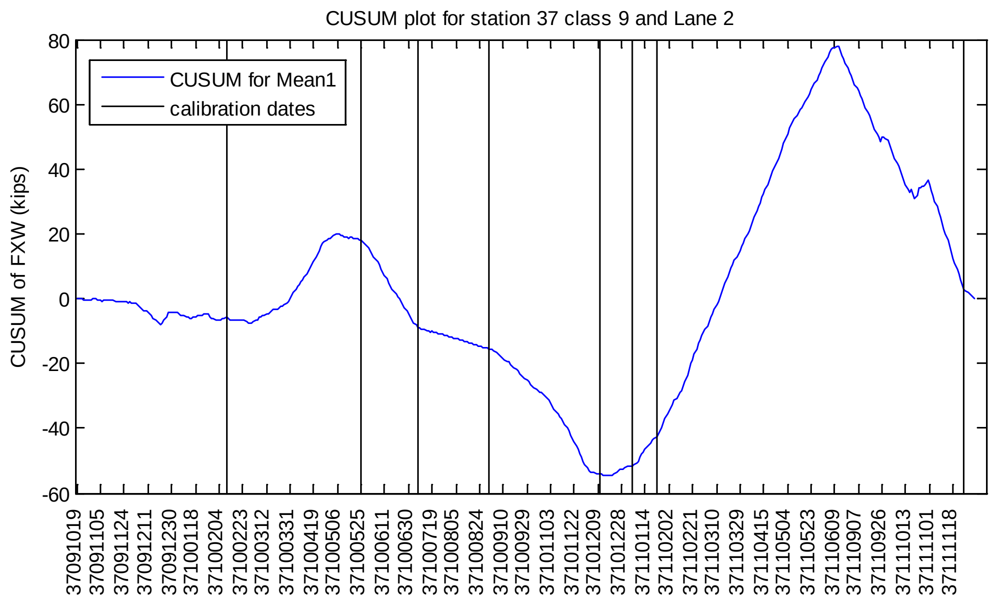

CUSUM plot for station 37 class 9 and Lane 2
CUSUM of GVW (kips)
CUSUM for Mean1
CUSUM for Mean2
CUSUM for Mean3
calibration dates
150
100
50
0
-50
-100
-150
-200
-250
-300
-350
37091019
37091105
37091124
37091211
37091231
37100119
37100205
37100224
37100315
37100401
37100420
37100507
37100526
37100614
37100701
37100720
37100806
37100825
37100913
37100930
37101104
37101123
37101213
37101230
37110118
37110204
37110223
37110314
37110331
37110419
37110506
37110525
37110711
37110914
37111004
37111027

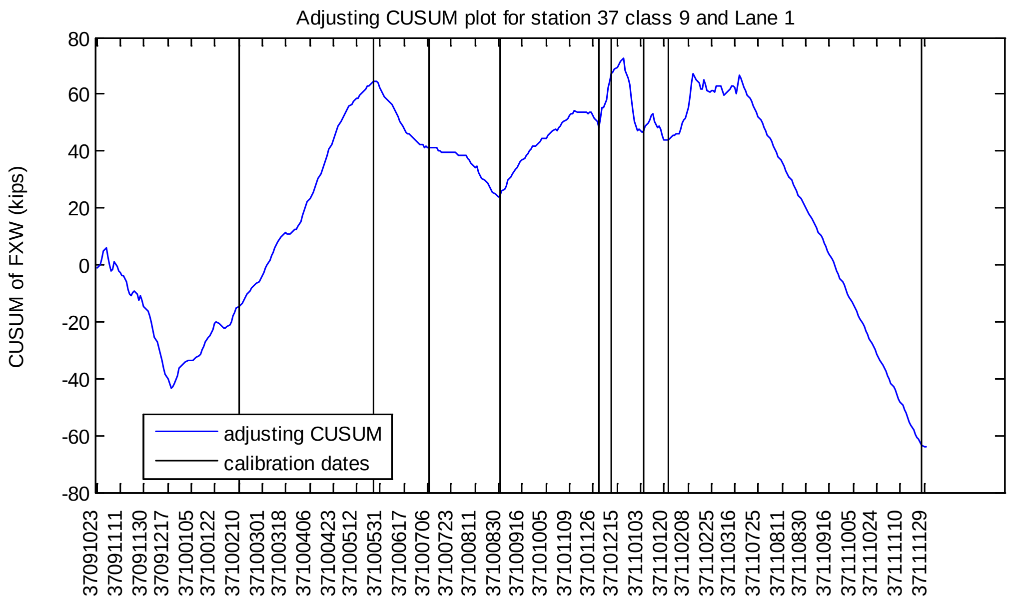

Adjusting CUSUM plot for station 37 class 9 and Lane 1
CUSUM of GVW (kips)
CUSUM1
CUSUM2
CUSUM3
calibration dates
140
120
100
80
60
40
20
0
-20
-40
-60
37091019
37091105
37091124
37091211
37091230
37100118
37100204
37100223
37100312
37100331
37100419
37100506
37100525
37100611
37100630
37100719
37100805
37100824
37100910
37100929
37101103
37101122
37101209
37101229
37110117
37110203
37110224
37110315
37110725
37110811
37110830
37110916
37111005
37111024
37111110
37111129

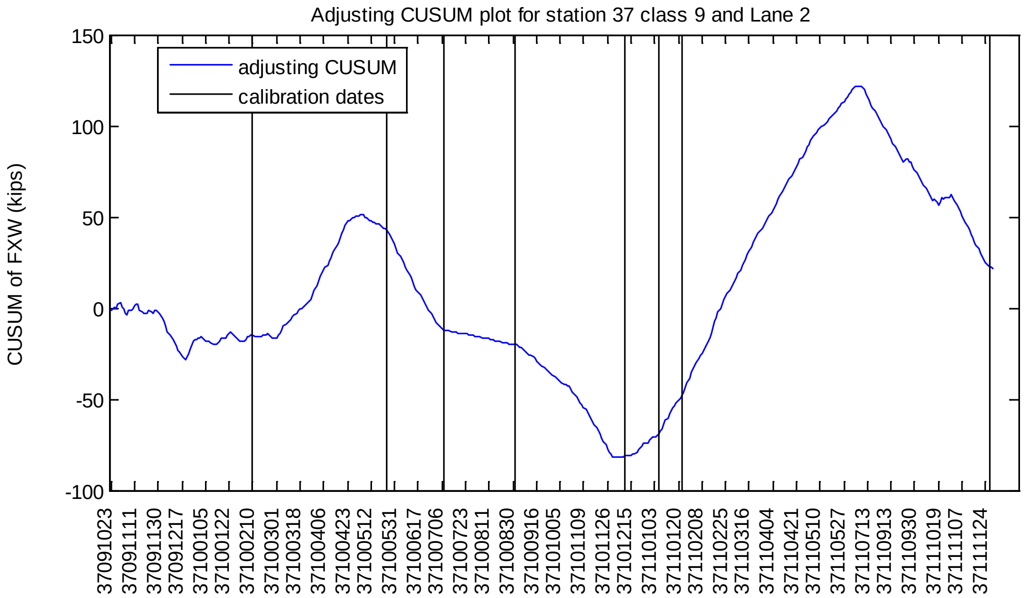



## C.2.3 Front Axle Weight (FXW)

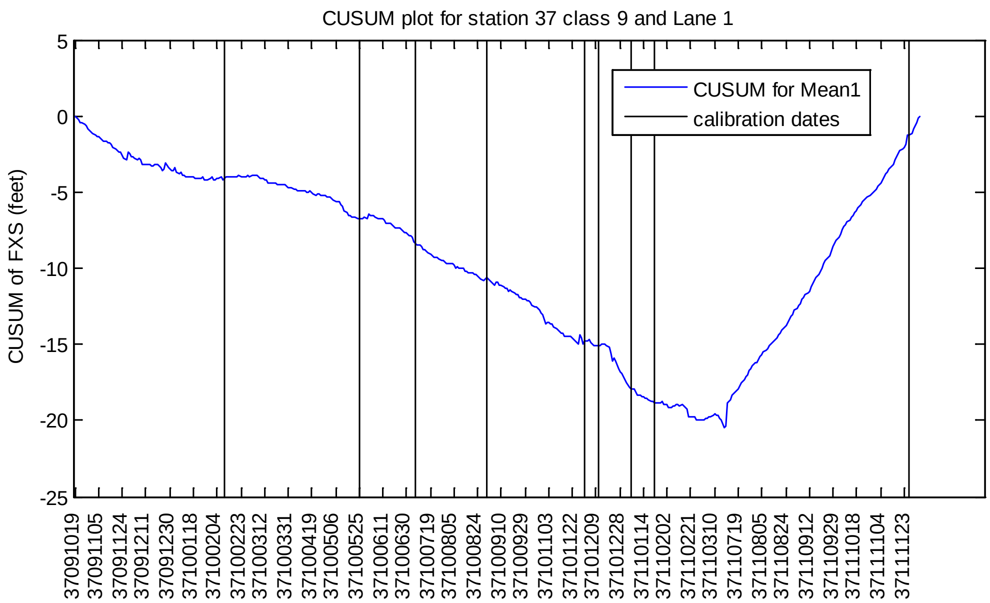


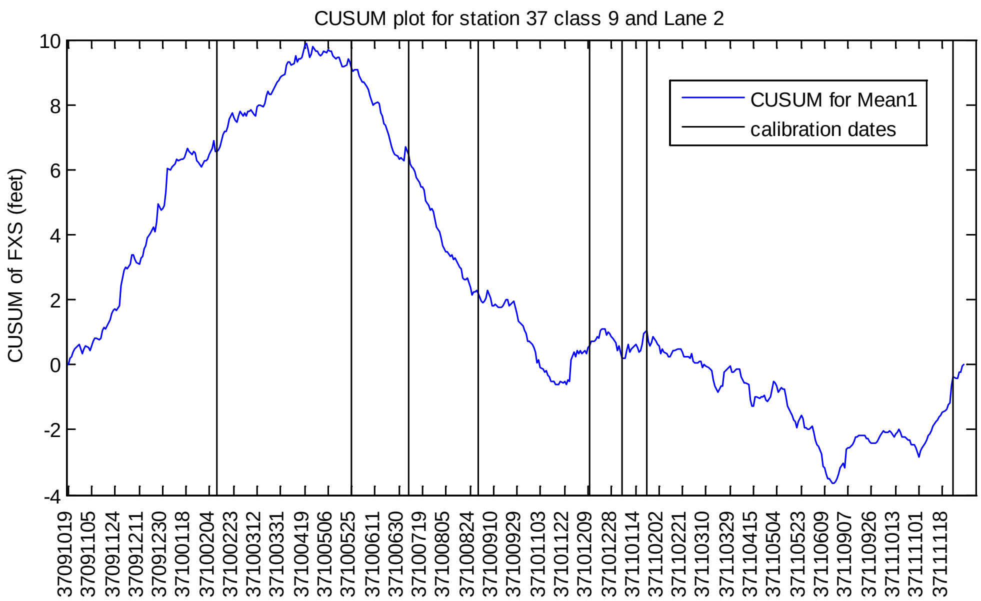

CUSUM plot for station 37 class 9 and Lane 2
CUSUM of FXW (kips)
CUSUM for Mean1
calibration dates
80
60
40
20
0
-20
-40
-60
37091019
37091105
37091124
37091211
37091230
37100118
37100204
37100223
37100312
37100331
37100419
37100506
37100525
37100611
37100630
37100719
37100805
37100824
37100910
37100929
37101103
37101122
37101209
37101228
37110114
37110202
37110221
37110310
37110329
37110415
37110504
37110523
37110609
37110907
37110926
37111013
37111101
37111118

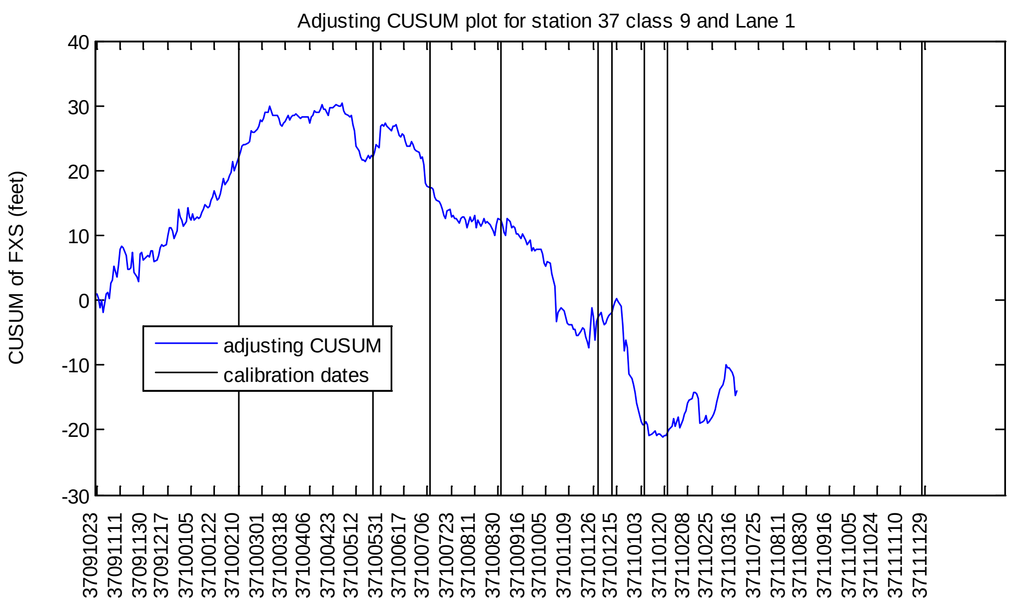

Adjusting CUSUM plot for station 37 class 9 and Lane 1
CUSUM of FXW (kips)
adjusting CUSUM
calibration dates
80
60
40
20
0
-20
-40
-60
-80
37091023
37091111
37091130
37091217
37100105
37100122
37100210
37100301
37100318
37100406
37100423
37100512
37100531
37100617
37100706
37100723
37100811
37100830
37100916
37101005
37101109
37101126
37101215
37110103
37110120
37110208
37110225
37110316
37110725
37110811
37110830
37110916
37111005
37111024
37111110
37111129

