Review of Traffic Monitoring Factor Groupings and the Determination of Seasonal Adjustment Factors for Cars and Trucks

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16. Abstract One of the most common traffic volume parameters reported by statewide traffic monitoring programs is annual average daily traffic (AADT). Departments of Transportation (DOT) and other state agencies use a series of continuous vehicle detection devices in association with smaller more mobile short-term counts. Once the short-term counts are recorded a series of adjustment factors (time of day, day of week, month of year, or seasonal) are applied to the short-term counts. The end result is an estimated AADT for a particular segment of roadway. Traditionally, as defined in section two of the Traffic Monitoring Guide (TMG), there are three methodologies, geographic/functional assignment of roads to groups, cluster analysis and the same road application factor. In each case, there are advantages and disadvantages and currently there is not a final peer reviewed nationally suggested method. The benefits associated with this research include an improved method for estimating AADT throughout Ohio.		
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LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
AAHDT	Annual Average Half Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ADT	Average Daily Traffic
AF	Adjustment Factor
AHDT	Average Half Daily Traffic
ART	Adaptive Resonance Theory
ATR	Automatic Traffic Recorder
ATRG	Automatic Traffic Recorder Group
CNT	Coordinated Network Test
CoV	Coefficient of Variation
DA	Discriminant Analysis
DOT	Department of Transportation
FHWA	Federal Highway Administration
FC	Functional Class
GIS	Geographic Information Systems
HPMS	Highway Performance Monitoring System
IAE	Index of Effectiveness
MAE	Mean Absolute Error

MAWDT	Monthly Average Weekday Daily Traffic
MDT	Mean Daily Traffic
MPO	Metropolitan Planning Organization
MSE	Mean Squared Error
NLFID	Network Linear Feature Identification
NN	Neural Network
QA/QC	Quality Assurance Quality Control
ODOT	Ohio Department of Transportation
PTC	Permanent Traffic Counters
RAF	Reciprocal of the Adjustment Factors
RAMP	Responsible Alcohol Management Program
RI	Roadway Inventory
SAF	Seasonal Adjustment Factor
SD	Standard Deviation
SQL	Structured Query Language
TKO	Traffic Keeper of Ohio
TMG	Traffic Monitoring Guide
TTMS	Telemetry Traffic Monitoring Site
VOL	Volume
WAADT	Weekly Annual Average Daily Traffic
WADT	Weekly Average Daily Traffic

WCOV	Weighted Coefficient of Variation
WIM	Weigh in Motion

Customary Unit	SI Unit	Factor	SI Unit	Customary Unit	Factor
Length			Length		
inches	millimeters	25.4	millimeters	inches	0.039
inches	centimeters	2.54	centimeters	inches	0.394
feet	meters	0.305	meters	feet	3.281
yards	meters	0.914	meters	yards	1.094
miles	kilometers	1.61	kilometers	miles	0.621
Area			Area		
square inches	square millimeters	645.1	square millimeters	square inches	0.00155
square feet	square meters	0.093	square meters	square feet	10.764
square yards	square meters	0.836	square meters	square yards	1.196
acres	hectares	0.405	hectares	acres	2.471
square miles	square kilometers	2.59	square kilometers	square miles	0.386
Volume			Volume		
gallons	liters	3.785	liters	gallons	0.264
cubic feet	cubic meters	0.028	cubic meters	cubic feet	35.314
cubic yards	cubic meters	0.765	cubic meters	cubic yards	1.308
Mass			\Mass		
ounces	grams	28.35	grams	ounces	0.035
pounds	kilograms	0.454	kilograms	pounds	2.205
short tons	megagrams	0.907	megagrams	short tons	1.102

CHAPTER I

INTRODUCTION

One objective of statewide traffic monitoring programs is to accurately estimate the Annual Average Daily Traffic (AADT) for many roadway segments within the state. As a result of the importance of coverage counts and the estimation of the AADTs, there has been a wide range of research within this field. This research ranges from traditional techniques, neural networks, Bayesian and regression methods. The majority of the departments of transportation (DOT) in the United States implement a traditional method developed by Drusch in 1966. According to this method, traffic volumes are collected continuously from automatic traffic recorders (ATRs) and supplemented with shorter duration 24, 48 or 72-hour coverage counts in areas where there are limited or no available ATRs. Prior to assigning the short-term counts with the ATRs, the ATRs are grouped together based on similar traffic patterns including functional and/or spatial characteristics or more advanced clustering techniques as recommended by the traffic monitoring guide (TMG). The most efficient factor groupings are then applied or "assigned" with the short-term counts. The final product from the ATR with the short-term counts is an estimated AADT for areas throughout the state with limited continuous counts.

