A Statistical Process Control Approach for Traffic Data Quality Verification and Sensor Calibration for Weigh-In-Motion Systems

Chen-Fu Liao
Indrajit Chatterjee
Gary A. Davis

MINNESOTA DEPARTMENT OF TRANSPORTATION

NATMEC 2016 Conference

Miami, FL

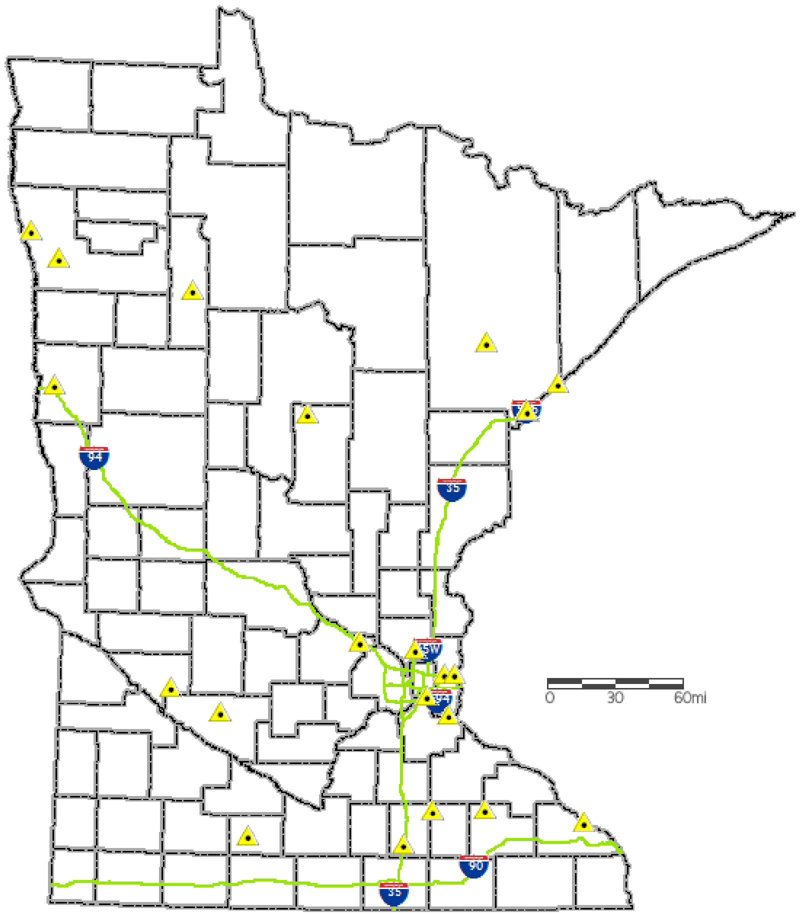
UNIVERSITY OF MINNESOTA
Driven to Discover℠

Outline

- Weigh-In-Motion (WIM) System
- Objectives
- Methodology
- Case Study
- Software Implementation
- Summary

WIM systems in MN

- 18+ WIM stations
- Interstate Highways, US and state routes.
- Data: Truck volume, vehicle class, speed, weight



Source: http://mndotgis.dot.state.mn.us/tfa/Map

WIM Sensor Drift

- WIM sensor sensitive to:
    - Road surface condition
    - Temperature
    - Vehicle Dynamics
    - Other external factors

- WIM sensor calibration essential

- MnDOT uses a fully loaded test truck (~ 80 kips) to calibrate WIM sensors twice a year

Typical Calibration Report

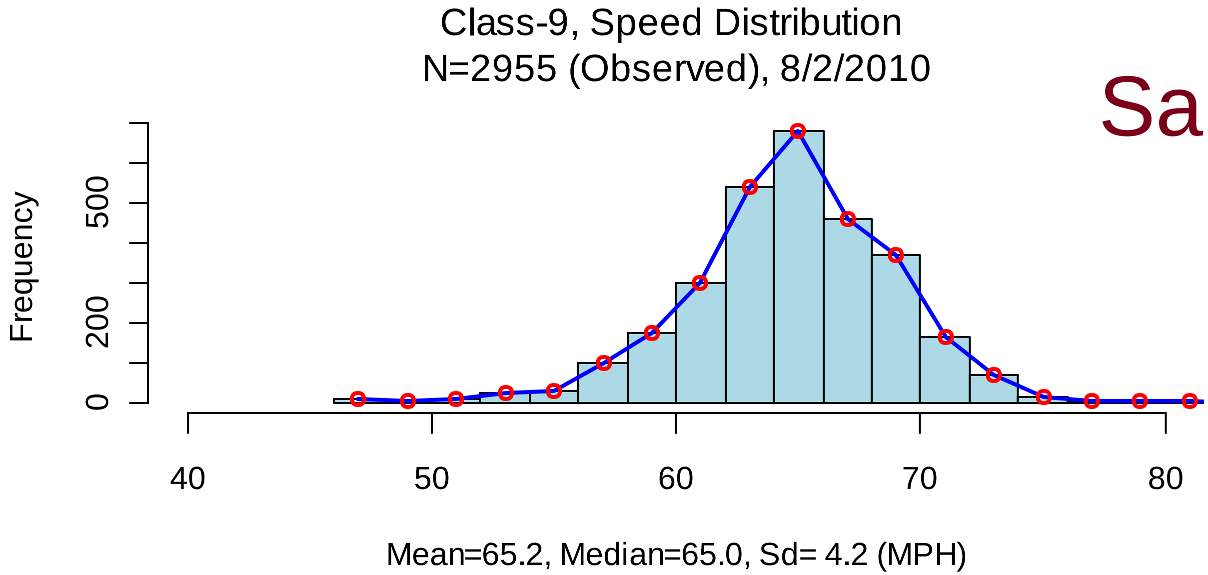
Station #40	Static Weight			
Site# W St Paul	GVW	Steer	1st Tandem	2nd Tandem
Test Vehicle	79.8	11.9	34.5	33.5

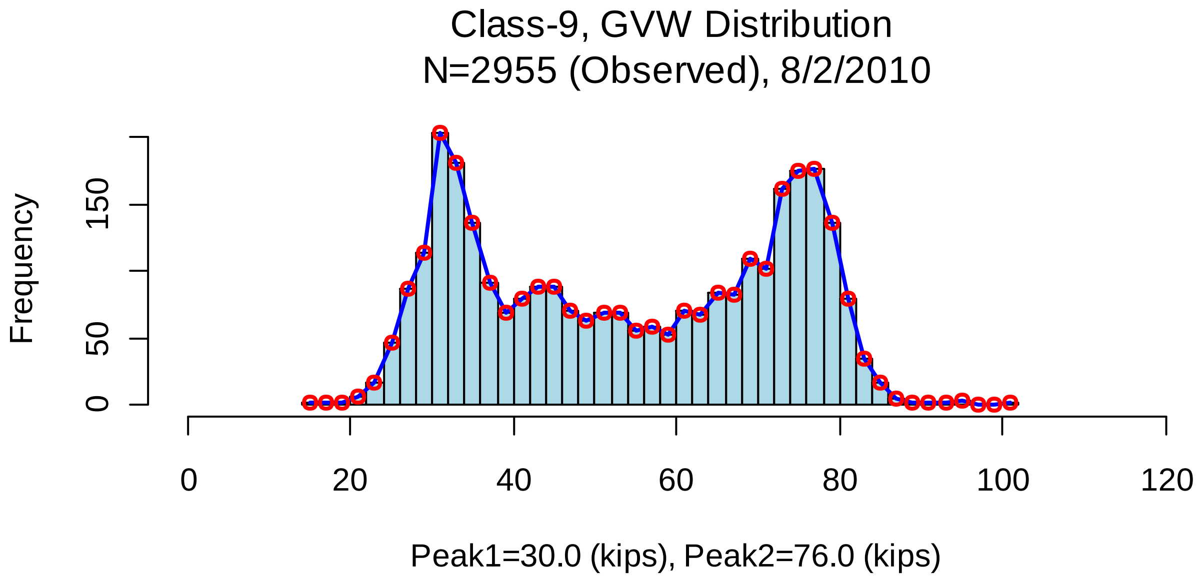
		Lap	Vehicle		WIM Weight	
Date	Time	Time	Number	Speed	GVW	**GVW (±5%)**
9/12/13	11:16:00	--	62935	57	77.8	-2.5%
9/12/13	11:24:00	0:08:00	63270	63	76.5	-4.1%
9/12/13	11:59:00	0:35:00	322	57	78.4	-1.8%
9/12/13	12:07:00	0:08:00	666	55	78.1	-2.1%
9/12/13	12:15:00	0:08:00	1034	55	79.7	-0.1%