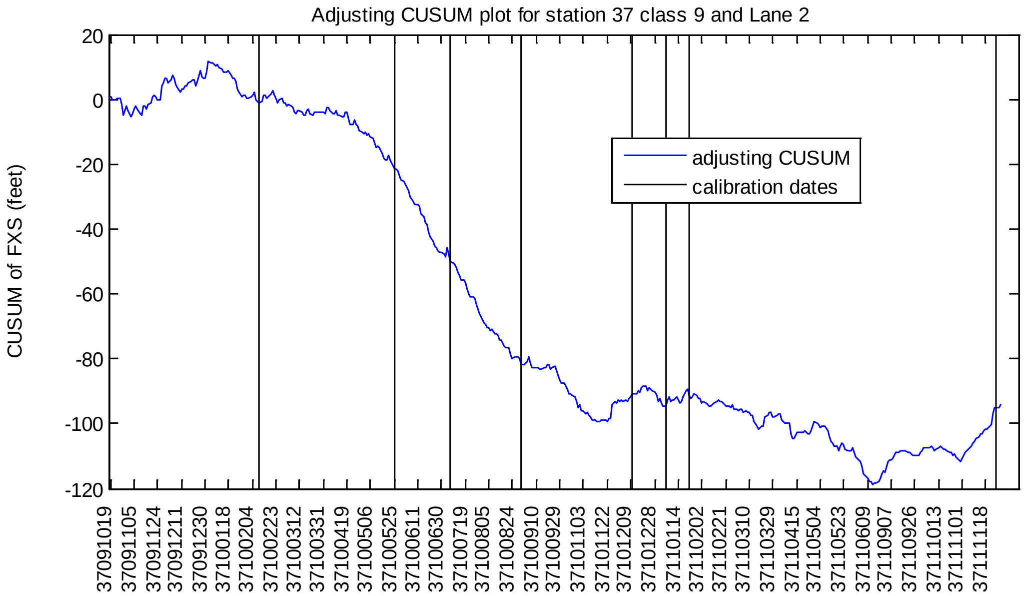



C.2.4 Front Axle Spacing (FXS)




CUSUM plot for station 37 class 9 and Lane 2
CUSUM of FXS (feet)
CUSUM for Mean1
calibration dates
10
8
6
4
2
0
-2
-4
37091019
37091105
37091124
37091211
37091230
37100118
37100204
37100223
37100312
37100331
37100419
37100506
37100525
37100611
37100630
37100719
37100805
37100824
37100910
37100929
37101103
37101122
37101209
37101228
37110114
37110202
37110221
37110310
37110329
37110415
37110504
37110523
37110609
37110907
37110926
37111013
37111101
37111118

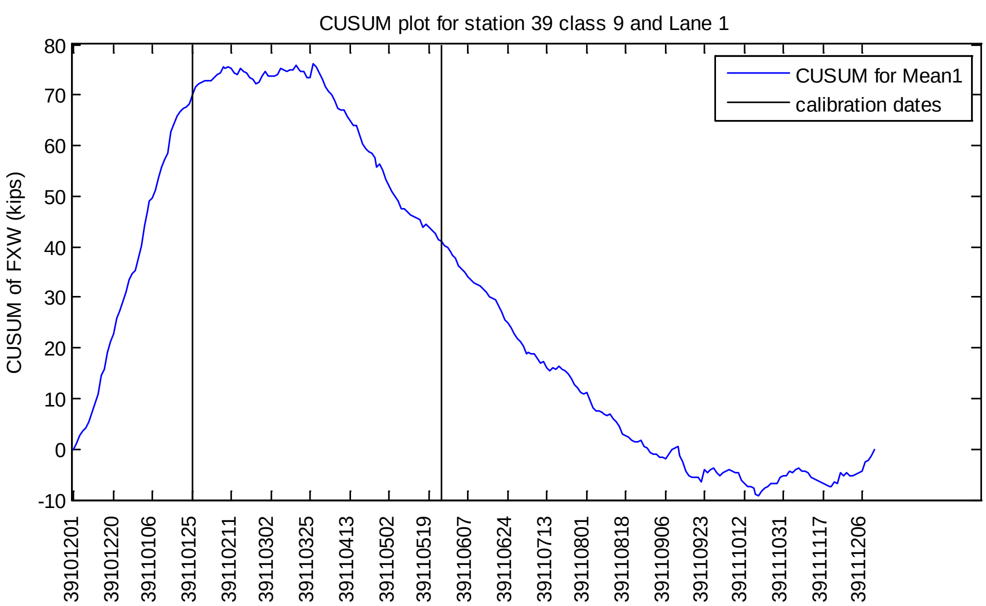

Adjusting CUSUM plot for station 37 class 9 and Lane 1
CUSUM of FXS (feet)
adjusting CUSUM
calibration dates
40
30
20
10
0
-10
-20
-30
37091023
37091111
37091130
37091217
37100105
37100122
37100210
37100301
37100318
37100406
37100423
37100512
37100531
37100617
37100706
37100723
37100811
37100830
37100916
37101005
37101109
37101126
37101215
37110103
37110120
37110208
37110225
37110316
37110725
37110811
37110830
37110916
37111005
37111024
37111110
37111129

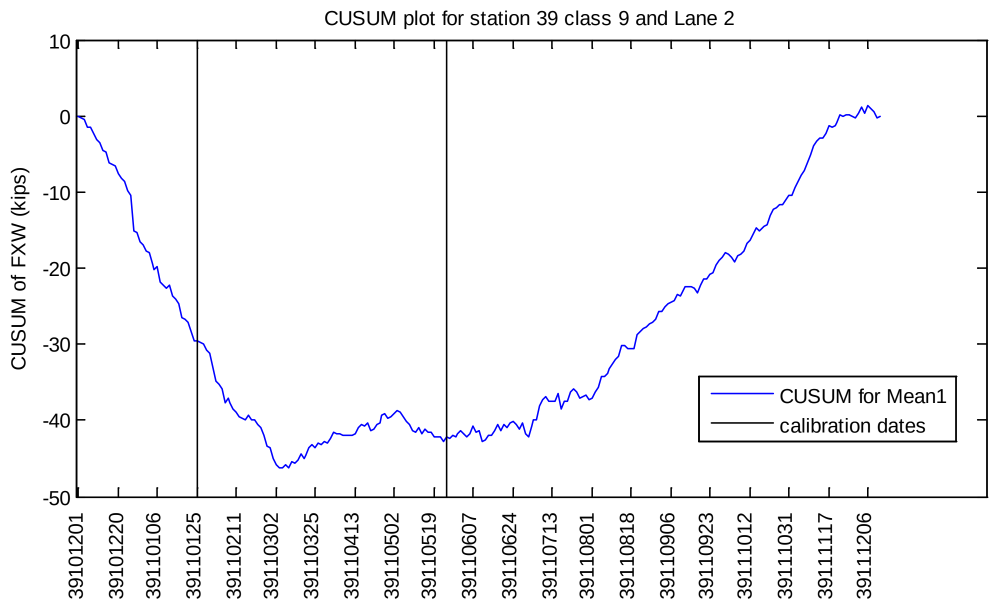



## C.3 WIM Station #39

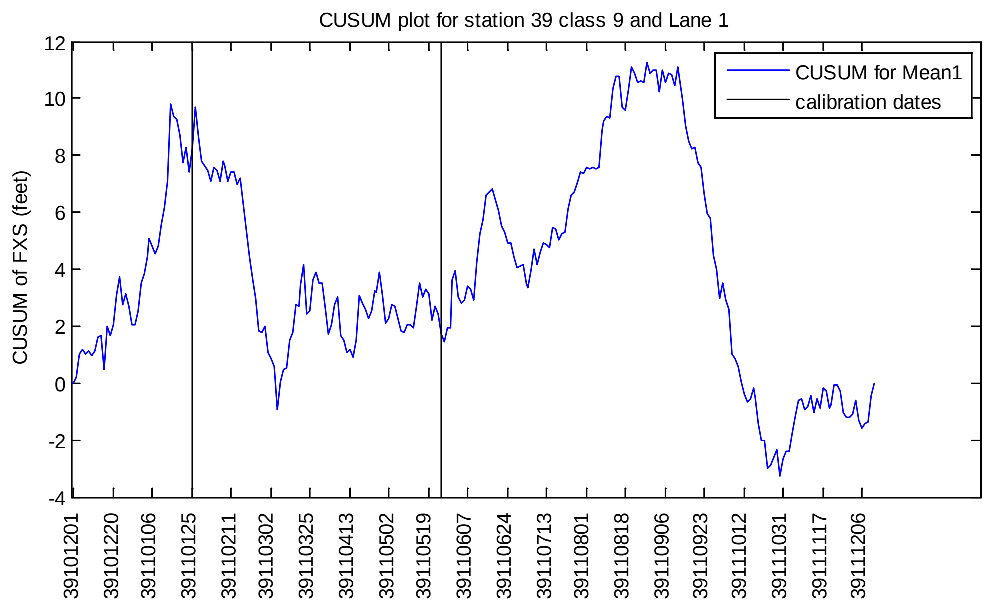
Calibration dates: 1/25/2011, 5/25/2011

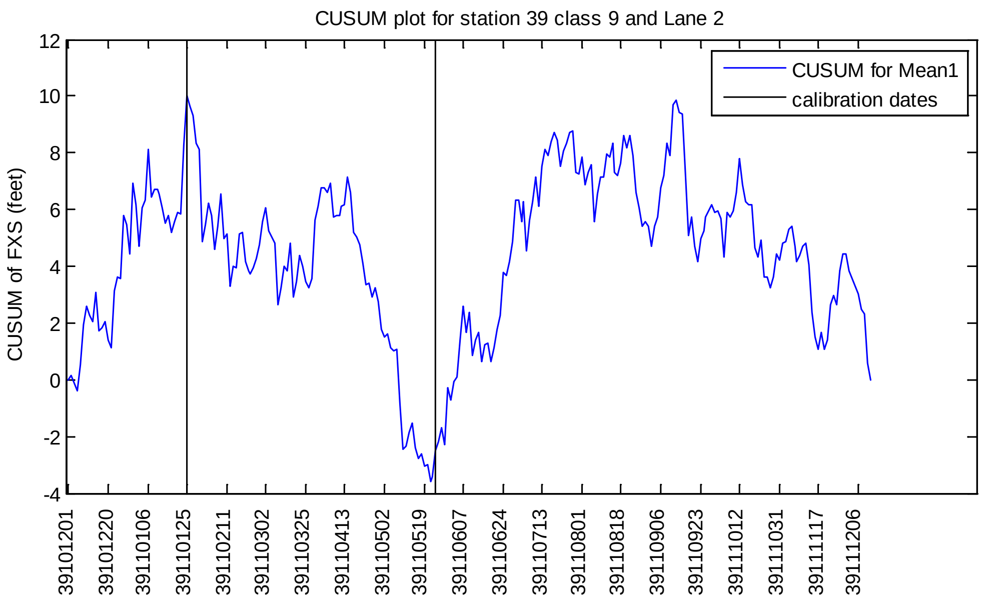
C.3.1 Front Axle Weight (FXW)






C.3.2 Front Axle Spacing (FXS)