1.1 Purpose and Objectives

The purpose of this research is to help the Ohio Department of Transportation evaluate the state-of-the-practice for estimating AADT. This may be achieved by adding new methodologies and optimize the traditional process for estimating AADT. The current practice and a significant portion of previous research have focused predominately on developing seasonal adjustment factors (SAFs) for total volume, which includes all vehicle types. The one limitation of the total volume SAFs are individual vehicle classes may have significantly different traffic patterns. The final goal of this study is to produce a new methodology developed for the estimation of AADT for total volume, cars and trucks. In order to achieve this research objective, there are four main areas that are examined within this study. These areas include:

- Research Area One - Literature Review:

  The first research area of this study is to review the current practice, guidelines and policies on AADT prediction. The literature review describes traditional methods developed for the estimation of the AADT.

- Research Area Two - Development of Seasonal Adjustment Factors:

  The second research area is the examination of former and new seasonal adjustment factors used in the estimation of AADT. New methods for estimating AADT are developed and compared with traditional approaches in order to select the most effective SAF. The main part of this research area includes five formulas to estimate AADT and seven SAFs. The SAFs are then applied to 13 individual vehicle classes, defined by FWHA (TMG, 2001), as well as groups of classes. This aggregation is conducted in order to determine the most effective SAFs per vehicle class and compare the AADT accuracy of individual vehicle classes against groups of classes.

- Research Area Three - Creation of Factor Groupings:

  The third research area is the examination of the most effective way of grouping permanent stations. To complete this area of research there are three steps. The first step is the development of eight grouping methods which include the current practice, other traditional methods and new statistical techniques. The second step is the development of performance measures used to assess the overall performance of each method. The third step is the selection of the most effective method for grouping continuous stations.

- Research Area Four - Assignment of Short-Term Counts to Factor Groupings:

  The fourth research area of this study is the development of new methodologies used with assigning short-term counts to ATR groupings. Three techniques are examined and used in the statistical development of the assignment of short-term groupings to ATRGs; the traditional method, discriminant analysis, and the coefficient of variation approach (CoV). These methods are evaluated against each other through a series of data validation procedures.

The remaining sections of this report provide additional detail on each of these research areas.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

The objective of this literature review is to provide the state-of-the-practice for the estimation procedure used in the development of annual average daily traffic (AADT) estimates. The summary of the state-of-the-practice is provided in the following sections of this literature review. These sections include research studies on traditional methods as well as new empirical practices. As a result of these studies, prior knowledge may be used to verify the accuracy of the current AADT estimates. The traditional method of estimating AADT has been examined in many studies (Garber et al., 1999; Davis, 1996; Sharma et al., 1996) and comprises of the following five steps.

- Step One – Collect and clean the traffic volume and classification data from the continuous count stations.
- Step Two – Estimate the adjustment factors (AF) or seasonal adjustment factors (SAF). AFs include hour-of-day, day-of-week, month-of-year, or season-of-year;
- Step Three – Group traffic data together according to their similar traffic patterns and based upon AFs or SAFs;
- Step Four – Assign roads or road segments where short-term counts are recorded and assigned to continuous counts; and
- Step Five – Apply the SAFs developed in Step Two to each short-term traffic count to produce an estimate of AADT for each segment of roadway.

The remaining section of the literature review provides some additional detail in regards to the five step process described above.

2.2 Task Two: Factoring

After the initial cleaning of the data set, the factoring process is the second task in the development of AADTs. In task two, the factors are developed through the estimation of several coefficients and SAFs from each permanent counter. In most cases, the volumes and/or classification data are initially organized and grouped by station. From these stations, a series of factors may be developed based upon daily, weekly and monthly factors. There are many methods for developing these factors and these factors are directly related to the development of AADTs. The simplest example of factoring is to take the average of the 365 ADTs per year. In most cases, however, this average does not account for daily, monthly or seasonal variations within the traffic stream. Some of the more in-depth studies include:

- AASHTO Guidelines for Traffic Data Programs;
- Traffic Monitoring Guide (TMG) Section 2; and
- Cambridge Systematics and Science Application International 1994.