Objectives

- Limitations of current practice
  - Fails to identify the time point when WIM system went out of calibration
  - Reliability of WIM data is questionable
  - Limited resources to perform frequent on-site calibration checks
- Goal
  - Systematic approach to identify time point when WIM system went out of calibration
  - Estimate the bias in WIM sensor

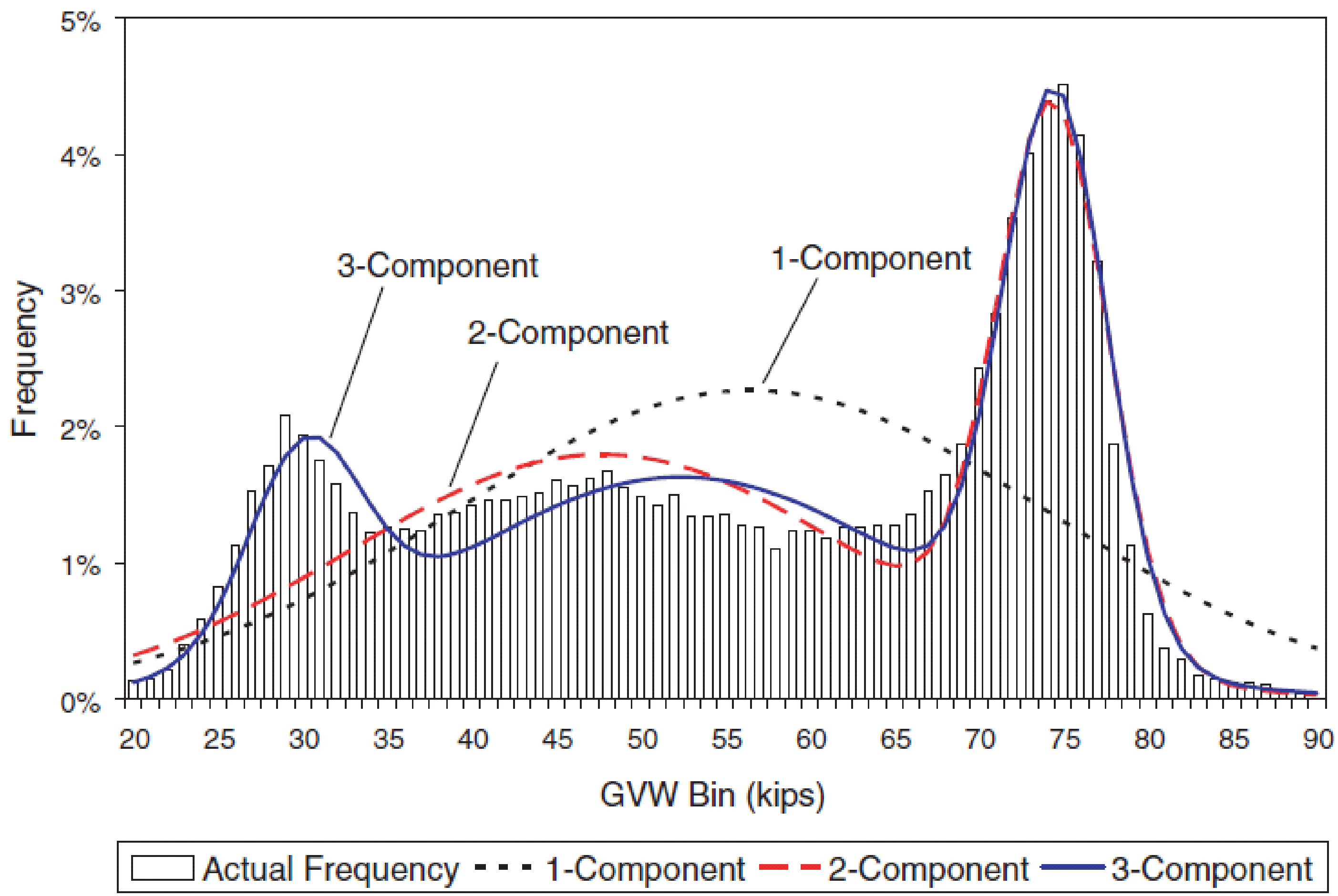
Sample WIM Data





Characteristics Class 9 GVW Distributions

Multi-component mixture models (Nicholas & Cetin, 2007)



Nichols and Cetin, 2007

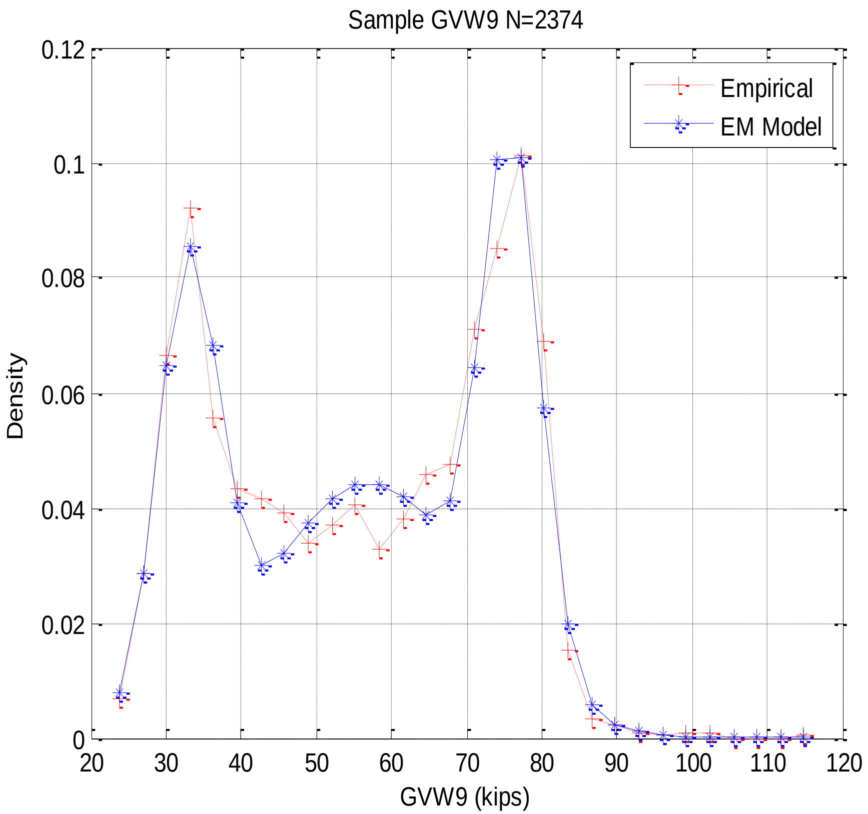
Characteristics Class 9 GVW Distributions (Con't)

- GVW distribution into 3 sub-groups (Dahlin,1992)
  - Unloaded (GVW< 40 kips)
  - Partially loaded (40< GVW< 70 kips)
  - Fully loaded (GVW> 70 kips)

- Expectation Maximization Algorithm (EM)

$$f(y) = \sum_{i=1}^{n} \lambda_i f_i(y) = \lambda_1 f_1(y) + \lambda_2 f_2(y) + \lambda_3 f_3(y) + \cdots$$