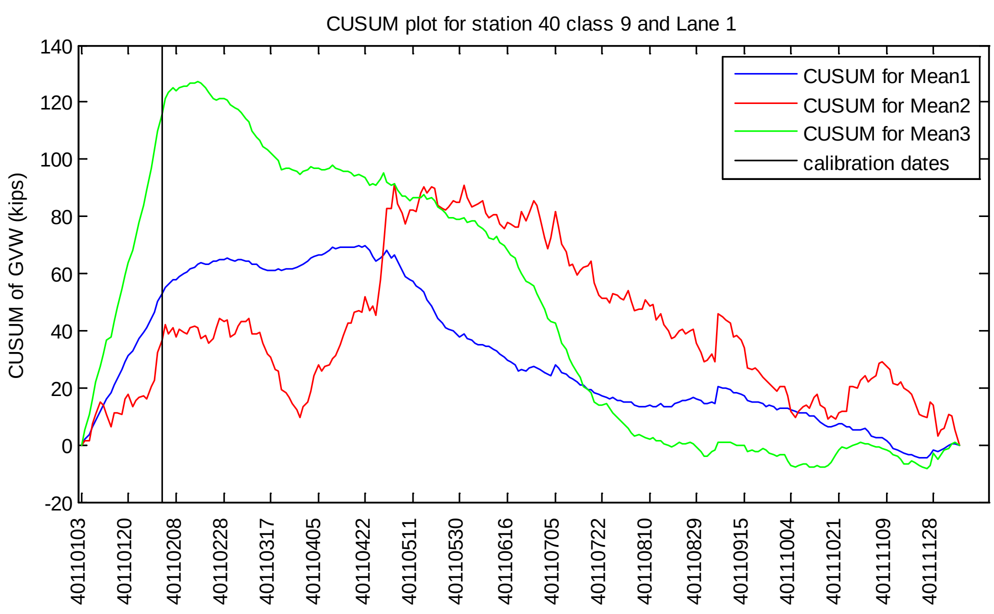


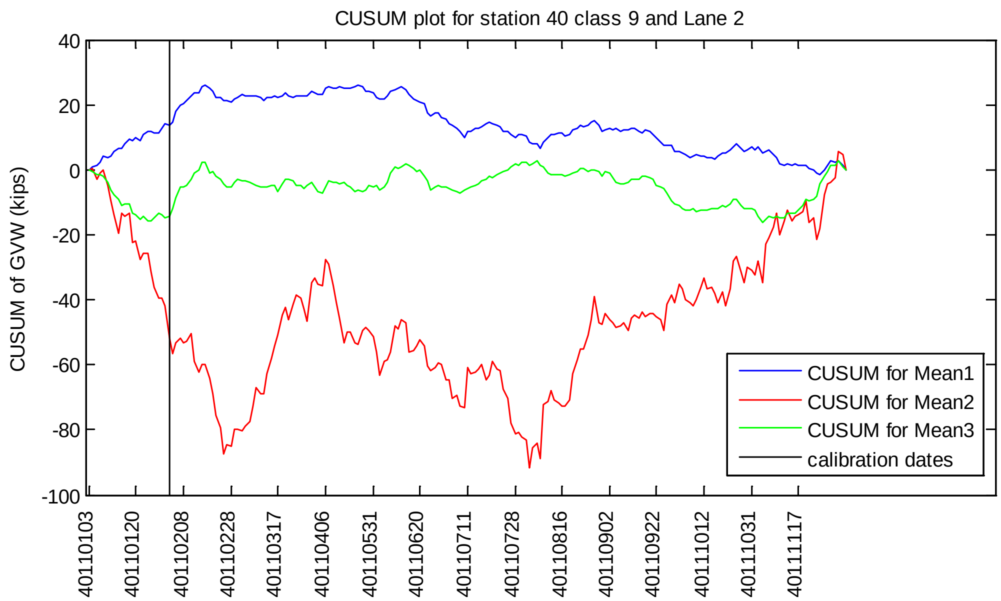


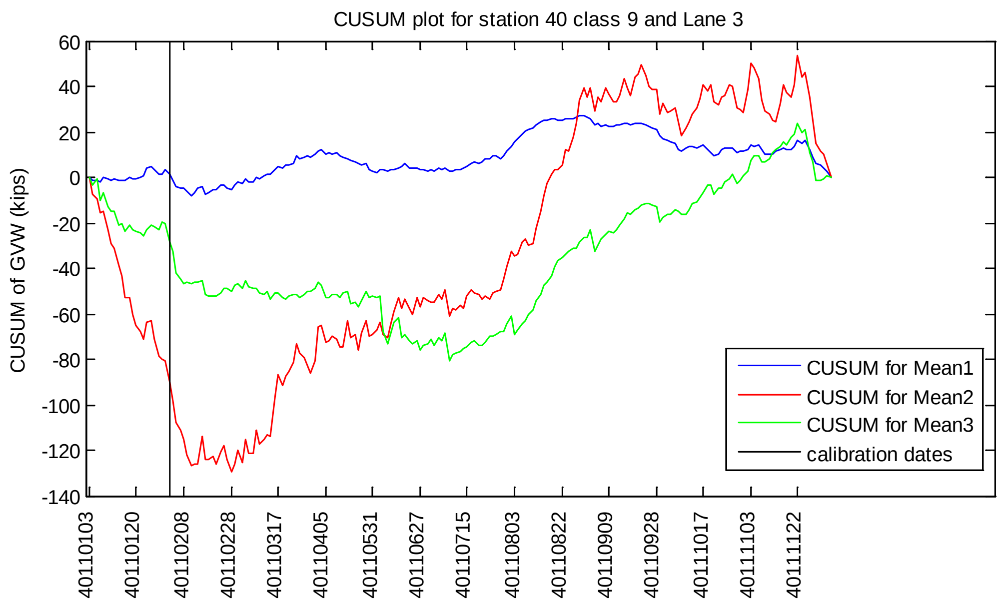

## C.4 WIM Station #40

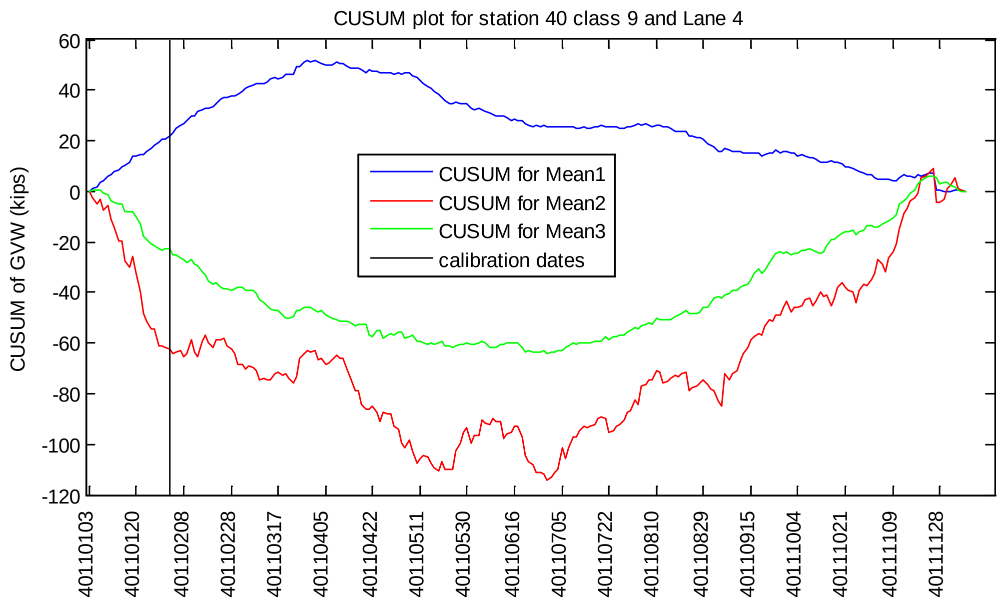
Calibration date: 2/2/2011

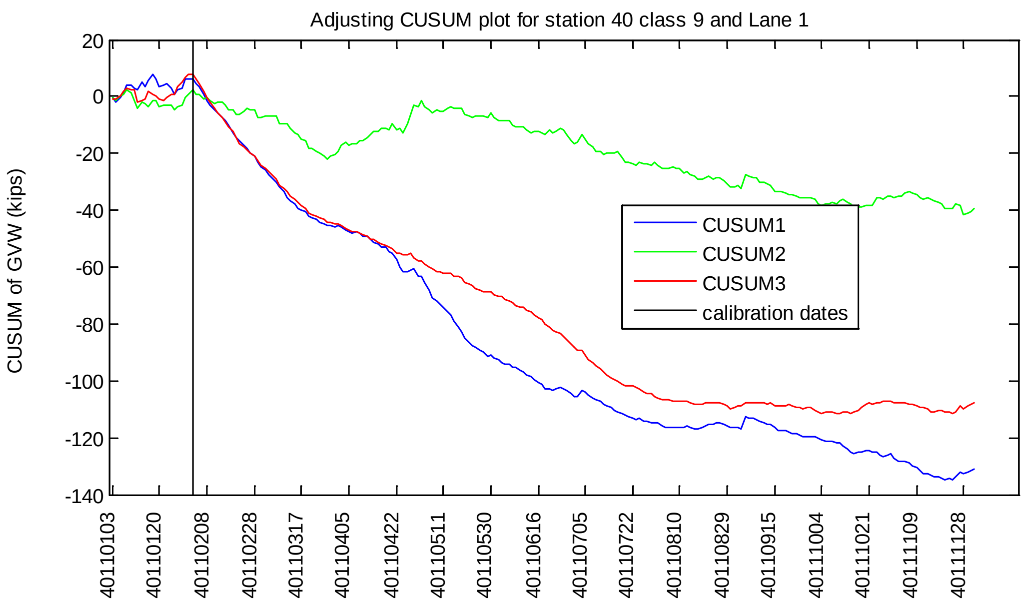
C.4.1 GVW

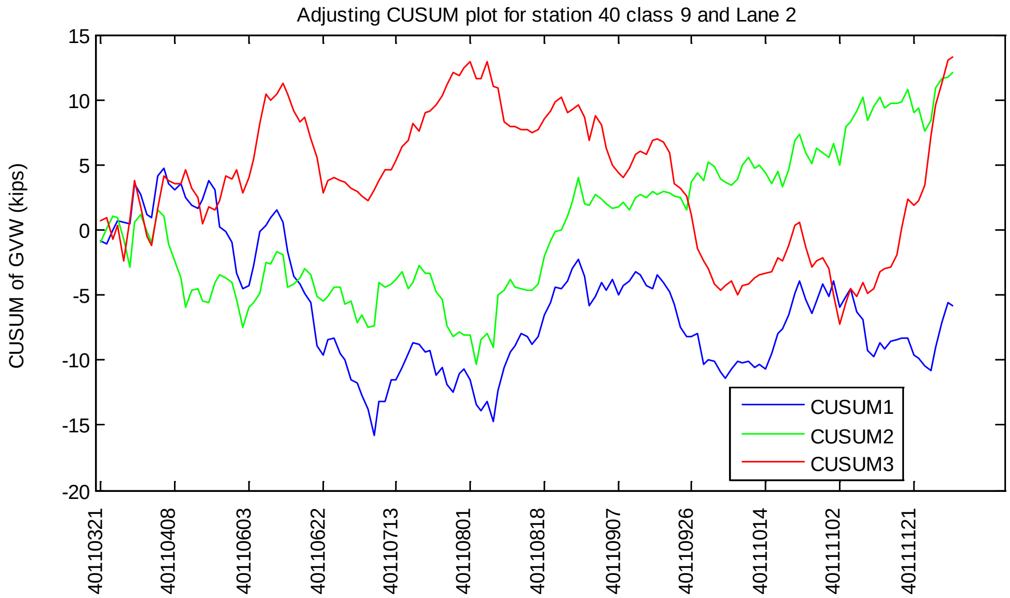



CUSUM plot for station 40 class 9 and Lane 2
CUSUM of GVW (kips)
40
20
0
-20
-40
-60
-80
-100
40110103
40110120
40110208
40110228
40110317
40110406
40110531
40110620
40110711
40110728
40110816
40110902
40110922
40111012
40111031
40111117
CUSUM for Mean1
CUSUM for Mean2
CUSUM for Mean3
calibration dates

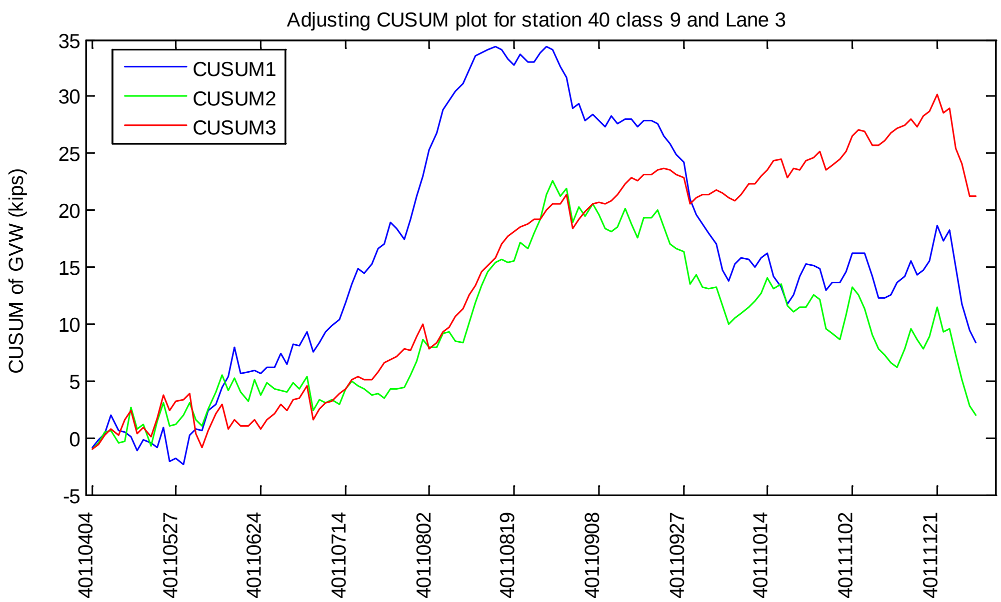

CUSUM plot for station 40 class 9 and Lane 3
CUSUM of GVW (kips)
60
40
20
0
-20
-40
-60
-80
-100
-120
-140
40110103
40110120
40110208
40110228
40110317
40110405
40110531
40110627
40110715
40110803
40110822
40110909
40110928
40111017
40111103
40111122
CUSUM for Mean1
CUSUM for Mean2
CUSUM for Mean3
calibration dates


CUSUM plot for station 40 class 9 and Lane 4
CUSUM of GVW (kips)
60
40
20
0
-20
-40
-60
-80
-100
-120
CUSUM for Mean1
CUSUM for Mean2
CUSUM for Mean3
calibration dates
40110103
40110120
40110208
40110228
40110317
40110405
40110422
40110511
40110530
40110616
40110705
40110722
40110810
40110829
40110915
40111004
40111021
40111109
40111128

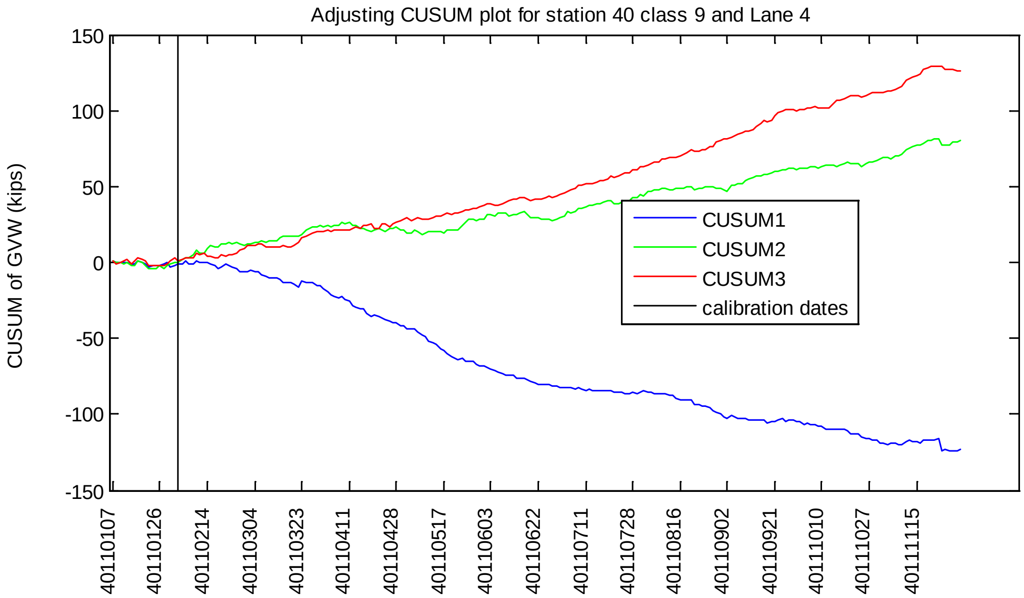

Adjusting CUSUM plot for station 40 class 9 and Lane 1
CUSUM of GVW (kips)
20
0
-20
-40
-60
-80
-100
-120
-140
CUSUM1
CUSUM2
CUSUM3
calibration dates
40110103
40110120
40110208
40110228
40110317
40110405
40110422
40110511
40110530
40110616
40110705
40110722
40110810
40110829
40110915
40111004
40111021
40111109
40111128