2.2.1 AASHTO

The AASHTO method first computes average monthly days of the week, 12 months by 7 days (84) values and then averages the values to calculate the seven average annual days of the week. Finally, these seven days are averaged to yield the AADT. The formula recommended by AASHTO is described in the following Equation:

$$AADT = \frac{1}{7}\sum_{i=1}^{7}\left[\frac{1}{12}\sum_{j=1}^{12}\left(\frac{1}{n}\sum_{k=1}^{n}VOL_{ijk}\right)\right] \qquad (2.1)$$

where:

VOL = daily traffic for day k, of day-of-week i and month of the year j,

k=1 = when the day is the first occurrence of that day of the week in a month, and

n = number of days of that day of the week during that month.

2.2.2 Traffic Monitoring Guide

The TMG recommends the use of AASHTO method for computing AADT since it produces accurate AADT estimates even when the number of missing days in a data set is significant. The simple average works well only if the data set is complete (TMG, 2001). Regarding the monthly factors, the numerator is recommended to be the AADT, whereas the denominator depends on the selected procedure. It may be equal to a simple average of the ADTs of that month, for example the average of 30 daily volumes, MADT or the average of the five weekdays, Monday to Friday within the same month, MAWDT. This means the monthly average weekday traffic, MAWDT is converted to the annual average daily traffic, AADT. Thus, a monthly factor may be computed either as AADT/MADT or AADT/MAWDT.

The TMG also recommends only including days in the computation if the denominator includes the same days as the data collection effort (TMG, 2001). For example, if no data exists for July 4th, the days before and after the holiday affect the traffic, and these days should also be excluded from the AADT estimation. The TMG also suggests that whichever method is selected for the AADT estimation, the same method should also be used for the monthly average weekday daily traffic estimation (MAWDT). This means the computation of the denominator should be consistent with that of the numerator. For example, if an average monthly day-of-week factor is selected, then the denominator is the simple average of the available daily volumes for that day of the week and month (TMG, 2001).

The TMG also provides guidance on weekly factors instead of monthly factors. In this case, the numerator remains the estimated AADT and the denominator is equal to the average of the seven days for the appropriate week. The TMG also suggests either including or excluding holidays depending on whether holidays are included in the AADT computation. Moreover, the TMG recommends calculating factors from data collected in the same year as short-term counts. For example, short-term counts taken in 2007 should be expanded using factors calculated from data collected in 2007. In this way, events that affect the traffic within a particular year are taken into consideration in the AADT estimation. Utilizing factors from previous years does not allow the incorporation of these events in the computing process, hence the results are subjected to bias.

2.2.3 Cambridge Systematics

A third study, conducted by Cambridge Systematics and Science Application International in 1994, developed SAFs based on the aggregation presented below:

- Procedure One - separate Month and Day-of-Week;
- Procedure Two - combine Month and Average Weekday;
- Procedure Three - separate Week and Day-of-Week;
- Procedure Four - combine Month and Day-of-Week;
- Procedure Five - combine Week and Average Weekday;
- Procedure Six - specific Day (ADT); and
- Procedure Seven - specific Day with Noon-to Noon Factor.

According to the findings of this study, the seven procedures produce unbiased results. The fourth procedure has the advantage that it may be used in conjunction with the AASHTO implicit imputation procedure and, therefore, does not require explicit imputation of missing counts. The last three procedures produce slightly better results but require the use of an explicit imputation method. The TMG recommends the above analysis should be done separately for cars, trucks and total volumes (TMG, 2001).

2.2.4 Other Studies

Virginia DOT examined a method to factor short-period classification counts by taking into consideration seasonal and weekly traffic variations (Weinblatt, 1996). Five different vehicle groups were developed and the final error was based on the difference between the actual AADT and the predicted

AADT. Wright (1997) examined five methods for estimating aggregate traffic volumes. These methods include:

- Simple average of all days;
- Average of monthly averages;
- Average of "day of week" averages;
- AASHTO method; and
- A weighted average of average of monthly weekday and weekend day averages.