EM Fitting of a 3-Component Mixture Model



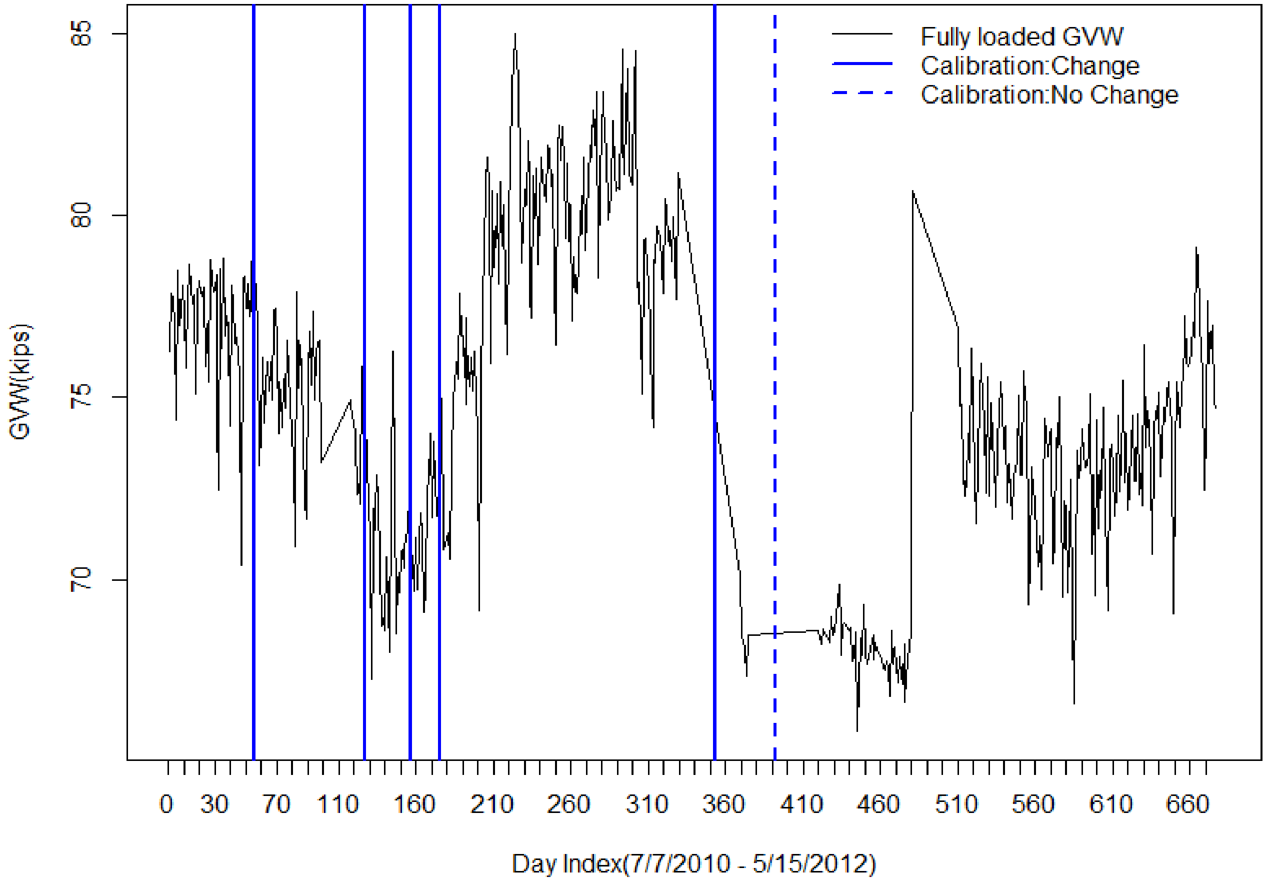
Component	Mean (kips)	SD (kips)	Proportion
Unloaded	33.0	4.1	0.25
Partially loaded	55.8	13.5	0.475
Fully loaded	76.0	3.8	0.275

WIM station #37, lane 1, on 05/15/2012

Methodology

- Fully loaded class 9 GVW
- Weekday daily average
- Use a Statistical Process Control (SPC) technique to detect significant shifts in the mean of a process.

WIM# 37 Lane 1, Vehicle Class 9 EM Estimated Daily Average Fully Loaded GVW



Statistical Process Control Technique

- Original CUSUM Approach

$$U_i = \frac{X_i - \mu}{\sigma}$$
$$S_n = S_{n-1} + U_n$$

- Decision Interval (DI) Based CUSUM
  - Upper CUSUM

$$S_0^+ = 0;\ S_n^+ = \max(0, S_{n-1}^+ + U_n - k)$$

  - Lower CUSUM

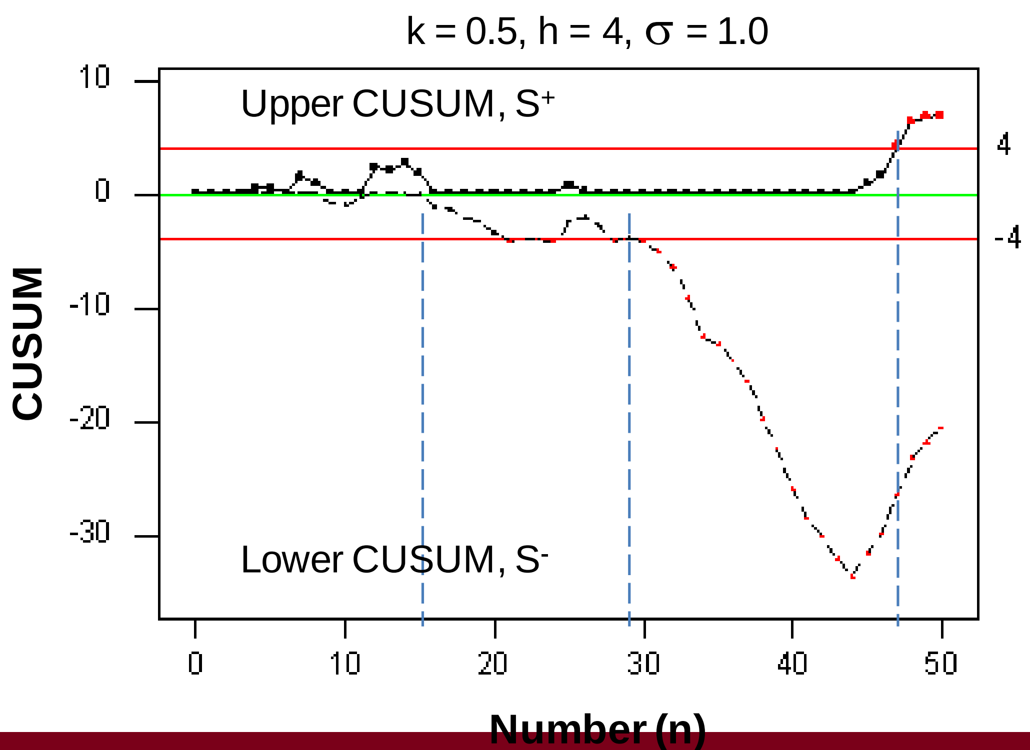
$$S_0^- = 0;\ S_n^- = \min(0, S_{n-1}^- + U_n + k)$$

Hawkins, D.M. & Olwell, D.H., (1998). *Cumulative Sum Charts and Charting for Quality Improvement*, Springer

Decision Interval Based CUSUM

$$S_0^+ = 0 \qquad S_n^+ = \max(0, \quad S_{n-1}^+ + U_n - \text{k})$$

$$S_0^- = 0 \qquad S_n^- = \min(0, \quad S_{n-1}^- + U_n + \text{k})$$



h: decision interval

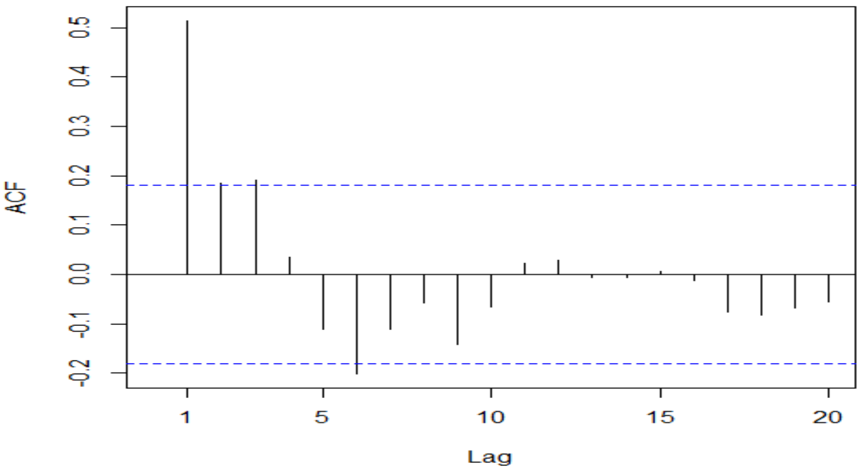
k: reference value

Out of control allowance

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

Auto-Correlation

- Independent assumption
- Autocorrelation function (ACF) plot from station# 29



- Presence of autocorrelation results in higher number of false alarms.