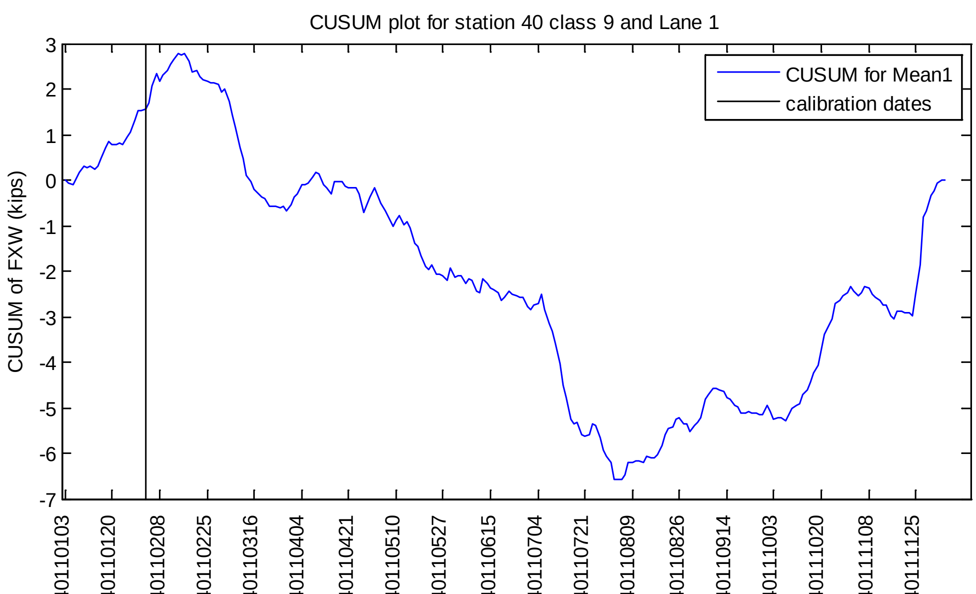
Adjusting CUSUM plot for station 40 class 9 and Lane 2
CUSUM of GVW (kips)
15
10
5
0
-5
-10
-15
-20
40110321
40110408
40110603
40110622
40110713
40110801
40110818
40110907
40110926
40111014
40111102
40111121
CUSUM1
CUSUM2
CUSUM3

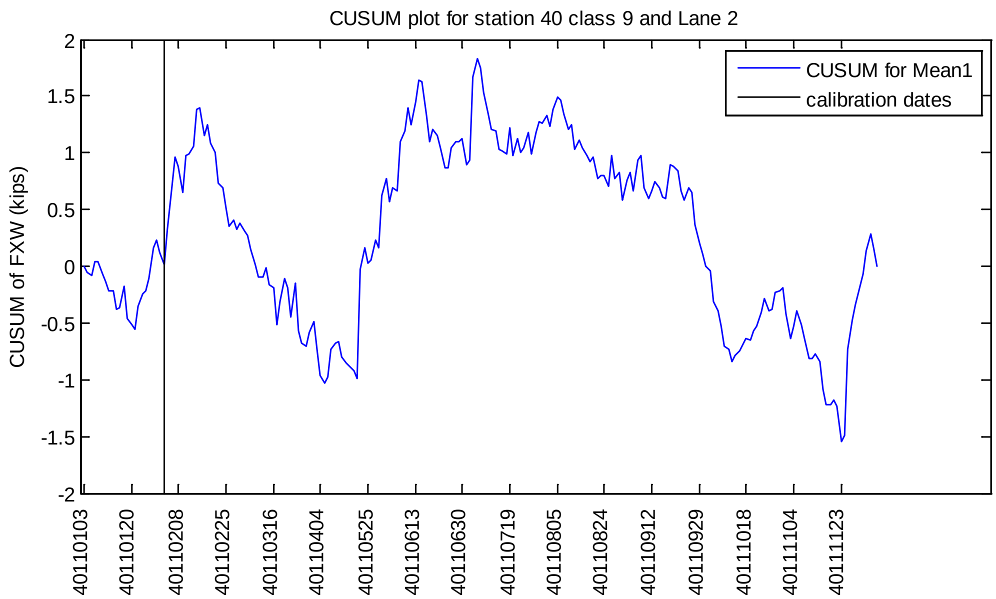



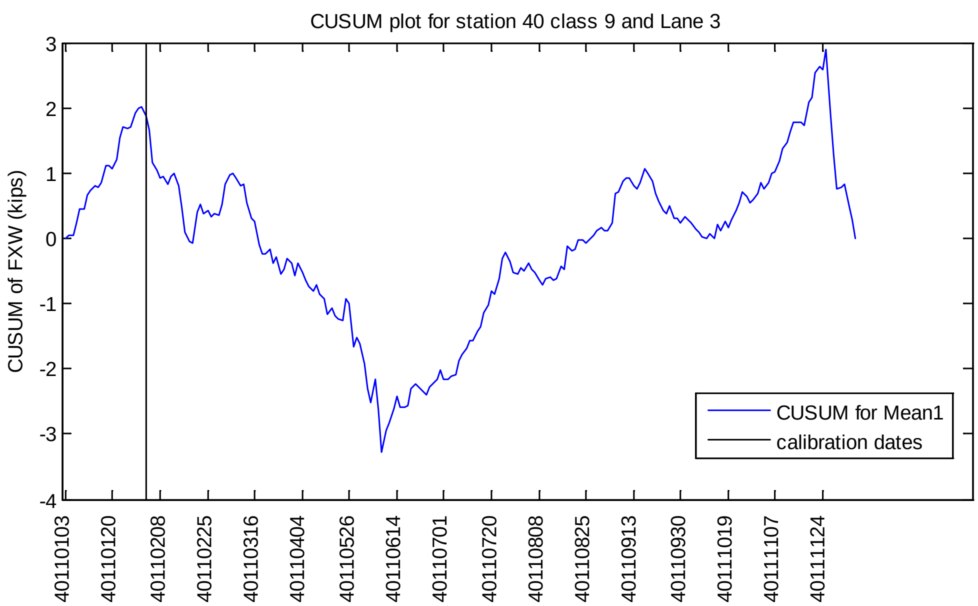
Adjusting CUSUM plot for station 40 class 9 and Lane 3
CUSUM of GVW (kips)
35
30
25
20
15
10
5
0
-5
40110404
40110527
40110624
40110714
40110802
40110819
40110908
40110927
40111014
40111102
40111121
CUSUM1
CUSUM2
CUSUM3

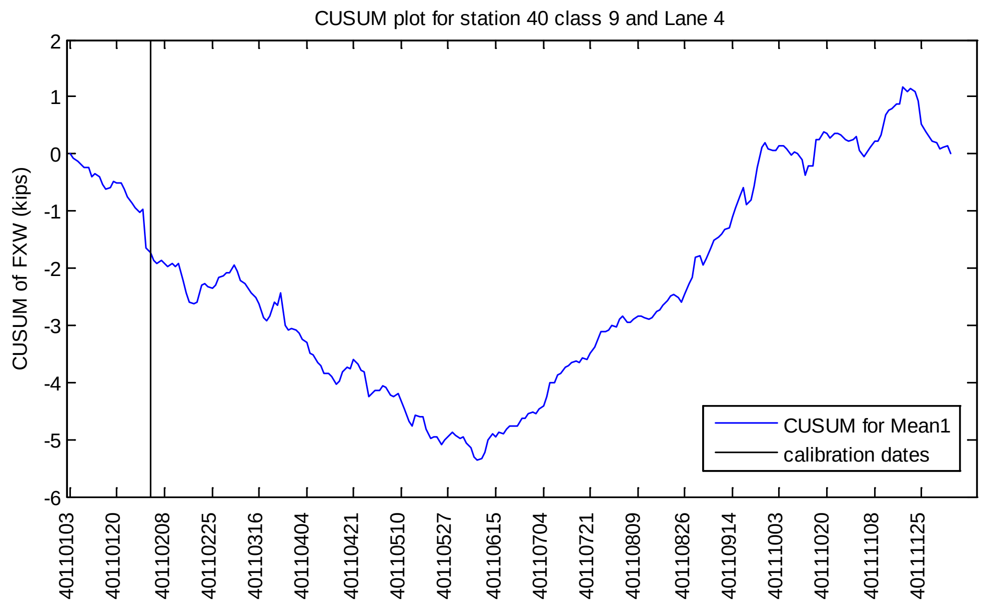



C.4.2 Front Axle Weight (FXW)

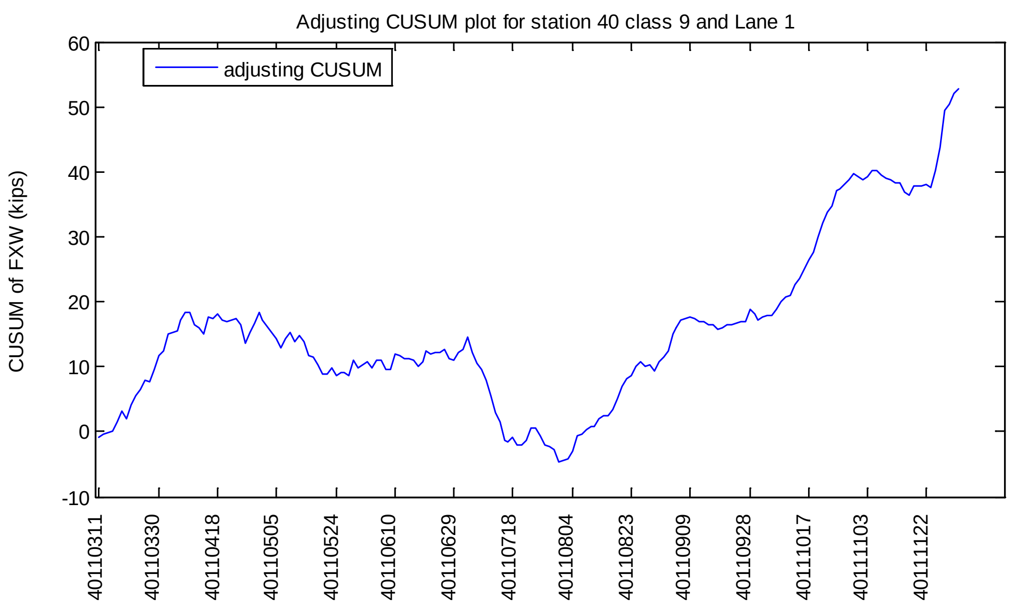



CUSUM plot for station 40 class 9 and Lane 2
CUSUM of FXW (kips)
CUSUM for Mean1
calibration dates
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
40110103
40110120
40110208
40110225
40110316
40110404
40110525
40110613
40110630
40110719
40110805
40110824
40110912
40110929
40111018
40111104
40111123

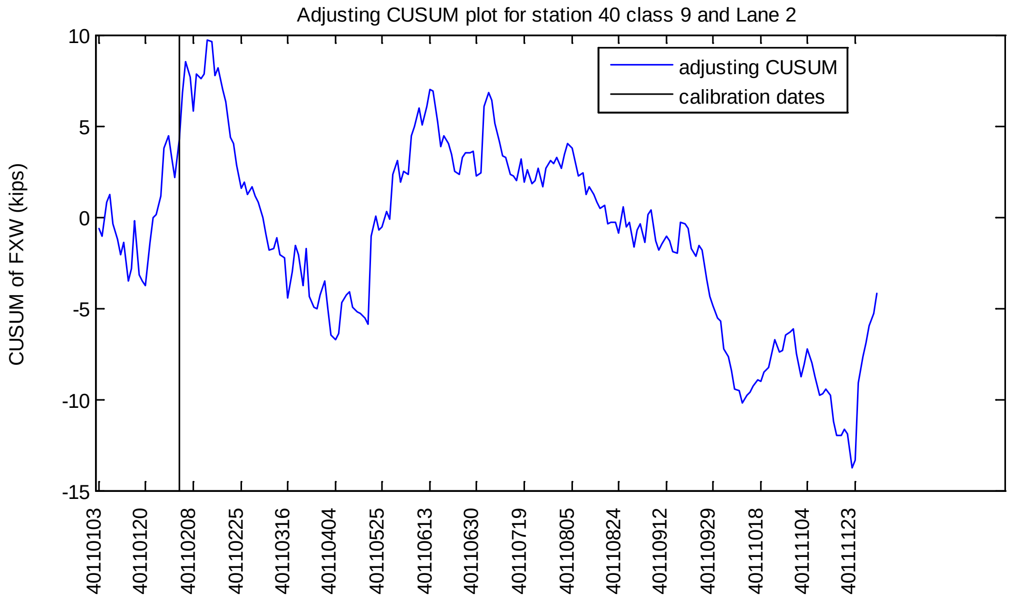

CUSUM plot for station 40 class 9 and Lane 3
CUSUM of FXW (kips)
CUSUM for Mean1
calibration dates
3
2
1
0
-1
-2
-3
-4
40110103
40110120
40110208
40110225
40110316
40110404
40110526
40110614
40110701
40110720
40110808
40110825
40110913
40110930
40111019
40111107
40111124



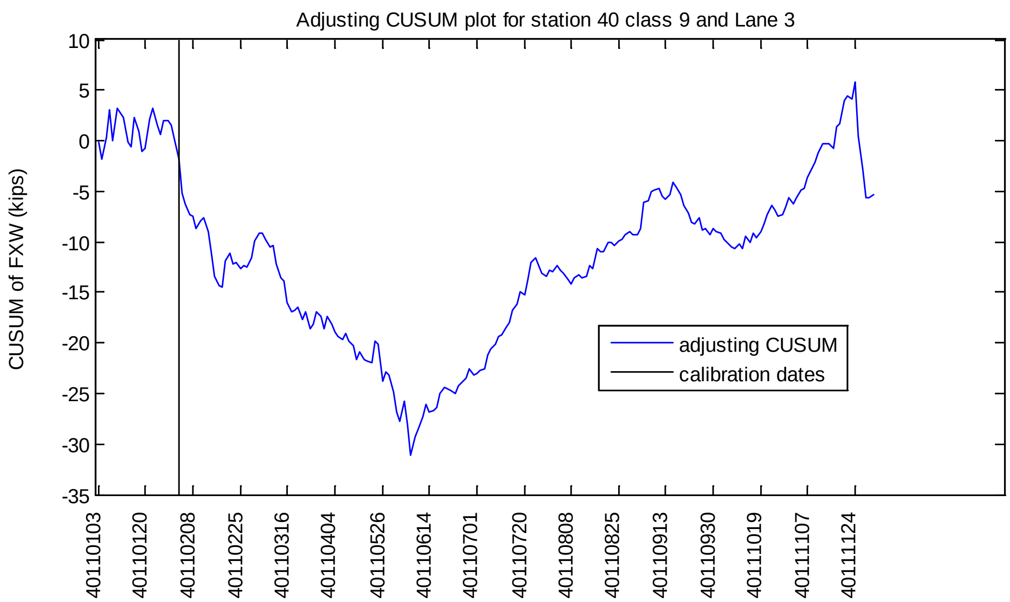
CUSUM plot for station 40 class 9 and Lane 4
CUSUM of FXW (kips)
2
1
0
-1
-2
-3
-4
-5
-6
CUSUM for Mean1
calibration dates
40110103
40110120
40110208
40110225
40110316
40110404
40110421
40110510
40110527
40110615
40110704
40110721
40110809
40110826
40110914
40111003
40111020
40111108
40111125