A potential comparison of the above techniques using the study data will show what is the most effective method.

2.3 Task Three: Grouping Seasonal Adjustment Factors

Traditionally, as defined in Section Two of the TMG, there are three recommended methodologies for grouping SAFs. These recommended methodologies include:

- Geographic or functional assignment of roads into groups;
- Cluster analysis; and
- The same road application factor with grouping traffic data.

There are advantages and disadvantages for each methodology. Currently there is no peer-reviewed, nationally-accepted method. The remaining portion of this section highlights some of the findings from grouping seasonal adjustment factors.

2.3.1 Geographical/Functional Assignment

Many efforts are made in creating groups of ATRs classified by roadway use, type and characteristics. This geographical/functional assignment method is primarily based upon the annual similarities of roadway SAFs which correspond to the period of time for a coverage count. This method is based upon the assumption that the assignment of roads into groups does not change over the year.

One of the original studies involving the geographical/functional assignment of SAFs was done by Drusch (1966). In this study, a criterion of 0.20 difference between the maximum and the minimum values of SAFs within each month for the roads of the same group is deemed acceptable (Drusch, 1966). Drusch also examined the average monthly SAFs of several consecutive years and then compares the results of this sampling technique with the Bureau of Roads current method. The results yield a smaller number of groups with higher errors in comparison to the current Bureau's method (Drusch, 1966).

Bellamy (1978) developed a method to determine the most appropriate group based upon the classification of ATR sites into four groups: recreational, low flow non-recreational, rural long-distance and urban-commuter (Bellamy, 1978). Sharma (1983) developed a method to group rural roads in Alberta, Canada based on trip purpose and trip length information. The monthly traffic patterns of the continuous sites are used to classify the roads in hierarchical order. This functional assignment resulted in five groups: commuter, commuter-recreational, commuter-recreational-tourist, tourist, and highly-recreational (Sharma, 1983).

Faghri (1995) applied the grouping method suggested in the TMG into four monthly groups: urban, rural, recreational and predominantly-recreational (Faghri et al., 1995). Sharma (1996) grouped ATR sites located on Minnesota's highway system into groups displaying similar patterns of temporal traffic volume variations (Sharma et al., 1996). The stratification was carried out according to a previous study (Sharma et al., 1981) and is based on the reciprocals shown below in Equation 2.2 for the estimated SAFs.

$$RAF = \frac{1}{AF} \tag{2.2}$$

where:

RAF = reciprocal of the AF (adjustment factor) (Sharma et al., 1981).

Stamatiadis (1997) used 84 combined month and day-of-week factors for different types of roadways to group short-term vehicle classification counts (Stamatiadis et al., 1997). More accurate

AADT values are produced when vehicle types are factored separately. The results allowed for individual AADTs for an entire roadway segment (Stamatiadis et al., 1997). Xu (1998) developed two traditional factor-approach models (Xu, 1998). This analysis is conducted with data from three 48 hour counts per week for a seven-month period. The first model is based only on one simple SAF, while the second model accounts for the road classification and the daily and the monthly traffic variation. The absolute values of errors for the estimated AADTs are estimated and the results indicate the latter model performed better (Xu, 1998).

2.3.2 Cluster Analysis

Cluster analysis is an exploratory data analysis method used with sorting objects into clusters (groups). In recent years, cluster analysis is used more frequently by a number of DOTs. The degree of association between two objects impacts the maximum number of objects within a group. Varying the degree of association may increase/decrease the number of assigned ATRs to each cluster. Clustering is based on seasonal variation since monthly factors are used as an input for the analysis. One advantage of the cluster analysis is the statistical comparison between groups, thus making the group selection less subject to bias. Unlike the geographical and functional methodology, the clusters are based on a statistical analysis program that uses a distance algorithm, Equation 2.3,

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} \left(x_j - \mu_i \right)^2 \tag{2.3}$$

where:

J = intra-cluster variance,

k = total number of clusters produced from cluster analysis,

i = 1, 2, ….., k,

x_j = data point,

μ_i = centroid of all the points $x_j \in S_i$, and

$(x_j - \mu_t)^2$ = is a distance measure (Hartigan et al., 1979)

to determine each group (TMG, 2001).