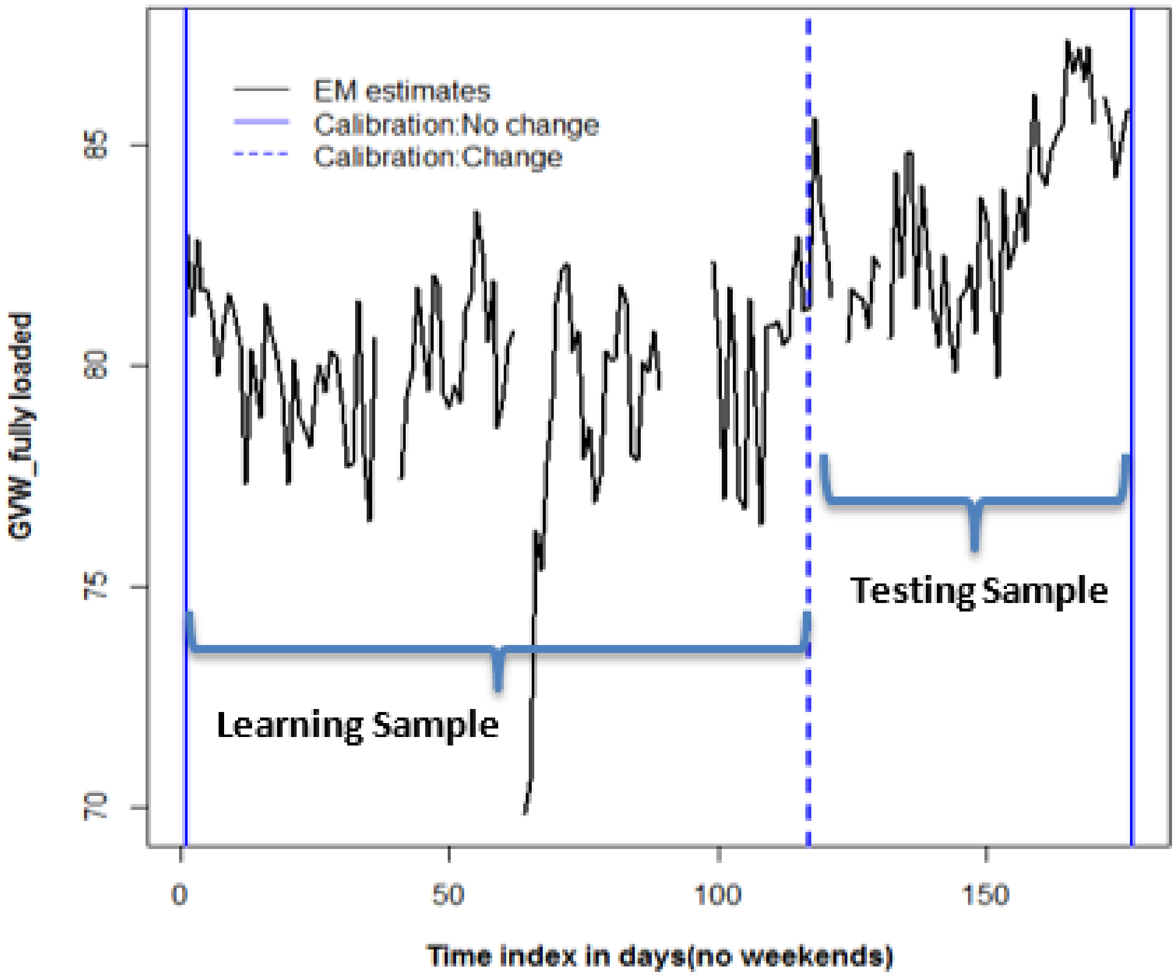
WIM Sensor Drift Analysis: Case Study

- Data from station#29, Lane 1 (Cotton, Hw 53)

  Average daily EM estimates of fully loaded class 9 vehicles

- Data partitioned into 2 subsets:
  - Learning Set
  - Testing Set

Average Daily GVW for Fully Loaded Trucks



Fitting Learning Sample

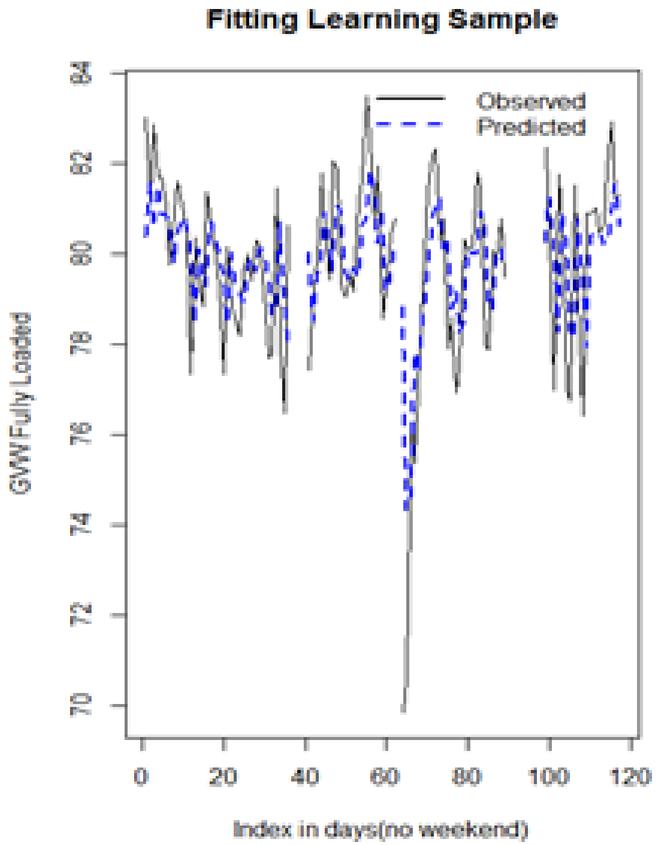
AR(1) Model:

$$X_t - \mu = \varphi(X_{t-1} - \mu) + \varepsilon_t \,; \qquad |\varphi| \leq 1$$

where, ε_t ~N(0,σ^2)

Estimated Parameters:

$$\hat{\varphi} = 0.55;\ \hat{\mu} = 79.86; \hat{\sigma} = 1.82$$



Prediction on Testing Sample

AR(1) Residuals:

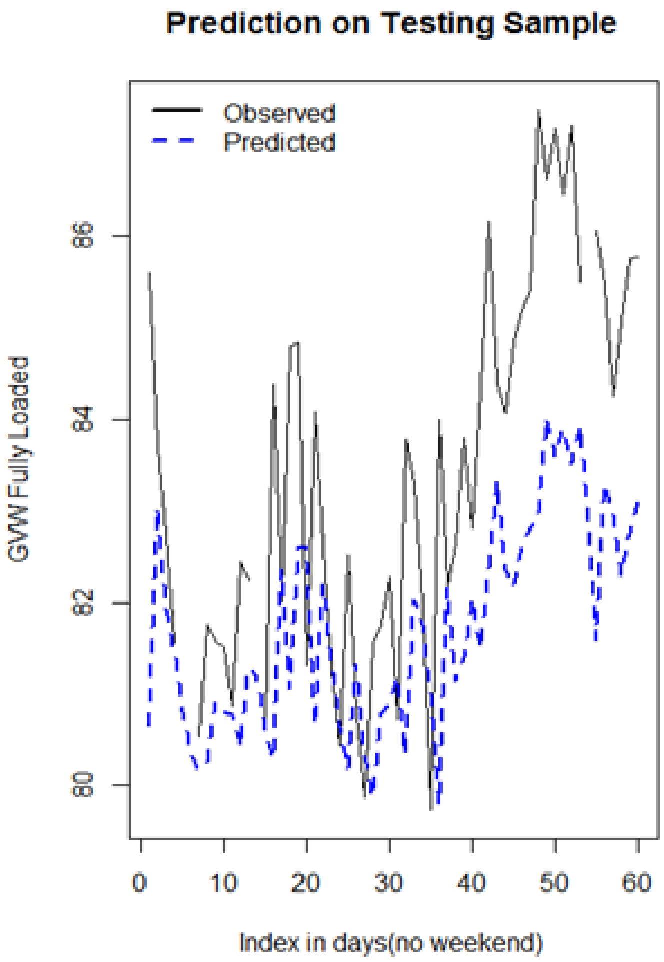
$$e_t = X_t - \hat{\mu} - \hat{\varphi}(X_{t-1} - \hat{\mu})$$

Upward CUSUM on standardized residuals:

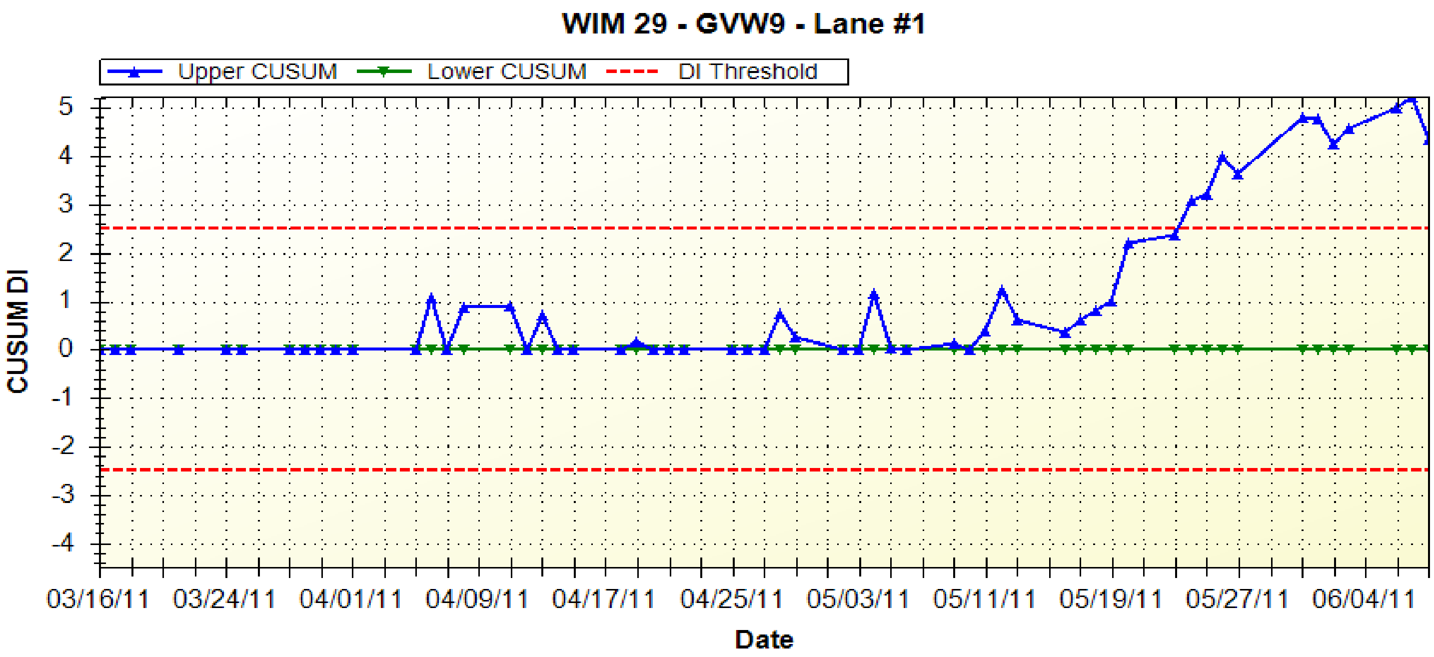
$$S_n = S_m + \sum_{i=m+1}^{n}(e_i - k)$$

Estimate of shift in Mean level:

$$\hat{\delta} = \frac{\sigma(k + \frac{S_n - S_m}{n-m})}{(1 - \varphi + \frac{\varphi}{n-m})}$$



DI Based CUSUM



Estimated shift, $\hat{\delta}$ =5.3 kips (6% of average daily GVW)
Time of the shift: 05/10/2011

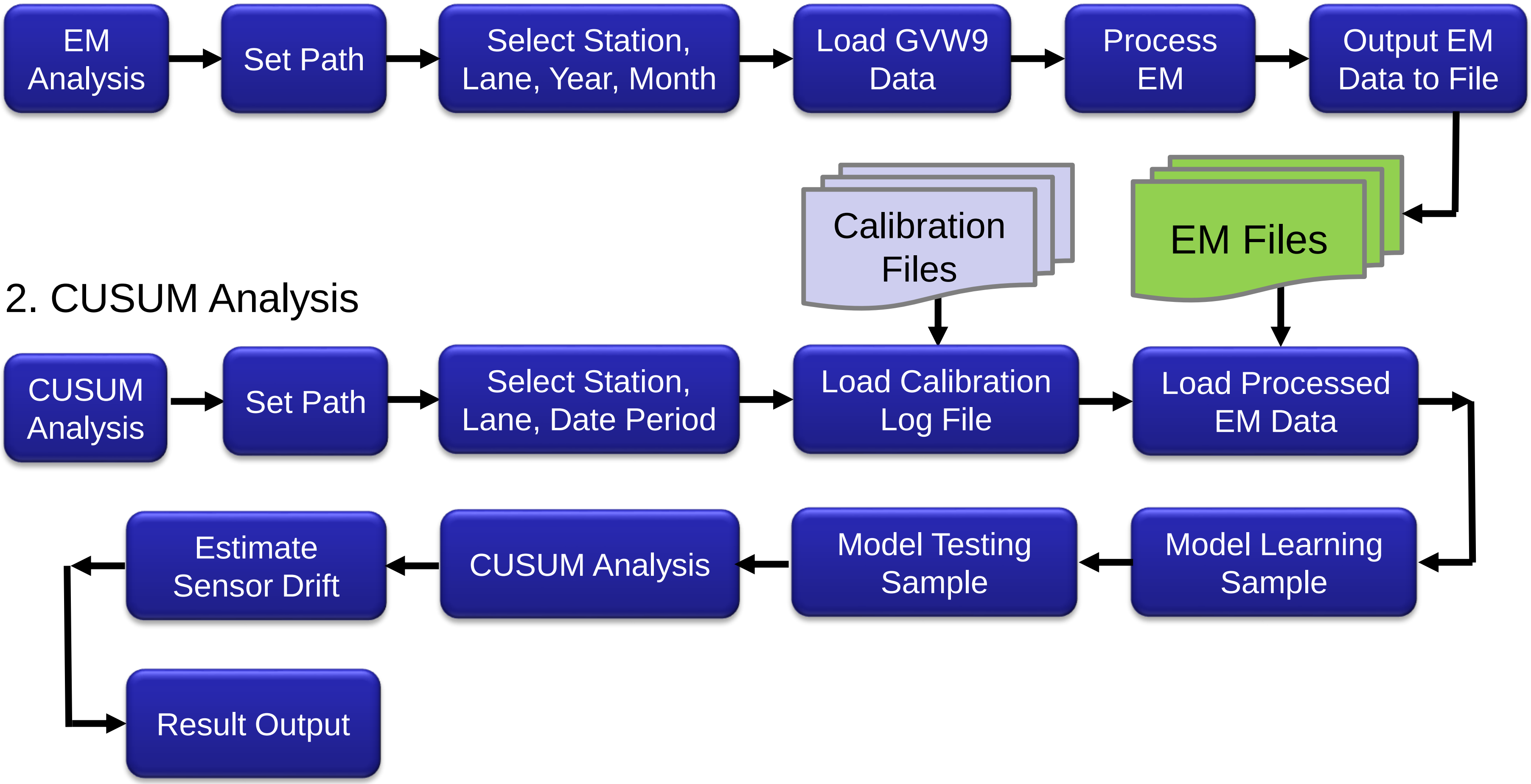
Validation: MnDOT's test run on 06/08/2011: shift by ~6 kips

Software Implementation

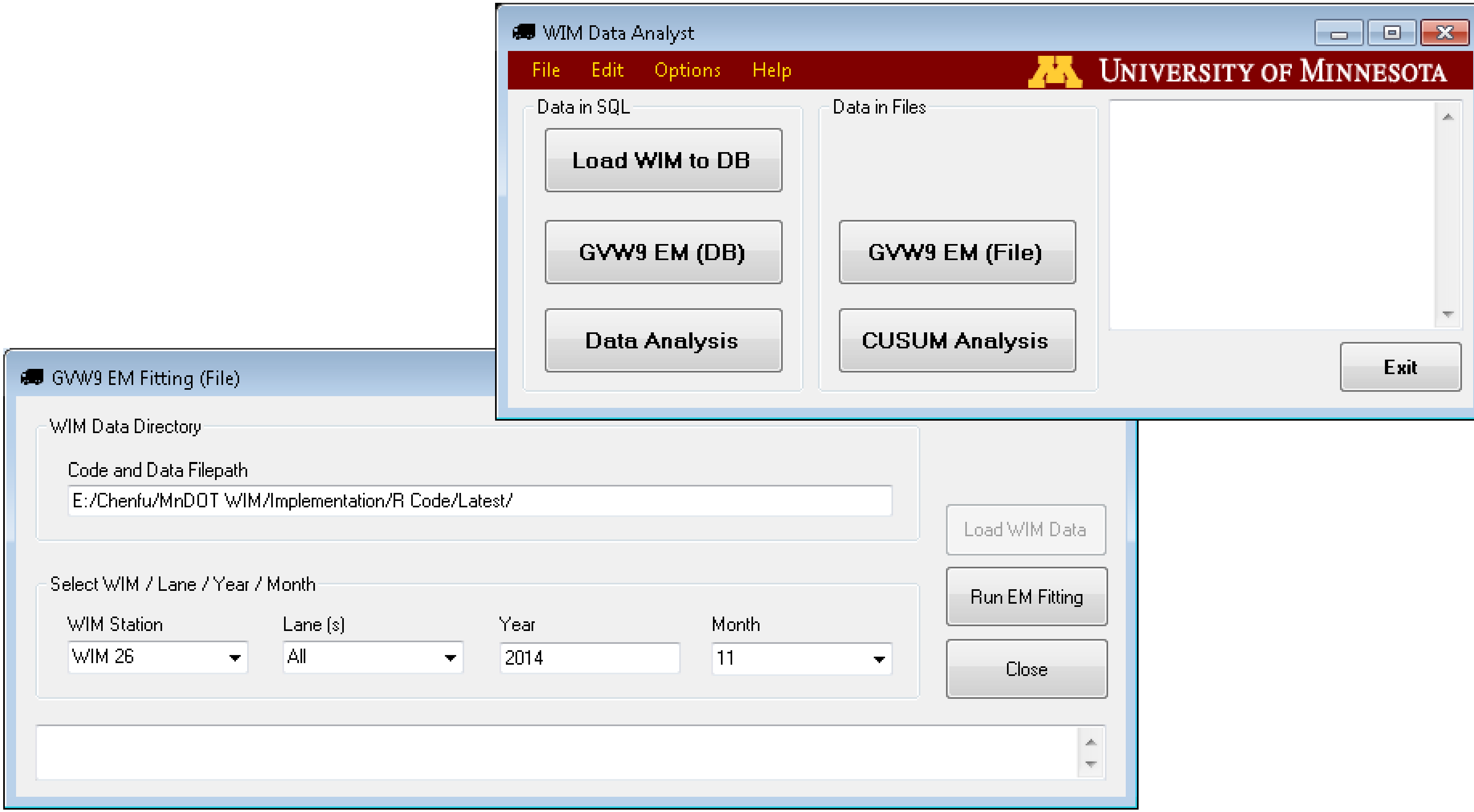
- Windows 7 & .NET framework 4
- Microsoft .NET based application
- Integrated with R statistical software through R.NET control (open source)