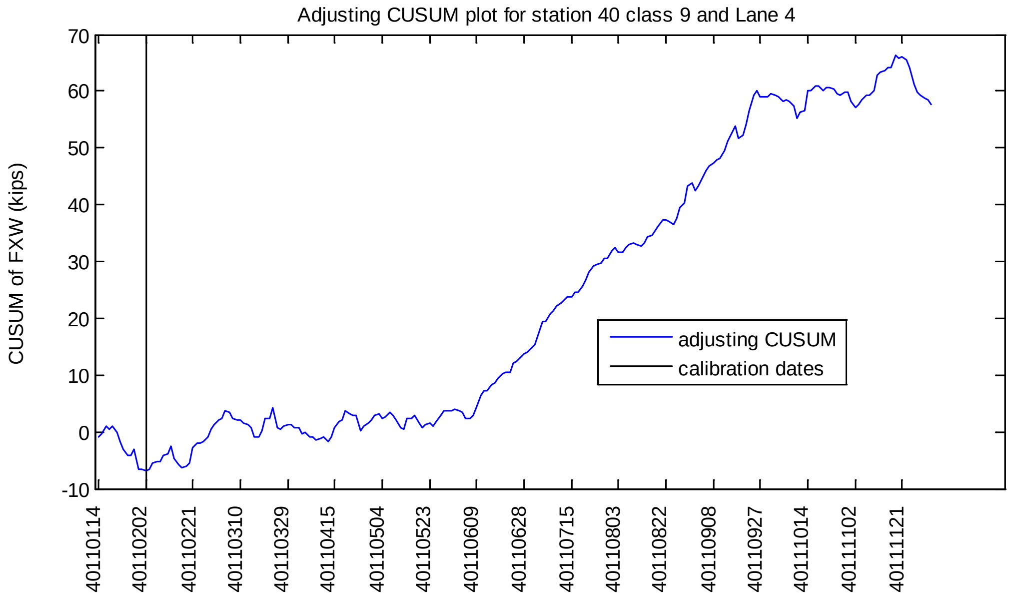
Adjusting CUSUM plot for station 40 class 9 and Lane 1
CUSUM of FXW (kips)
60
50
40
30
20
10
0
-10
adjusting CUSUM
40110311
40110330
40110418
40110505
40110524
40110610
40110629
40110718
40110804
40110823
40110909
40110928
40111017
40111103
40111122



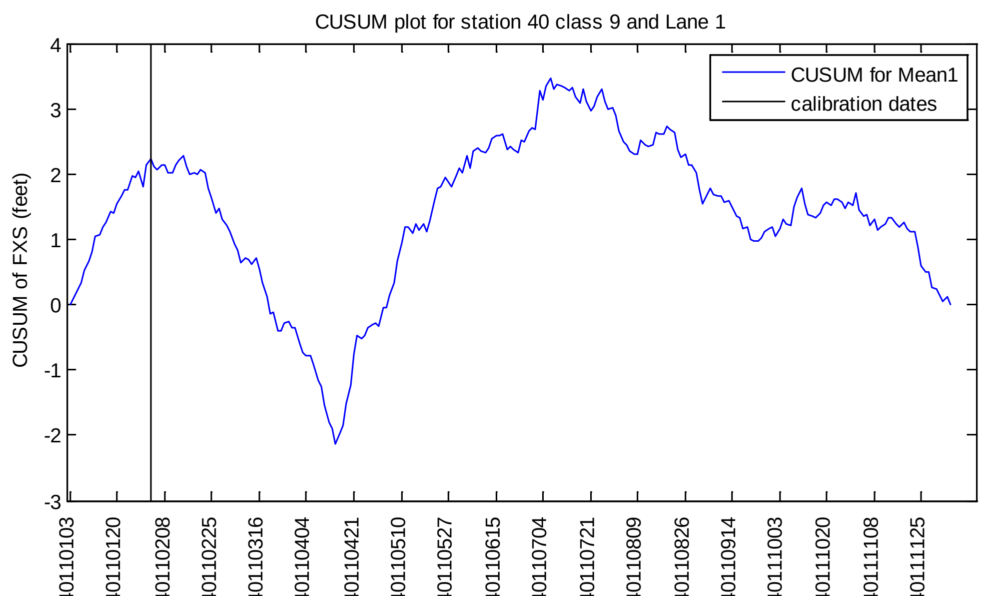
Adjusting CUSUM plot for station 40 class 9 and Lane 2
adjusting CUSUM
calibration dates
CUSUM of FXW (kips)
10
5
0
-5
-10
-15
40110103
40110120
40110208
40110225
40110316
40110404
40110525
40110613
40110630
40110719
40110805
40110824
40110912
40110929
40111018
40111104
40111123

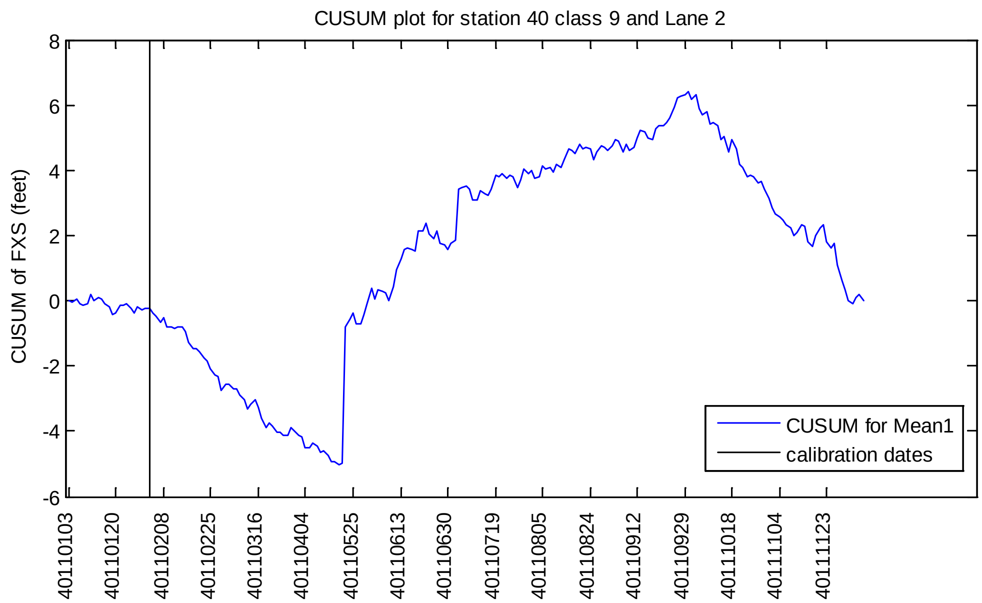



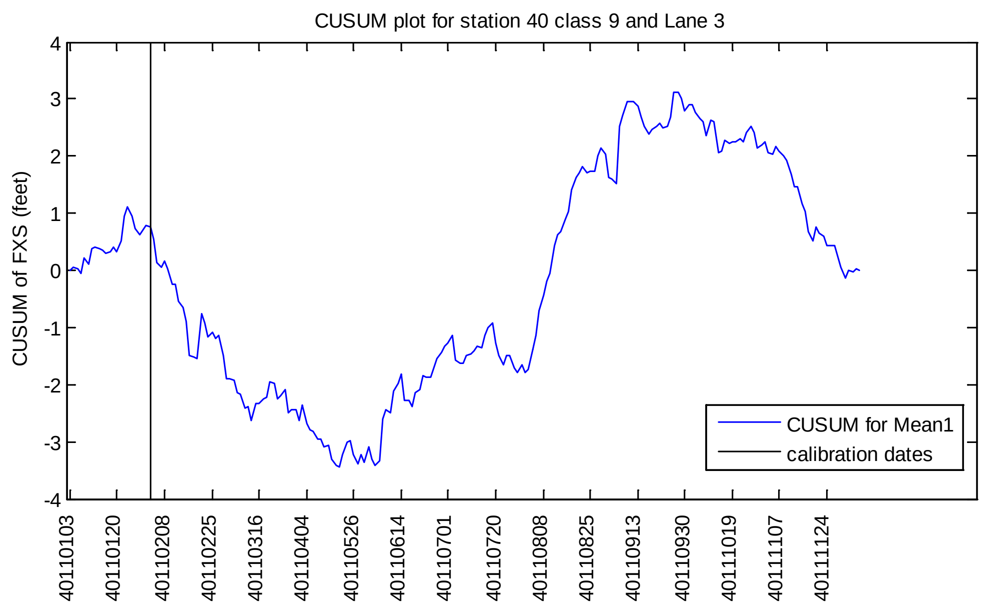
Adjusting CUSUM plot for station 40 class 9 and Lane 3
adjusting CUSUM
calibration dates
CUSUM of FXW (kips)
10
5
0
-5
-10
-15
-20
-25
-30
-35
40110103
40110120
40110208
40110225
40110316
40110404
40110526
40110614
40110701
40110720
40110808
40110825
40110913
40110930
40111019
40111107
40111124

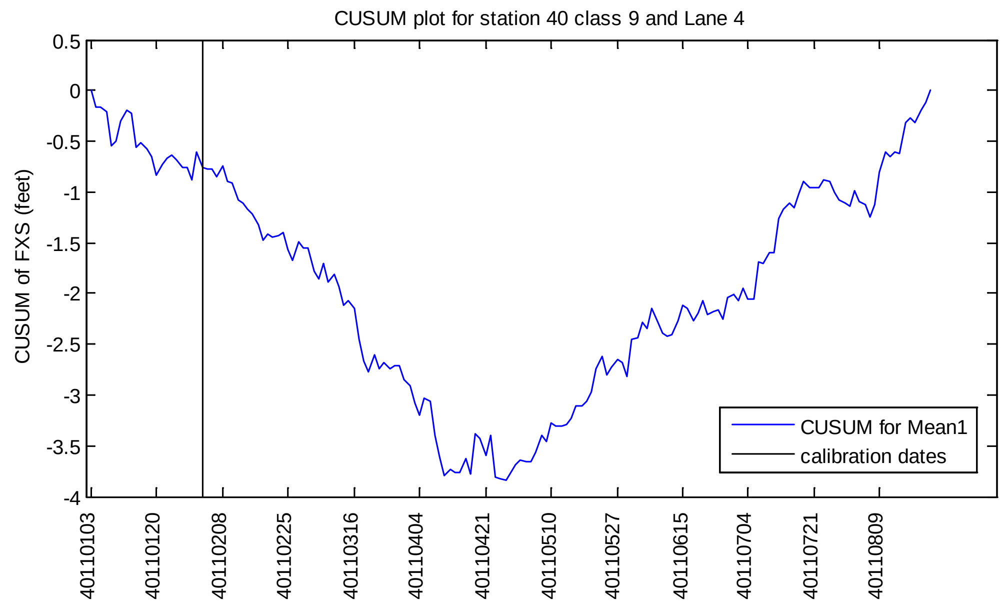


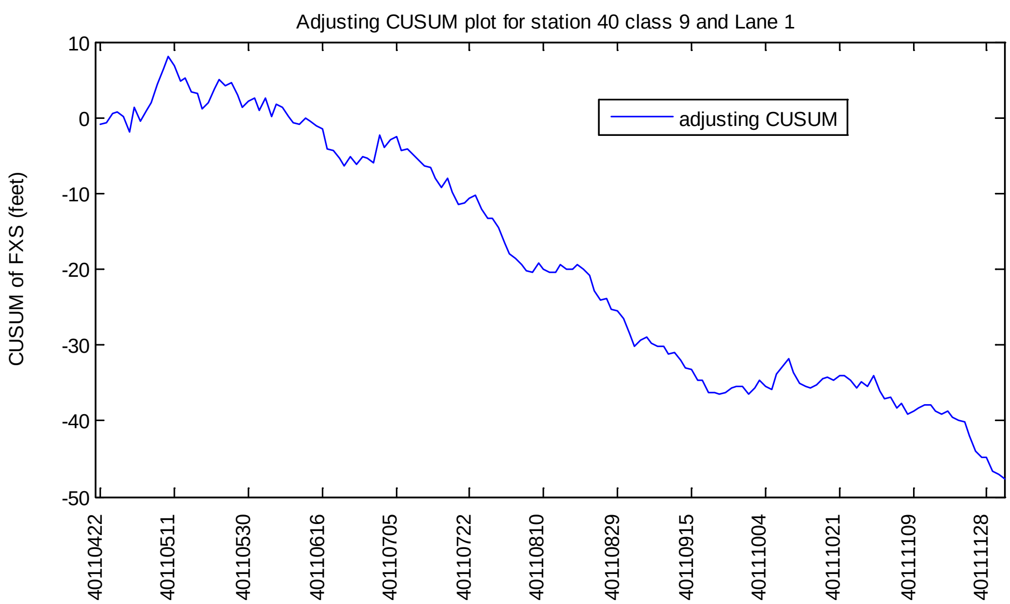

C.4.3 Front Axle Spacing (FXS)