Moreover, differences in traffic patterns that are not obvious visually may be identified through statistical means (Zhao et al., 2004). In most cases, as suggested by Aunet (2000), three to six clusters for urban and rural areas provides an acceptable tradeoff between aggregation and assignment errors (Aunet, 2000). The main disadvantage of this method is that the rationale producing the results may be difficult to interpret correctly.

One of the original cluster studies is developed by Shah (1981) in cooperation with the Louisiana Department of Transportation and Development (Shah et al., 1981). The primary objective of this study is to determine the feasibility of reducing the number of count stations for estimation of AADT by applying computerized cluster analysis. Roadway functional classification and spatial features are taken into consideration along with the number of clustered sites. A detailed review of several clusters indicates the possibility of estimating the ADT at some locations from sample traffic counts. The results indicate that AADT estimates may be improved if more explanatory variables are taken into account (Shah et al., 1981).

Sharma (1981) reviewed the past practice in grouping continuous count sites and proposed a grouping process that utilizes two methods, a hierarchical clustering method based on the twelve monthly SAFs of a year and the Scheffe's S-method which compares group means to determine the optimal number of groups. The study found eight to nine clusters are optimal for the 45 ATRs examined in Alberta, Canada (Sharma et al., 1981). In 1993, the same procedure is used by Sharma in grouping 61 ATRs. A total of seven ATR groups are identified and associated with different functional roadway types such as commuter routes, average commuter routes and recreational routes (Sharma et al., 1993).

Faghri (1995) compared the performance of cluster analysis, regression analysis and an adaptive resonance theory (ART) model. The statistic MSE is estimated for each method and the MSE is used as a comparative tool. Faghri concluded that the formatted groups change from year to year and the clustering technique is not effective for the coming years and sometimes can not accurately assign road segments to groups (Faghri et al., 1995).

The Florida DOT applied nonparametric agglomerative hierarchical models and parametric model-based hierarchical clustering methods to group permanent traffic counters (PTC) located on Florida's urban and rural roads (Zhao et al., 2004). The model-based clustering was conducted using a software developed by the University of Washington (Fraley et al., 2002), an extension of the SAS software. For the evaluation of the agglomerative hierarchical clustering methods, 13 methods are used (SAS, 1999) with the four steps: seasonal factors verification, identification of outliers through the performance of preliminary cluster analyses, the factor groups evaluation using data without outliers and the selection of the optimal clustering method.

Zhao (2004) found that the single linkage and the average linkage clustering methods produce significantly more outlying data points than other methods (Zhao et al., 2004). Other results show that the McQuitty's model is more effective in grouping ATRs. The analysis process includes the input of geographical coordinates of each ATR in the data matrix and application of ten models for clustering two groups to 100 groups. The application of model-based agglomerative hierarchical clustering is employed initially, followed by the implementation of an Expectation-Maximization algorithm. Finally, the optimal number of clusters was determined through the Bayesian Information Criterion. Preliminary groupings are formed after comparing the geographic location between the groups and examining the results from the previous step. This process has the advantage of combining the given data, that is, seasonal fluctuation patterns for each ATR, with the spatial characteristics of both ATRs and seasonal groups. Examining and assessing the seasonal factor groups individually allows the identification of ATRs with different seasonal patterns within one group. The final step of the process is the reassignment of ATRs into different groups, the creation of new groups or merger of existing groups (Zhao et al., 2004). Zhao concluded that the spatial location of an ATR and not the roadway functionality plays the most important role in seasonal grouping (Zhao et al., 2004).

2.4 Task Four: Assignment of Short-Term Counts to Factor Groups

After the ATR groups are defined and the average adjustment factors are calculated, the adjustment factors may then be applied to the short-term counts to estimate the AADTs. The allocation of short-term counts to particular SAFs is known as the "assignment procedure". The existing practice for assigning short counts to ATR groups is highly dependent on researcher/practitioner judgment. The allocation should be developed from statistical techniques instead of engineering judgment (Ritchie et al., 1986). One potential risk, according to a study by Sharma (1996), suggests AADT estimation errors are very sensitive to the effectiveness of short-term count allocation to a specified group (Sharma et al., 1996). Other studies suggest that the current research offers little guidance on how to achieve assignment accuracy necessary for obtaining reliable AADT forecasts from short-term counts (Sharma et al., 1999).