Flowchart of Data Analyst Software

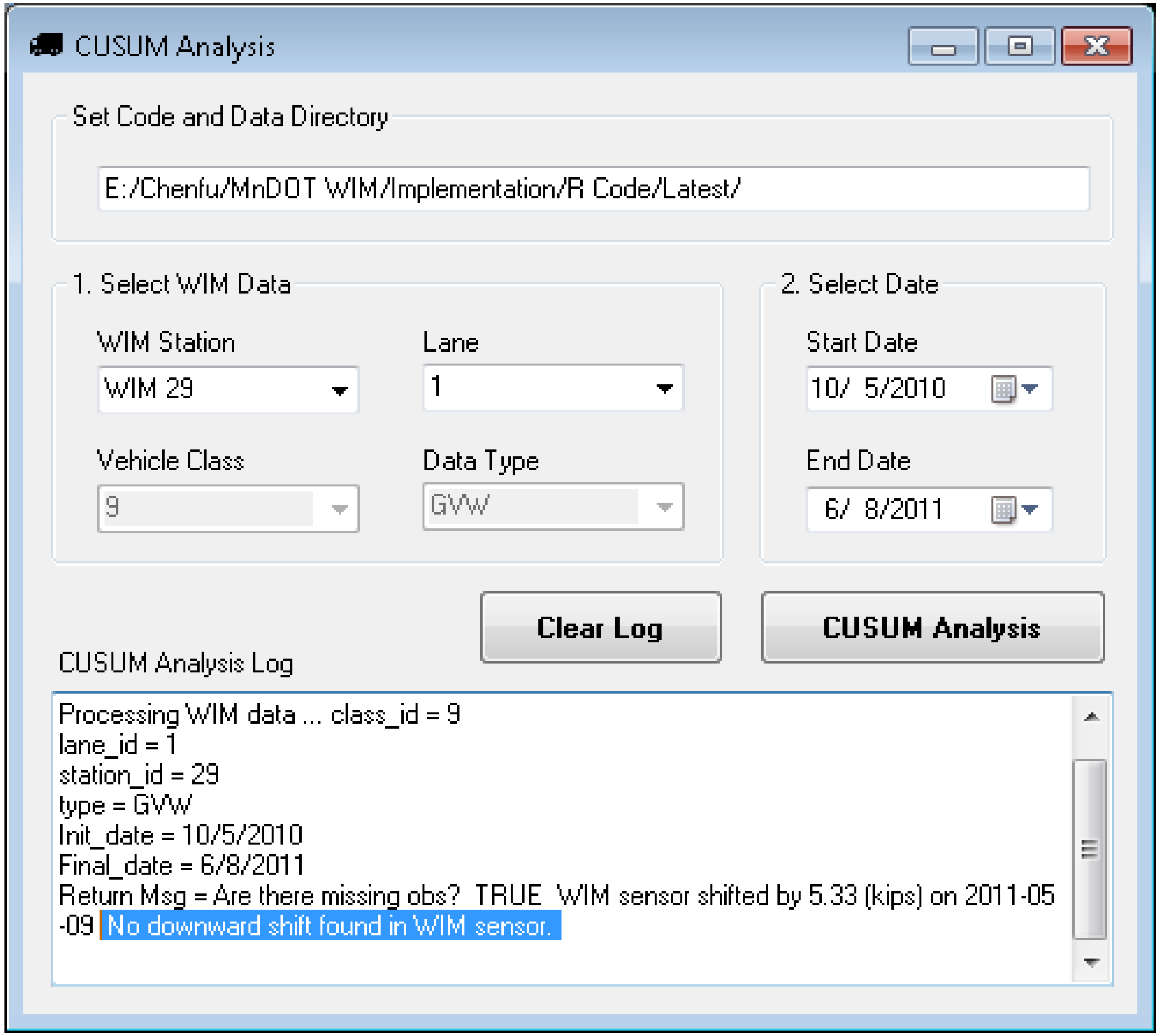
1. EM Analysis



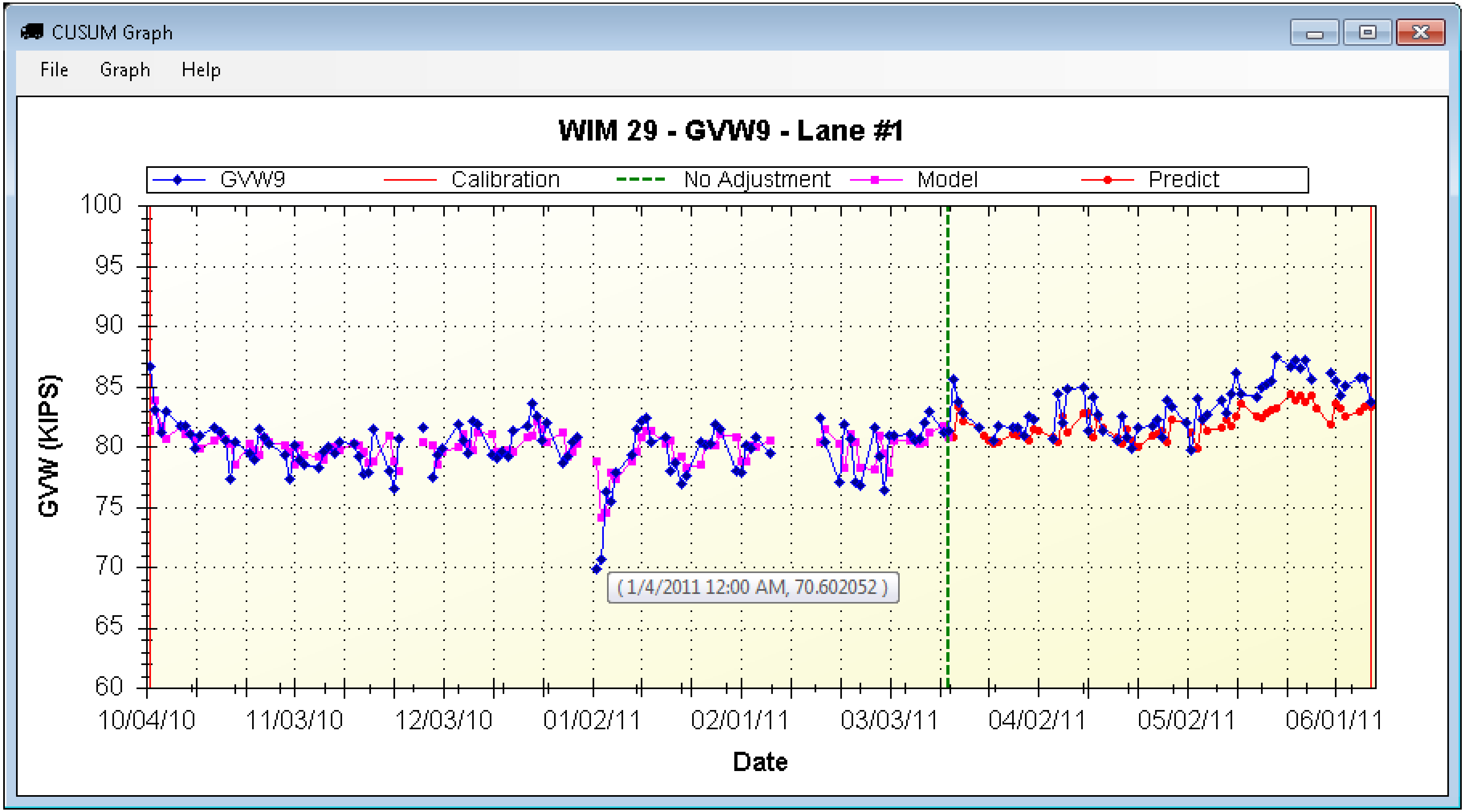
WIM Data Analyst Interface



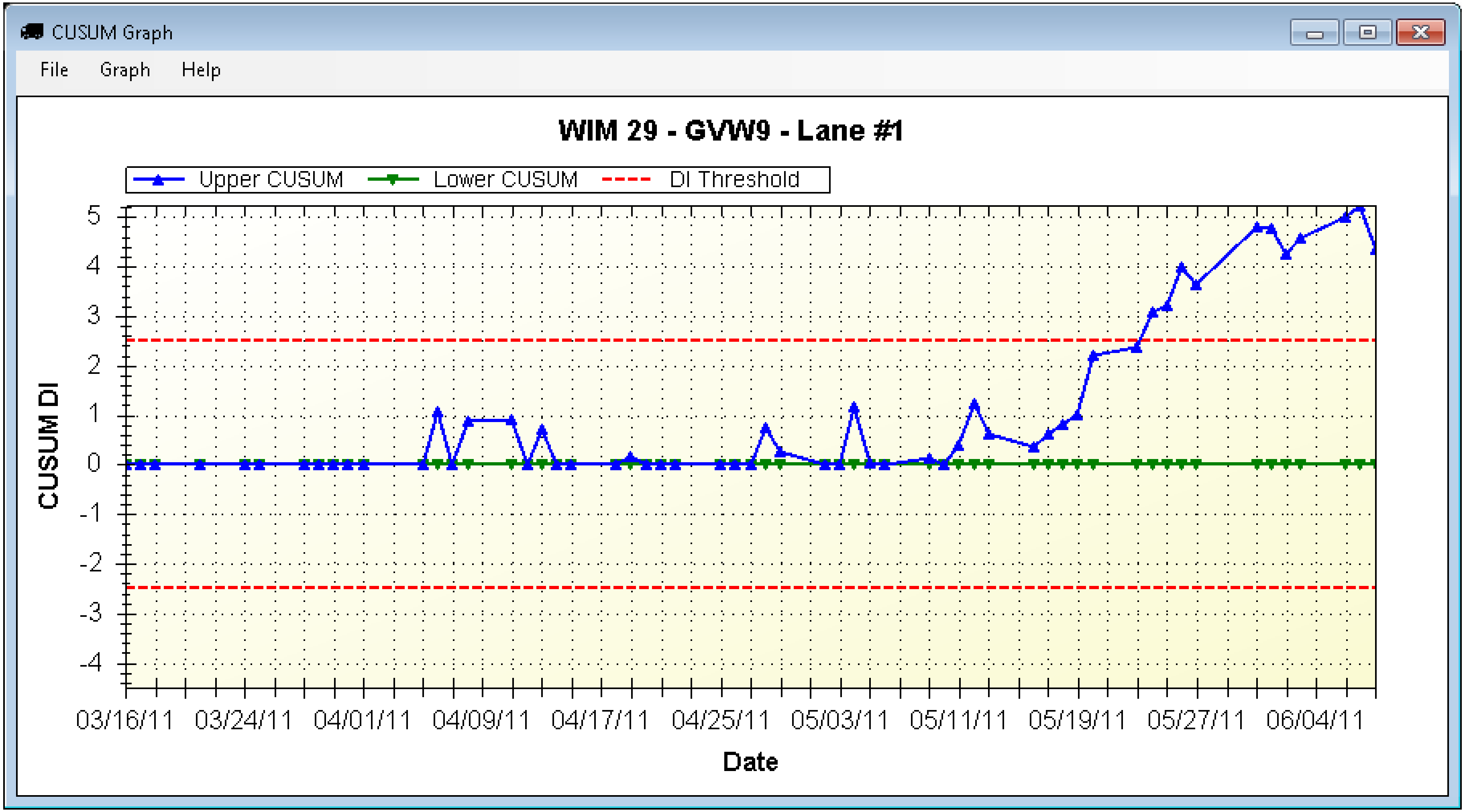
WIM Data Analyst Interface



WIM Data Analyst Interface

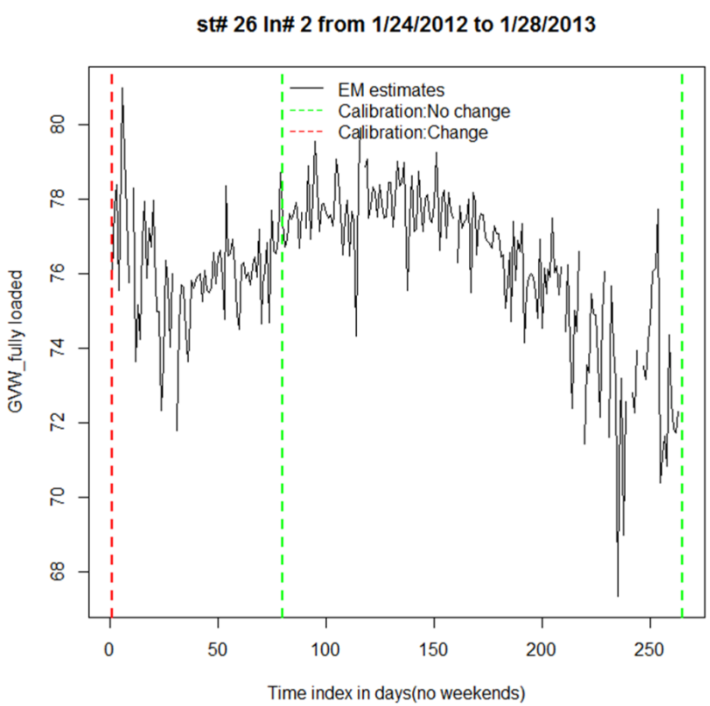


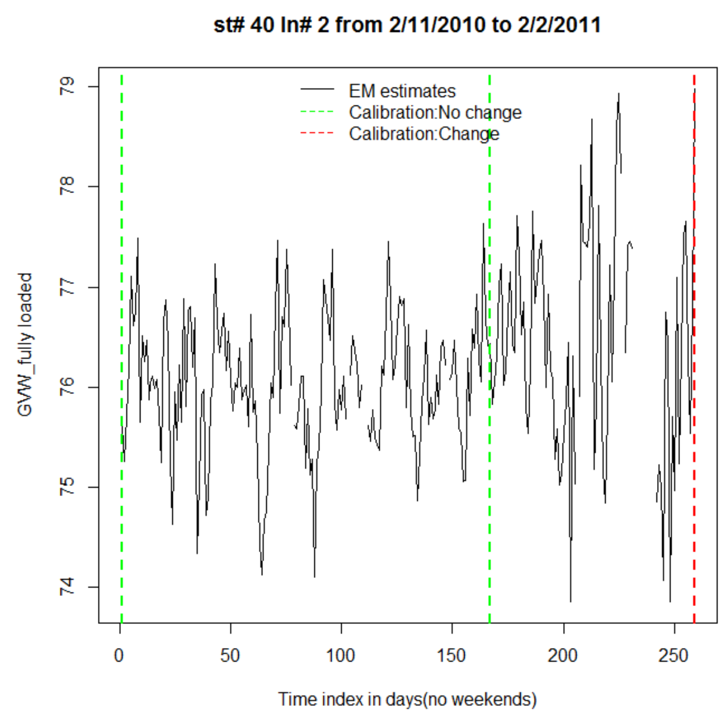
WIM Data Analyst Interface



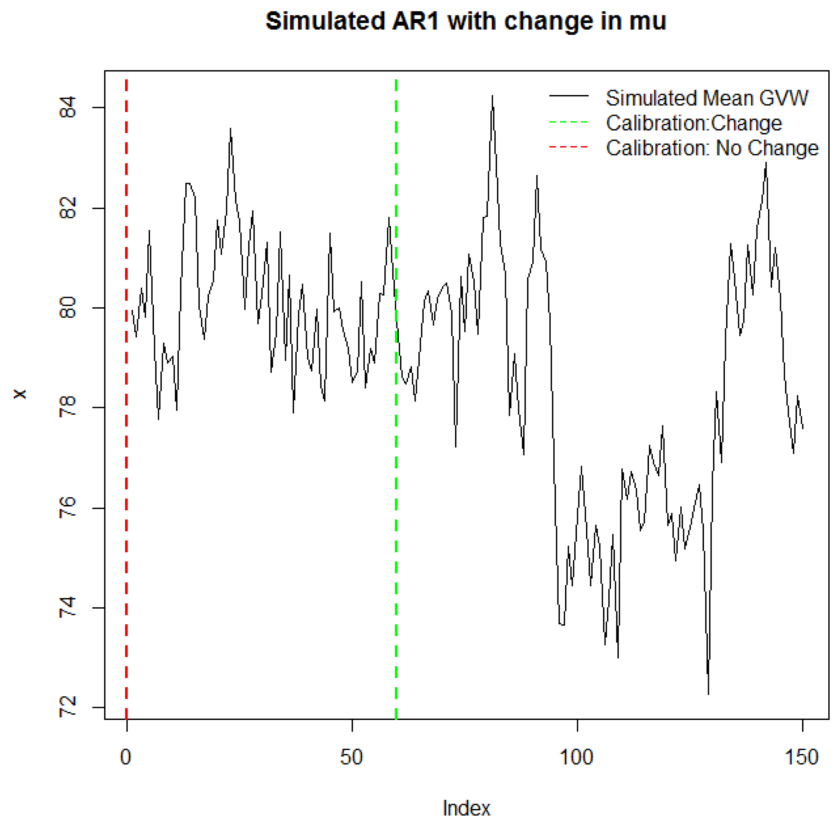
Limitations

- Underlying assumption:
  - ➢ Stationary truck population.
  - ➢ E.g. Seasonal changes in truck population is not accounted