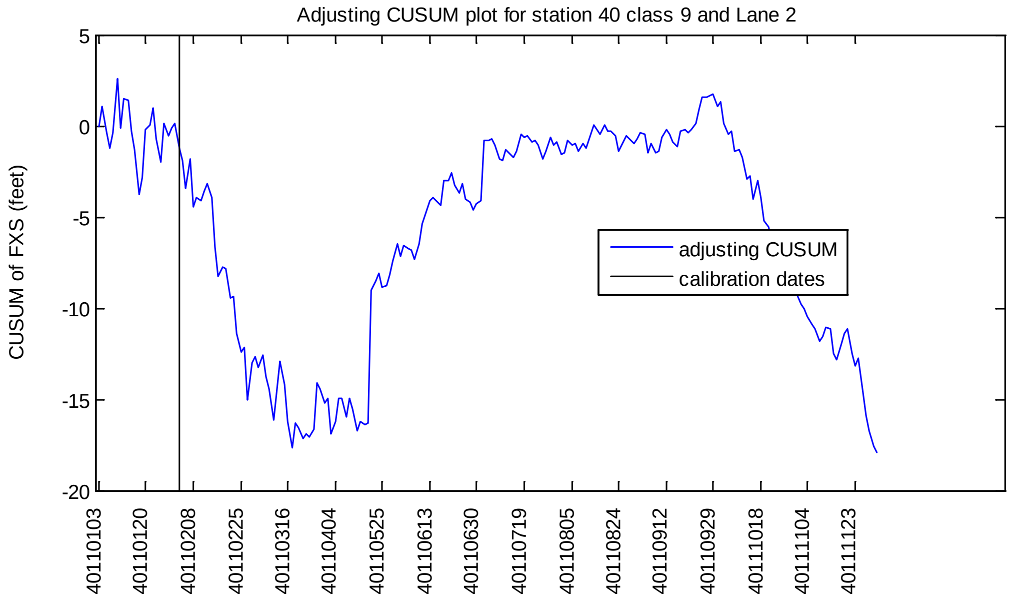


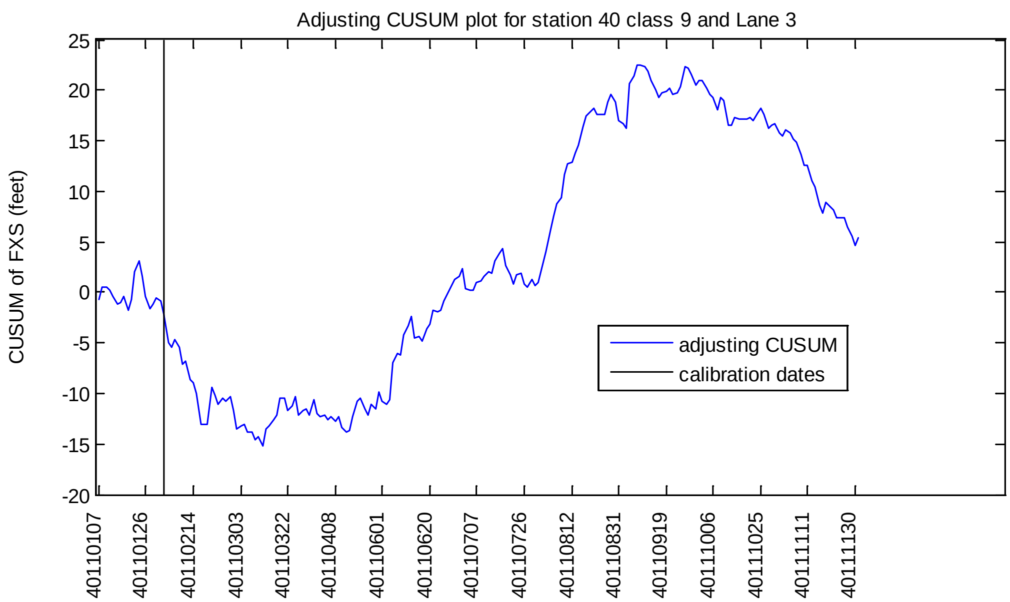

CUSUM plot for station 40 class 9 and Lane 2
CUSUM of FXS (feet)
CUSUM for Mean1
calibration dates
40110103
40110120
40110208
40110225
40110316
40110404
40110525
40110613
40110630
40110719
40110805
40110824
40110912
40110929
40111018
40111104
40111123

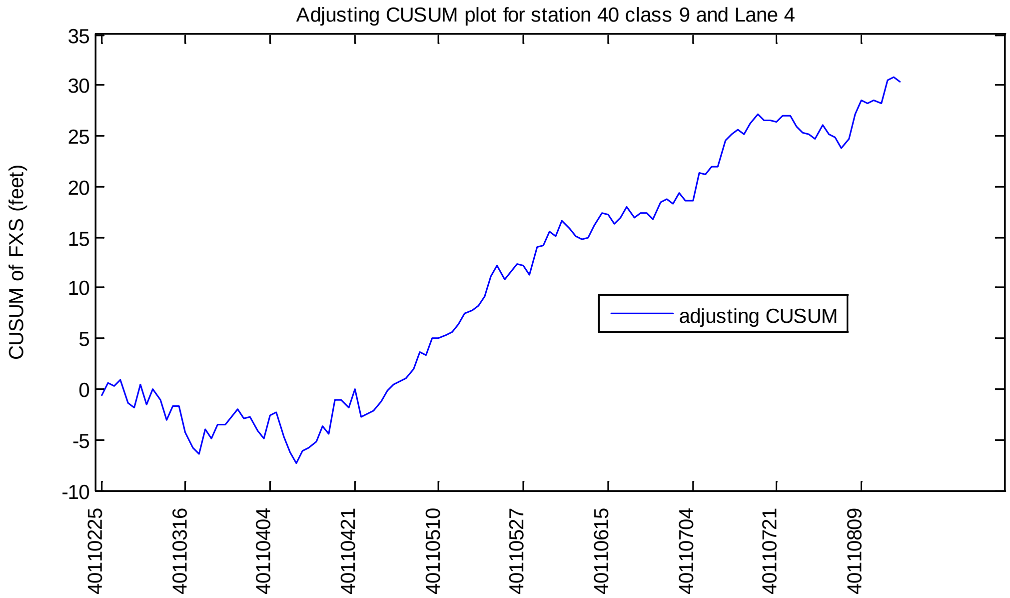

CUSUM plot for station 40 class 9 and Lane 3
CUSUM of FXS (feet)
CUSUM for Mean1
calibration dates
40110103
40110120
40110208
40110225
40110316
40110404
40110526
40110614
40110701
40110720
40110808
40110825
40110913
40110930
40111019
40111107
40111124


CUSUM plot for station 40 class 9 and Lane 4
CUSUM of FXS (feet)
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
40110103
40110120
40110208
40110225
40110316
40110404
40110421
40110510
40110527
40110615
40110704
40110721
40110809
CUSUM for Mean1
calibration dates


Adjusting CUSUM plot for station 40 class 9 and Lane 1
CUSUM of FXS (feet)
10
0
-10
-20
-30
-40
-50
40110422
40110511
40110530
40110616
40110705
40110722
40110810
40110829
40110915
40111004
40111021
40111109
40111128
adjusting CUSUM


Adjusting CUSUM plot for station 40 class 9 and Lane 2
CUSUM of FXS (feet)
5
0
-5
-10
-15
-20
adjusting CUSUM
calibration dates
40110103
40110120
40110208
40110225
40110316
40110404
40110525
40110613
40110630
40110719
40110805
40110824
40110912
40110929
40111018
40111104
40111123


Adjusting CUSUM plot for station 40 class 9 and Lane 3
CUSUM of FXS (feet)
25
20
15
10
5
0
-5
-10
-15
-20
adjusting CUSUM
calibration dates
40110107
40110126
40110214
40110303
40110322
40110408
40110601
40110620
40110707
40110726
40110812
40110831
40110919
40111006
40111025
40111111
40111130



Adjusting CUSUM plot for station 40 class 9 and Lane 4
CUSUM of FXS (feet)
35
30
25
20
15
10
5
0
-5
-10
adjusting CUSUM
40110225
40110316
40110404
40110421
40110510
40110527
40110615
40110704
40110721
40110809

# APPENDIX D: DATA PROCESSING INSTRUCTIONS

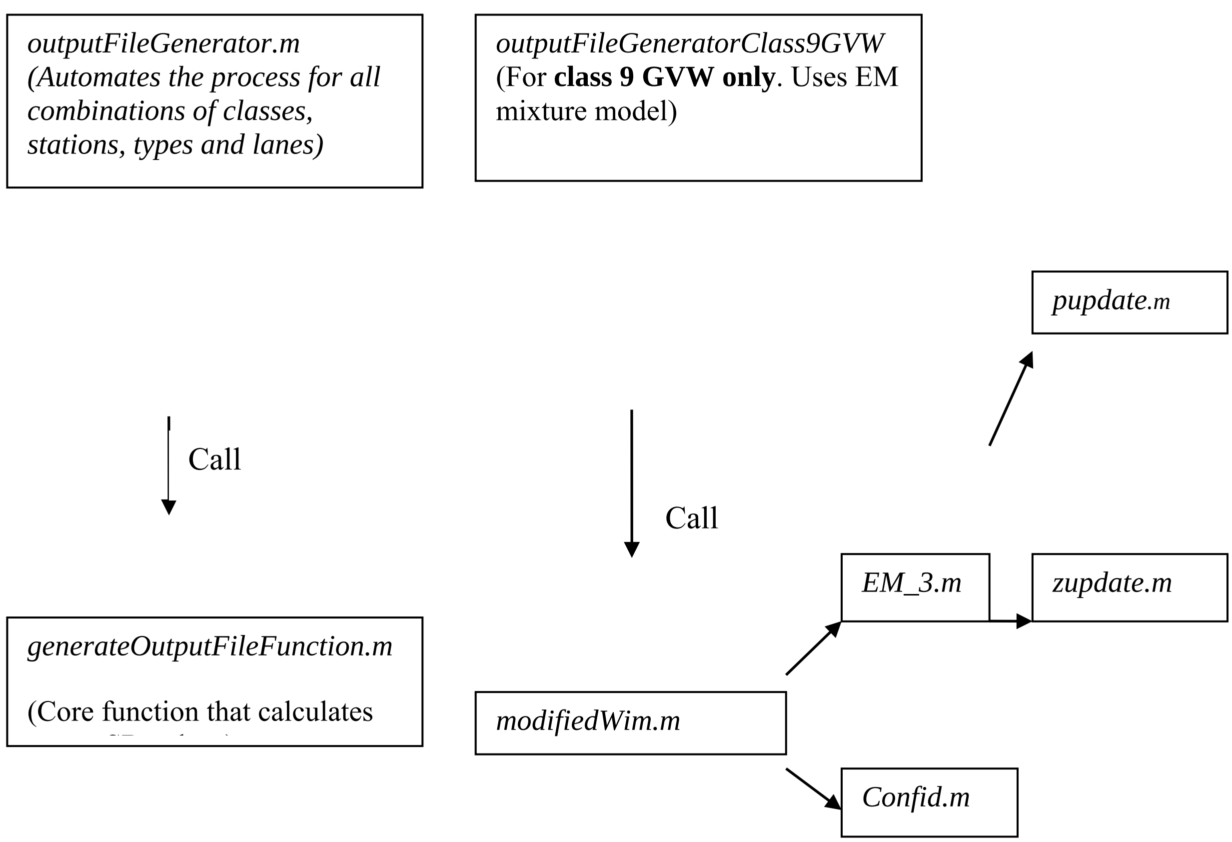
**D.1 Generate Output Files**

The codebase directory contains code files named "generateOutputFileFunction.m" which is the core function that handles various conditions and calculates the mean, SD values for class 2,3 (GVW,FXW,FXS) and class 9 (FXW,FXS). No mixture model is used by this function. The function accepts parameters like station_id, class_id, lane_id etc.

The 'outputFileGenerator.m" file in the same directory automates the process of generating the files for combinations of stations ,classes ,lanes and types (all except class 9 GVW which requires a mixture model). The 'type' variable in this file can be changed accordingly.

The "outputFileGeneratorClass9GVW.m" file is responsible for the output files of class 9, GVW and uses the mixture model to generate the output.

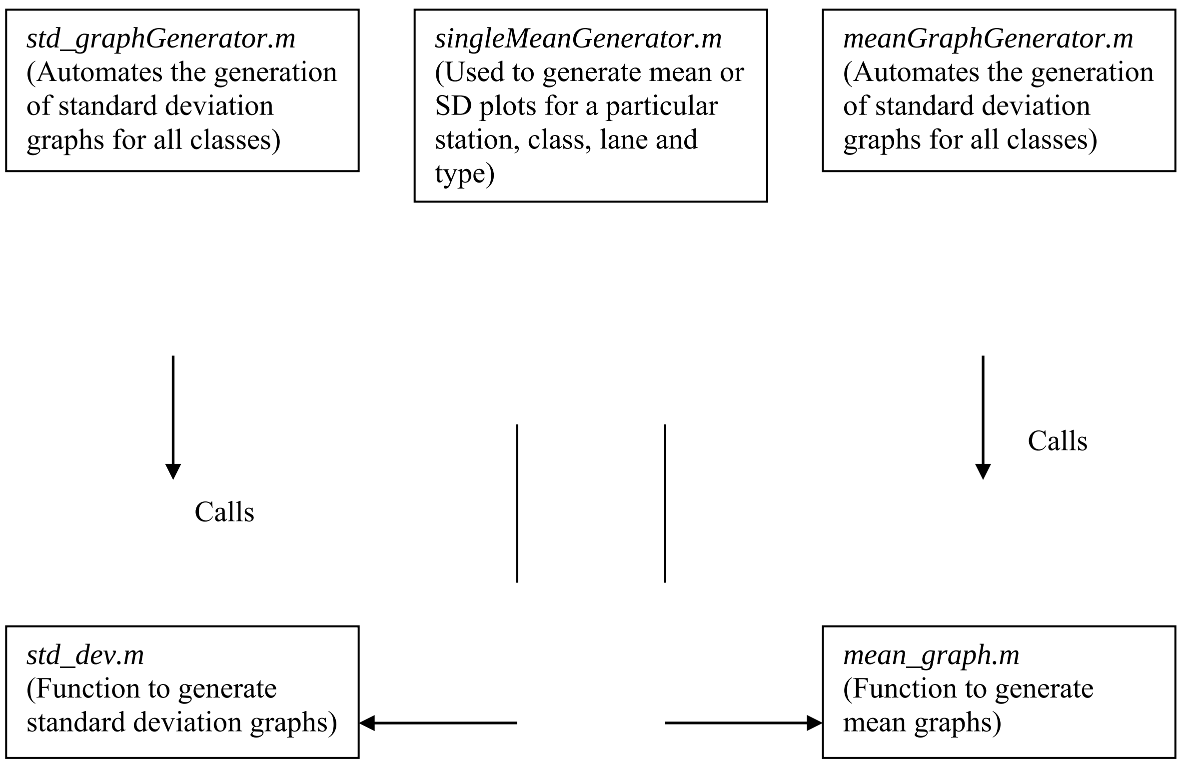
Flow chart for generation of .csv output files:




These output files are located under "~ \processedOutput" directory with the following naming scheme *output_station_id_Classclass_id_Lnlane_id_type.csv* .