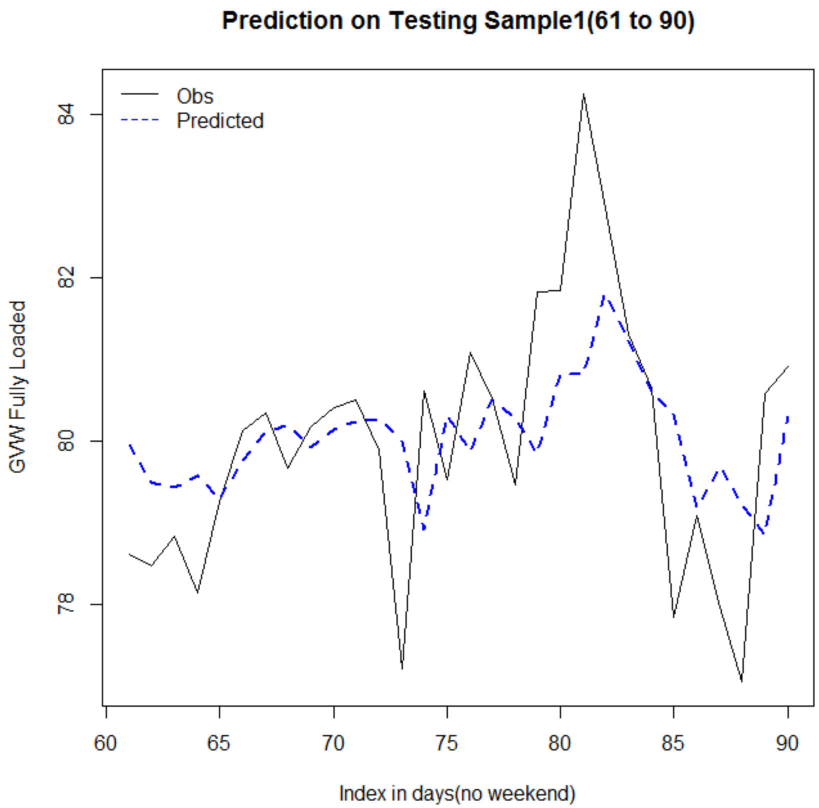
Identifying Unstable Behavior

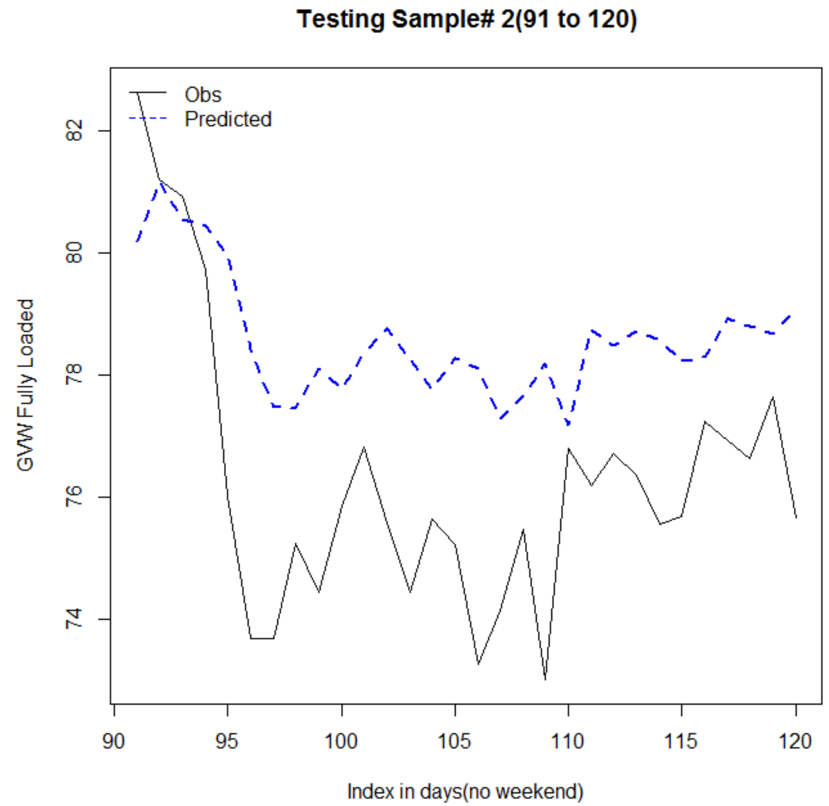


- Split the data into 30-day period
- Estimates from learning period

	phi	mu
Estimate	0.4118	80.105
Std. error	0.116	0.258
σ^2	1.416	

Splitting Testing Sample





Software Output:

No upward shift found in WIM sensor

No downward shift found in WIM sensor

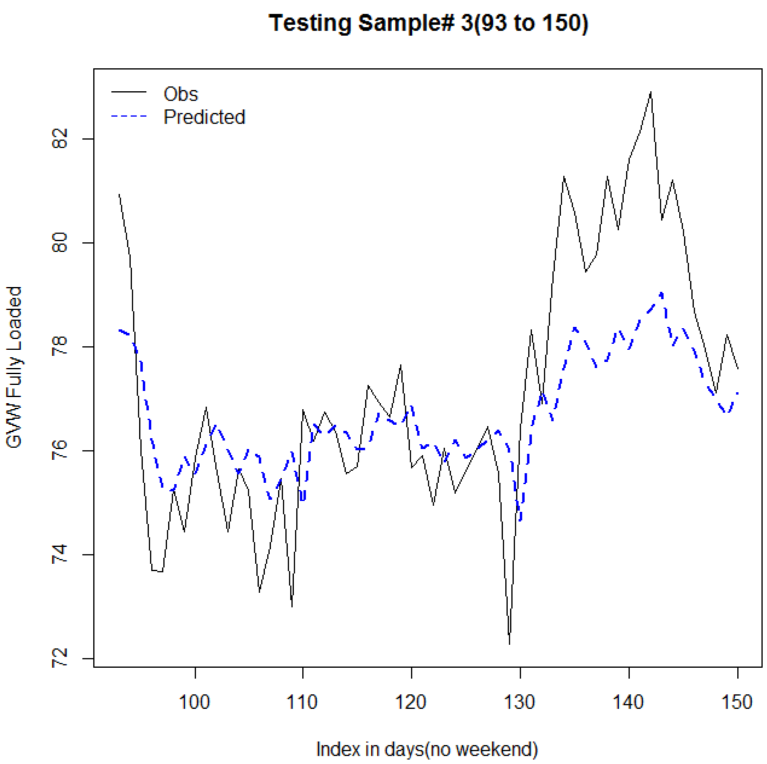
Software Output:

No upward shift found in WIM sensor

WIM sensor shifted by -3.79 (kips) at index= 93

Consistency of WIM Sensor Shift

Updated Mean level: $\mu' = \mu + \hat{\delta} = 80 - 3.79 = 76.2$



Warning message:

Estimated WIM sensor bias is not consistent

Summary

- Multi-mixture characterization of WIM data
- WIM sensor drift problem
- Systematic process
  - Identify the out-of calibration point
  - Estimate the sensor bias
  - Limitations with Unstable Truck Population
- Software implementation

Thank You !

Chen-Fu Liao
Minnesota Traffic Observatory
Department of Civil Engineering
University of Minnesota
(612) 626-1697
cliao@umn.edu