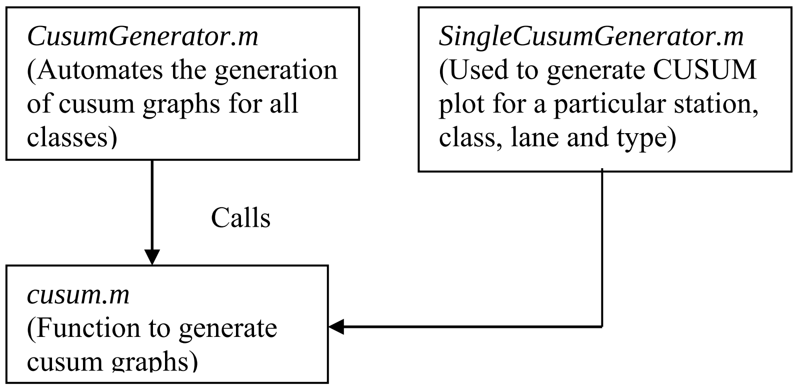
### D.2 Generate Mean and SD Graphs

The mean and SD graphs is generated by the functions – “mean_graph.m” and “std_dev.m” core files. These handle the various conditions involved for different types, lanes and classes. The “std_graphGenerator.m” and “meanGraphGenerator.m” automate the process of generating these graphs for different combinations of stations, lanes, classes and types.



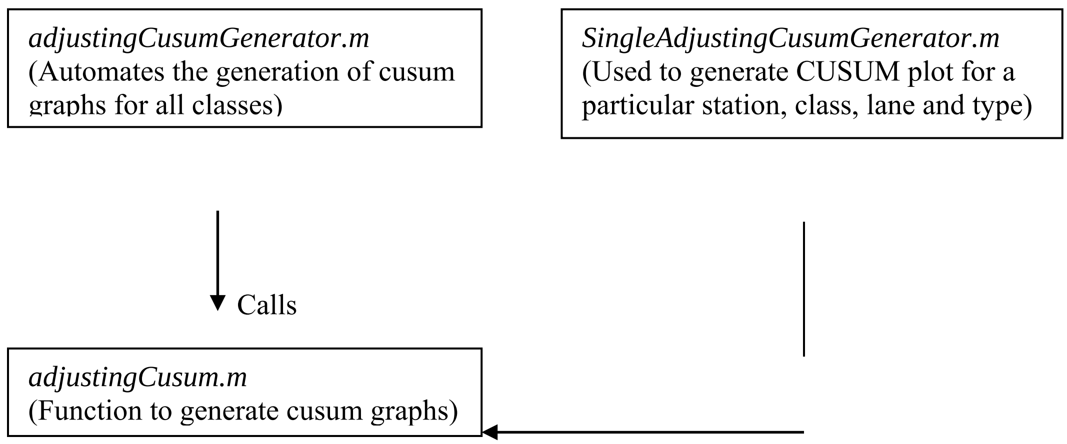
**D.3 Generate CUSUM Graphs**

The CUSUM plots are generated by the Cusum.m file. The CusumGenerator.m file automates the generations of CUSUM plots for all combinations of stations, classes, lanes and types.




**D.4 Generate Adjusting CUSUM Graphs**

The adjusting CUSUM plots are generated by adjustingCusum.m function. The adjustingCusumGenerator.m file automates the generations of adjusting CUSUM plots for all combinations of stations, classes, lanes and types. The singleAdjustingCusumGenerator.m is used to generate adjusting CUSUM plot for a particular station, class, lane and type)




**D.5 Generate Resetting Adjusting CUSUM Graphs**

The adjusting CUSUM graphs that reset at each calibration date are generated by CalibAndAdjustingCusum.m function. The CalibAndAdjustingCusumGenerator.m automates the generations of adjusting CUSUM plots for all combinations of stations, classes, lanes and types. The function uses Station37_IndexedCAlibrationDates.csv to map the calibration dates to their index positions. This csv file was manually generated.

**D.6 Generate Percentage Adjusting CUSUM Graphs**

The adjusting CUSUM percentage graphs are generated by PercentageAdjustingCusum.m function. The PercentageAdjustingCusumGenerator.m automates the generations of adjusting CUSUM plots for all combinations of stations, classes, lanes and types.

**D.7 Generate Decision Interval Adjusting CUSUM Graphs**

The decision interval adjusting CUSUM graphs are generated by DecisionIntervalAdjustingCusum.m function. The DecisionIntervalAdjustingCusumGenerator.m automates the generation of DI adjusting CUSUM plots for all combinations of stations, classes, lanes and types. The input to this is in C:\~\processedOutput folder as Copy (i) foutput_37_Class9_Ln1_GVW.csv file, where i denotes the different data files corresponding to different date ranges.

**D.8 Execute the Code**

To run the code use the singleGenerator.m file for generating graph for a particular combination of station, class, lane and type (Set the appropriate values for the variables in the function). To generate the graphs for all possible combinations use the ‘generator’ function directly.

NOTE: Do not run any code without first creating a backup, as this will overwrite the existing files. To trial run the codes, comment out the lines which save graphs or overwrite a file.

# APPENDIX E: DATA PROCESSING SCRIPTS

### E.1 R Code

The R software is an open source software tool for statistical computing and graphics (http://www.r-project.org/).

```
# MNDOT WIM

procdays<-read.csv("C: /MnDOT Data/processdays_37.csv", header=F)

numdays=length(procdays$V1)

stationID=37

laneID=2

out_filename=paste("C: /MnDOT
Data/weekday_output_",stationID,"_Ln",laneID,".csv",sep="")

for (i in c(1:numdays)) { #numdays

 if (procdays[i,2]>0 & procdays[i,2]<6) {

   dateStr=sprintf("%06d",procdays[i,1])

   filename=paste("C:/MnDOT Data/",stationID,"/", stationID, dateStr, ".asc", sep="")

   data<-read.csv(filename, header=F)

   # CLASS 9

   class9=subset(data, data[12]==9 & data[10]==laneID) # class & lane num

   speed9=class9[,11]

   GVW9=class9[,14]

   hgvw=hist(GVW9, breaks=mybreaks, plot=FALSE)

   brks=length(hgvw$breaks)

   mid=brks/2

   idx1=min(which(hgvw$counts == max(hgvw$counts[1:mid-1])))

   idx2=max(which(hgvw$counts == max(hgvw$counts[mid:brks-1])))

   # ESAL

   ESAL9=class9[,15]

   # Front Axle Weight, column 16

   group1=subset(class9, class9[14]<32)

   group2=subset(class9, class9[14]>=32 && class9[14]<70)

   group3=subset(class9, class9[14]>=70)
```

```
Wax1g1=group1[,16]

Wax1g2=group2[,16]

Wax1g3=group3[,16]

if (length(Wax1g1)>0) {

   g1_stat = c(length(Wax1g1),mean(Wax1g1),median(Wax1g1),sd(Wax1g1))

} else {

   g1_stat = c(0,0,0,0)

}

if (length(Wax1g2)>0) {

   g2_stat = c(length(Wax1g2),mean(Wax1g2),median(Wax1g2),sd(Wax1g2))

} else {

   g2_stat = c(0,0,0,0)

}

if (length(Wax1g3)>0) {

   g3_stat = c(length(Wax1g3),mean(Wax1g3),median(Wax1g3),sd(Wax1g3))

} else {

   g3_stat = c(0,0,0,0)

}

# Front Axle Spacing, 1-2, Column 17

XSP9_12=class9[,17]

# Normal Quamtile-Quantile Plot, Shapiro-Wilk Test

if (length(Wax1g1)>=3 && length(Wax1g1)<=5000) {

   nt1=shapiro.test(Wax1g1)

   w1=mean(nt1$statistic)

} else {

   w1=0

}

if (length(Wax1g2)>=3 && length(Wax1g2)<=5000) {

   nt2=shapiro.test(Wax1g2)
```

```
      w2=mean(nt2$statistic)

   } else {

      w2=0

   }

   if (length(Wax1g3)>=3 && length(Wax1g3)<=5000) {

      nt3=shapiro.test(Wax1g3)

      w3=mean(nt3$statistic)

   } else {

      w3=0

   }

   output=c(dateStr, length(speed9),mean(speed9),median(speed9),sd(speed9),

   hgvw$breaks[idx1], hgvw$breaks[idx2],

   mean(ESAL9),median(ESAL9),sd(ESAL9),

   g1_stat,g2_stat,g3_stat,

   mean(XSP9_12),median(XSP9_12),sd(XSP9_12),

   w1,w2,w3)

   write.table(t(output), file=out_filename, append=TRUE, sep=",", qmethod = "double",
row.names=FALSE, col.names=FALSE)

 } # if

} # for loop

write.table(GVW9, file="C:/temp/2010_08_03_Lane2_GVW9.csv", append=TRUE, sep=",",
qmethod = "double", row.names=FALSE, col.names=FALSE)

# =======================================

#dateStr="100717" #Sat

dateStr="100803"

laneID=1

stationID=37

filename=paste("C:/Chenfu/ITS_CTS/ITS/ATR_WIM/MnDOT Data/",stationID,"/", stationID,
dateStr, ".asc", sep="")

data<-read.csv(filename, header=F)

# CLASS, column 12
```

```
#class=data[,12]

#hist(class, breaks=15, xlab="Class",

#main=sprintf("Class Distribution \nN=%d (Observed),
%s/%s/20%s",length(class),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue", xlim=c(0,15))

par(mfrow=c(2,1))

# CLASS 9

class9=subset(data, data[12]==9 & data[10]==laneID)

speed9=class9[,11]

# SPEED, column 11

mybreaks=20

hspd=hist(speed9, breaks=mybreaks, xlab=sprintf("Mean=%4.1f, Median=%4.1f, Sd=%4.1f
(MPH)",mean(speed9),median(speed9),sd(speed9)),

main=sprintf("Class-9, Speed Distribution, Lane %d \nN=%d (Observed),
%s/%s/20%s",laneID,length(speed9),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue", xlim=c(40,80))

lines(hspd$mids, hspd$counts, type="l", col = 4, lty = 1, lwd = 2, ljoin="round")

lines(hspd$mids, hspd$counts, type="p", col = 2, lty = 1, lwd = 2)

# GVW, column 14

mybreaks=40

GVW9=class9[,14]

hgvw=hist(GVW9, breaks=mybreaks, plot=FALSE)

brks=length(hgvw$breaks)

mid=brks/2

idx1=min(which(hgvw$counts == max(hgvw$counts[1:mid-1])))

idx2=max(which(hgvw$counts == max(hgvw$counts[mid:brks-1])))

hgvw=hist(GVW9, breaks=mybreaks, xlab=sprintf("Peak1=%4.1f (kips), Peak2=%4.1f
(kips)",hgvw$breaks[idx1], hgvw$breaks[idx2]),

main=sprintf("Class-9, GVW Distribution, Lane %d\nN=%d (Observed),
%s/%s/20%s",laneID,length(GVW9),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue", xlim=c(0,120))

lines(hgvw$mids, hgvw$counts, type="l", col = 4, lty = 1, lwd = 2, ljoin="round")

lines(hgvw$mids, hgvw$counts, type="p", col = 2, lty = 1, lwd = 2)

# ESAL, column 15
```

```
ESAL9=class9[,15]

esal_stat=c(mean(ESAL9),median(ESAL9),sd(ESAL9))

esal_stat

# Front Axle Weight, column 16

group1=subset(class9, class9[14]<32)

group2=subset(class9, class9[14]>=32 && class9[14]<70)

group3=subset(class9, class9[14]>=70)

Wax1g1=group1[,16]

Wax1g2=group2[,16]

Wax1g3=group3[,16]

if (length(Wax1g1)>0) {

   g1_stat = c(length(Wax1g1),mean(Wax1g1),median(Wax1g1),sd(Wax1g1))

} else {

   g1_stat = c(0,0,0,0)

}

if (length(Wax1g2)>0) {

   g2_stat = c(length(Wax1g2),mean(Wax1g2),median(Wax1g2),sd(Wax1g2))

} else {

   g2_stat = c(0,0,0,0)

}

if (length(Wax1g3)>0) {

   g3_stat = c(length(Wax1g3),mean(Wax1g3),median(Wax1g3),sd(Wax1g3))

} else {

   g3_stat = c(0,0,0,0)

}

g1_stat

g2_stat

g3_stat

# Front Axle Spacing, 1-2, Column 17
```

```
XSP9_12=class9[,17]

XSP9_12_stat=c(mean(XSP9_12),median(XSP9_12),sd(XSP9_12))

XSP9_12_stat

# ========================

par(mfrow=c(2,2))

# Normal Quamtile-Quantile Plot, Shapiro-Wilk Test

if (length(Wax1g1)>=3 && length(Wax1g1)<=5000) {

   nt1=shapiro.test(Wax1g1)

   w1=mean(nt1$statistic)

} else {

   w1=0

}

if (length(Wax1g2)>=3 && length(Wax1g2)<=5000) {

   nt2=shapiro.test(Wax1g2)

   w2=mean(nt2$statistic)

} else {

   w2=0

}

if (length(Wax1g3)>=3 && length(Wax1g3)<=5000) {

   nt3=shapiro.test(Wax1g3)

   w3=mean(nt3$statistic)

} else {

   w3=0

}

qqnorm(Wax1g1, main=sprintf("GVW < 32 kips, w=%5.3f",w1),font.main=1, col=4)

qqline(Wax1g1, col=2)

qqnorm(Wax1g2, main=sprintf("GVW 32 ~ 70 kips, w=%5.3f",w2),font.main=1, col=4)

qqline(Wax1g2, col=2)

qqnorm(Wax1g3, main=sprintf("GVW > 70 kips, w=%5.3f",w3),font.main=1, col=4)
```

```
qqline(Wax1g3, col=2)

# ================================

dateStr="110305"

laneID=1

filename=paste("C:/Chenfu/ITS_CTS/ITS/ATR_WIM/MnDOT Data/",stationID,"/", stationID,
dateStr, ".asc", sep="")

data<-read.csv(filename, header=F)

par(mfrow=c(2,1))

# CLASS 15

class15=subset(data, data[12]==15 & data[10]==laneID)

speed15=class15[,11]

# SPEED, column 11

mybreaks=20

hspd=hist(speed15, breaks=mybreaks, xlab=sprintf("Mean=%4.1f, Median=%4.1f, Sd=%4.1f
(MPH)",mean(speed9),median(speed9),sd(speed9)),

main=sprintf("Class-15, Speed Distribution, Lane %d \nN=%d (Observed),
%s/%s/20%s",laneID,length(speed9),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue", xlim=c(40,80))

lines(hspd$mids, hspd$counts, type="l", col = 4, lty = 1, lwd = 2, ljoin="round")

lines(hspd$mids, hspd$counts, type="p", col = 2, lty = 1, lwd = 2)

# GVW, column 14

mybreaks=40

GVW15=class15[,14]

hgvw=hist(GVW15, breaks=mybreaks, plot=FALSE)

brks=length(hgvw$breaks)

mid=brks/2

idx1=min(which(hgvw$counts == max(hgvw$counts[1:mid-1])))

idx2=max(which(hgvw$counts == max(hgvw$counts[mid:brks-1])))

hgvw=hist(GVW15, breaks=mybreaks, xlab=sprintf("Peak1=%4.1f (kips), Peak2=%4.1f
(kips)",hgvw$breaks[idx1], hgvw$breaks[idx2]),

main=sprintf("Class-15, GVW Distribution, Lane %d\nN=%d (Observed),
%s/%s/20%s",laneID,length(GVW9),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue", xlim=c(0,120))
```

```
lines(hgvw$mids, hgvw$counts, type="l", col = 4, lty = 1, lwd = 2, ljoin="round")

lines(hgvw$mids, hgvw$counts, type="p", col = 2, lty = 1, lwd = 2)

# ====================================

# CLASS 2

par(mfrow=c(2,1))

class2=subset(data, data[12]==2)

speed2=class2[,11]

# SPEED, column 11

y=hist(speed2, breaks=18, xlab=sprintf("Mean=%4.1f, Median=%4.1f, Sd=%4.1f
(MPH)",mean(speed2),median(speed2),sd(speed2)),

main=sprintf("Class-2, Speed Distribution \nN=%d (Observed),
%s/%s/20%s",length(speed2),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue")

lines(y$mids, y$counts, type="l", col = 4, lty = 1, lwd = 2, ljoin="round")

lines(y$mids, y$counts, type="p", col = 2, lty = 1, lwd = 2)

# GVW, column 14

GVW2=class2[,14]

y=hist(GVW2, breaks=20, xlab=sprintf("Mean=%4.1f, Median=%4.1f, Sd=%4.1f
(kips)",mean(GVW2),median(GVW2),sd(GVW2)),

main=sprintf("Class-2, GVW Distribution \nN=%d (Observed),
%s/%s/20%s",length(GVW2),data[1,2],data[1,3],data[1,1]),freq=T, font.main=1,
col="lightblue", xlim=c(0,10))

lines(y$mids, y$counts, type="l", col = 4, lty = 1, lwd = 2, ljoin="round")

lines(y$mids, y$counts, type="p", col = 2, lty = 1, lwd = 2)
```

## E.2 MATLAB Script – Mixture Modeling Using EM Fitting

MATLAB, developed by the MathWorks, Inc. (http://www.mathworks.com/index.html), is a programming environment for algorithm development, data analysis, visualization, and numerical computation.

```
======= WIM_Main.m =======

% WIM GVW9 EM fitting

% calls EM_3.m

% Created by Chen-Fu Liao, 7/20/2011

clear ;

em_tolerance = 0.001;

station_id = 37;

lane_id = 2 ;

dates=importdata(sprintf('C:/MnDOT Data/processdays_%d.csv', station_id));

% select weekdays

weekdays=dates(find(dates(:,2)>0 & dates(:,2)<6),1) ;

num_days=length(weekdays) ;

% results = zeros(num_days, 12) ;

out_filename=sprintf('C:/MnDOT/Outputs/output_%d_Ln%d_CI_spd50.csv',station_id,lane_id
) ;

fid = fopen(out_filename,'a') ;

% data file header

fprintf(fid,
'Date,N,Mu1_L,Mu1,Mu1_U,Mu2_L,Mu2,Mu2_U,Mu3_L,Mu3,Mu3_U,SD1,SD2,SD3,p1,p2,p3,nIter\n')
;

for ith_day=1:num_days % 200:207 %

    date_str=sprintf('%d%06d',station_id,weekdays(ith_day));

    %date_str=sprintf('%d%06d',station_id,dates(1:1));

    %date_str='37100803';

    wim_data=importdata(sprintf('C:/MnDOT Data/%d/%s.asc', station_id,date_str));

    % lane # (col 10), class (col 12), GVW (col 14)

    y=wim_data(find(wim_data(:,10)==lane_id & wim_data(:,12)==9 & wim_data(:,11)>=50),
14);
```

```
    % EM fitting

    EM_3;

    if any(any(pfinal))>0

        % 95% Confidence interval

        muband=CONFID(y,pfinal,zfinal) ;

        % output date, data length, pfinal, n_iter

        fprintf(fid, '%s,%d,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%d\n',
date_str,
length(y),muband(1,1),muband(1,2),muband(1,3),muband(2,1),muband(2,2),muband(2,3),muba
nd(3,1),muband(3,2),muband(3,3),sqrt(pfinal(1,2)), sqrt(pfinal(2,2)),
sqrt(pfinal(3,2)), pfinal(1,3), pfinal(2,3), pfinal(3,3), niter) ;

        disp(sprintf('Day %d of %d, %d iterations', ith_day, num_days, niter)) ;

    else

        disp(sprintf('Day %d of %d, %d iterations ignored.', ith_day, num_days,
niter)) ;

    end

end

fclose(fid) ;



======= EM3.m =======

% initialization

n=length(y) ;

z0=zeros(n,3);

unit=ones(n,1);

cuts=[40 70]; % 32, 70, cutoffs, kips

for i=1:n

  if(y(i)<=cuts(1))

    z0(i,1)=0.98;

  elseif (y(i) >= cuts(2))

    z0(i,3)=0.98;

  else

    z0(i,2)=0.98;
```

```
  end
end
% Estimate updates
if min(sum(round(z0))) >= 20
      p0=pupdate(z0,y) ;
    % EM 3 modes
    pold=p0;
    niter=0 ;
    n_diff=[999,999,999] ;
    % mean_diff <= em_tolerance, variance_diff <= em_tolerance
    while n_diff(1)>em_tolerance || n_diff(2)>em_tolerance
     znew=zupdate(pold,y);
     zold=znew;
     pnew=pupdate(zold,y);
      % added by chen-fu
     diff = pnew-pold ;
     n_diff=[norm(diff(:,1)), norm(diff(:,2)), norm(diff(:,3))] ;
     % end of addition
     pold=pnew;
     niter=niter+1 ;
    end
    n_diff ;
    %disp(sprintf('niter= %d', niter)) ;
    pfinal=pnew ;
    zfinal=znew ;
else
  pfinal=zeros(3,3) ;
end
```

======= CONFID.m =======

```
function muband=confid(yy,pp,zz)

% function muband=confid(yy,pp,zz)

% computes approximate 95 percent confidence intervals for compenent means

% using empirical information matrix

% muband= [lower mean upper]

% lower = 3x1 vector of lower bounds for confidence intervals

% upper = 3x1 vector of upper bounds for confidence intervals

% yy = nx1 vector of observations

% pp = 3x3 matrix of maximum likelihood estimates of component parameters

% zz = nx3 matrix of estimated membership probabilities


nn=size(yy);

n=nn(1);

F=zeros(8,8);

for i=1:n

for j=1:3

  diff=(yy(i,1)-pp(j,1));

  stemp(j)=zz(i,j)*(diff/pp(j,2));

  diff2=(diff^2)/pp(j,2);

  stemp(j+3)=(zz(i,j)/(2*pp(j,2)))*(diff2-1);

 end

 stemp(7)=(zz(i,1)/pp(1,3))-(zz(i,3)/(1-pp(1,3)-pp(2,3)));

 stemp(8)=(zz(i,1)/pp(1,2))-(zz(i,3)/(1-pp(1,3)-pp(2,3)));

 F=F+stemp'*stemp;

end

C=inv(F);

se(1)=sqrt(C(1,1));

se(2)=sqrt(C(2,2));
```

```
se(3)=sqrt(C(3,3));
for j=1:3
  lower(j)=pp(j,1)-1.96*se(j);
  upper(j)=pp(j,1)+1.96*se(j);
end
muband=[lower' pp(:,1) upper'];
return
```

```
======= EMverify.m =======
% initialization
em_tolerance = 0.001;
load lane1.dat ;
y=lane1 ;
nn=size(y);
n=nn(1);
z0=zeros(n,3);
unit=ones(n,1);
cuts=[32 70]; % cutoffs
for i=1:n
  if(y(i)<=cuts(1))
    z0(i,1)=1;
  elseif (y(i) >= cuts(2))
    z0(i,3)=1;
  else
    z0(i,2)=1;
  end
end
```

```
p0=pupdate(z0,y) ;

% EM1

pold=p0;

niter=0 ;

n_diff=[999,999,999] ;

while n_diff(1)>em_tolerance || n_diff(2)>em_tolerance

 znew=zupdate(pold,y);

 zold=znew;

 pnew=pupdate(zold,y);

  % added by chen-fu

 diff = pnew-pold ;

 n_diff=[norm(diff(:,1)), norm(diff(:,2)), norm(diff(:,3))] ;

 % end of addition

 pold=pnew;

 niter=niter+1 ;

end

n_diff ;

disp(sprintf('niter= %d', niter)) ;

pfinal=pnew ;

% compare model output with data

gvw = y ;

[counts,ints]=hist(gvw,30);

n=sum(counts);

pemp=counts/n;

muplot=pfinal(:,1);

sigplot=sqrt(pfinal(:,2));

piplot=pfinal(:,3);
```

```
picon=sqrt(2*pi);

for i=1:30

    for j=1:3

       ztemp=(ints(i)-muplot(j,1))/sigplot(j,1);

       px(i,j)=piplot(j,1)*(exp(-.5*ztemp^2)/(sigplot(j,1)*picon));

    end

pmod(i)=sum(px(i,:));

end

pmod=pmod/sum(pmod);

h1=plot(ints,pemp, 'r:+');

xlabel('GVW9 (kips)') ;

ylabel('Density') ;

title(sprintf('Sample GVW9 N=%d', length(y))) ; hold on ;

h2=plot(ints,pmod, 'b*-');

legend([h1, h2],'Empirical', 'EM Model') ;grid ; hold off ;
```

# APPENDIX F: VEHICLE CLASSIFICATION SCHEME

### F.1 FHWA Vehicle Classification

Automatic vehicle classifiers need an algorithm to interpret axle spacing information to correctly classify vehicles into these categories. The algorithm most commonly used is based on the "Scheme F" developed by Maine DOT in the mid-1980s. The FHWA does not endorse "Scheme F" or any other classification algorithm. More detail at Traffic Monitoring Guide, section 4 – vehicle classification monitoring at http://www.fhwa.dot.gov/ohim/tmguide/tmg4.htm#app4c.

Class 1 -

Motorcycles: All two- or three-wheeled motorized vehicles. Typical vehicles in this category have saddle type seats and are steered by handle bars rather than wheels. This category includes motorcycles, motor scooters, mopeds, motor-powered bicycles, and three-wheeled motorcycles.

Class 2 -

Passenger Cars: All sedans, coupes, and station wagons manufactured primarily for the purpose of carrying passengers and including those passenger cars pulling recreational or other light trailers.

Class 3 -

Other Two-Axle, Four-Tire, Single Unit Vehicles: All two-axle, four-tire, vehicles other than passenger cars. Included in this classification are pickups, panels, vans, and other vehicles such as campers, motor homes, ambulances, hearses, carryalls, and minibuses. Other two-axle, four-tire single unit vehicles pulling recreational or other light trailers are included in this classification.

Class 4 -

Buses: All vehicles manufactured as traditional passenger-carrying buses with two axles and six tires or three or more axles. This category includes only traditional buses (including school buses) functioning as passenger-carrying vehicles. Modified buses should be considered to be trucks and be appropriately classified.

Note: In reporting information on trucks the following criteria should be used:

a. Truck tractor units traveling without a trailer will be considered single unit trucks.
b. A truck tractor unit pulling other such units in a “saddle mount” configuration will be considered as one single unit truck and will be defined only by axles on the pulling unit.
c. Vehicles shall be defined by the number of axles in contact with the roadway. Therefore, “floating” axles are counted only when in the down position.
d. The term “trailer” includes both semi- and full trailers.

Class 5 -

Two-Axle, Six-Tire, Single Unit Trucks: All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., having two axles and dual rear wheels.

Class 6 -

Three-axle Single unit Trucks: All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., having three axles.

Class 7 -

Four or More Axle Single Unit Trucks:  All trucks on a single frame with four or more axles.

Class 8 –

Four or Less Axle Single Trailer Trucks: All vehicles with four or less axles consisting of two units, one of which is a tractor or straight truck power unit.

Class 9 -

Five-Axle Single Trailer Trucks:  All five-axle vehicles consisting of two units, one of which is a tractor or straight truck power unit.

Class 10 -

Six or More Axle Single Trailer Trucks: All vehicles with six or more axles consisting of two units, one of which is a tractor or straight truck power unit. .

Class 11 -

Five or Less Axle Multi-Trailer Trucks: All vehicles with five or less axles consisting of three or more units, one of which is a tractor or straight truck power unit .

Class 12 -

Six-Axle Multi-Trailer Trucks:  All six-axle vehicles consisting of three or more units, one of which is a tractor or straight truck power unit.

Class 13 -

Seven or More Axle Multi-Trailer Trucks: All vehicles with seven or more axles consisting of three or more units, one of which is a tractor or straight truck power unit.