Sharma (1993) examined a statistical method to assign seasonal traffic counts to permanent traffic count groups (Sharma et al., 1993). Initially, Sharma first computed an array of MSEs related with the assignment of seasonal counts to groups, and then the effectiveness of the assignment was determined for each assignment. The error term is calculated in the following equation:

$$MSE_i = \frac{1}{12}\sum_{j=1}^{12}(f_{xj} - f_{ij})^2 \tag{2.4}$$

where:

f_{xj}	=	monthly factor of seasonal count for month j and
f_{ij}	=	average monthly factor of group i for month j.

Following the seasonal traffic factors, traffic volumes (AADTs and ADTs) and an index of assignment effectiveness are calculated in Equations 2.5 and 2.6 for each station and group. These equations are shown below:

$$AE_i = \frac{\max MSE - MSE}{\max MSE - \min MSE} \tag{2.5}$$

$$IAE = \frac{1}{N} n_i \sum_{i=1}^{l} (AE_i) \tag{2.6}$$

where:

AE = effectiveness of assignment of group i,

IAE = index of effectiveness,

n_i = number of times the sample site is assigned to group i,

l = total number of factor groups, and

N = total number of samples of a given S(L,F) taken at a sample site (Sharma et al., 1993).

The effectiveness of sample schedules is determined as the difference between the true AADT for each group and the estimated AADT values for each seasonal count (Sharma et al., 1993). The same technique is employed by Sharma (1994) for assigning seasonal counts to continuous site groups (Sharma et al., 1994).

Sharma (1996) investigated the precision of AADT estimates from short-term counts in Minnesota (Sharma et al., 1996). A confidence level of 95% is used to compute the absolute precision limit for AADT estimation errors and is shown in Equation 2.7.

$$PB95 = \left| \pm Z_{0.025} \right| \times S_e \tag{2.7}$$

where:

$Z_{0.025}$ = standard normal statistic, and

S_e = standard deviation (SD) of errors for an ATR group (ATRG) (Sharma et al., 1996).

Sharma also determined the impact of short period count assignments to groups by developing Equation 2.8 as described below:

$$AE_i = \frac{\max MDE - MDE_i}{\max MDE - \min MDE} \times 100 \tag{2.8}$$

where:

AE_i = assignment effectiveness for ATR_i, and

MDE_i = mean squared error for ATR_i.

The main finding of this study is the allocation of short-term counts to ATR groups is significantly important in the accuracy of the AADTs. These results suggest the assignment procedure may influence the AADT estimates in a greater extent than the duration of short-term counts (Sharma et al., 1996).

Davis (1996) described an approach based on Bayesian statistics to assign short-term counts to factor groups (Davis et al., 1996). Davis developed a method using the Mean Daily Traffic (MDT) to obtain a sample count with the goal of minimizing the likelihood of assigning a count to a wrong group (Davis et al., 1996). Davis shows the MDT estimation errors lower than ±10% are difficult to obtain if seasonal counts of one day to two weeks duration are available. The shorter the counts, the corresponding errors are expected to be even greater, with an average error of ±20% (Davis et al., 1996). The main limitation of the assignment method and the MDT estimator approach is that it performs reliably with 14 day samples. Although the developed technique is data-driven and is able to produce MDT values when count assignments are vague, these results are not considerably improved over those of previous studies. North Carolina DOT developed a data-driven geographic information systems (GIS) to assign short-term counts to ATRGs (McDonald, 1999). Statistical correlation was used as criterion to determine the most effective group for each short-period count. Li (2006) utilized an artificial intelligence technique, "fuzzy logic" decision tree, to assign seasonal groups to short-count stations. The decision tree was developed based on predefined factor groups and their land use characteristics (Li et al., 2006). According to the findings of this study, the decision tree is an objective method in a limited extent.

As stated in the preceding section, engineering judgment is necessary since the data utilized in such techniques are likely to be insufficient, which entails unreasonable or even poor results. The k-nearest neighbor algorithm method suggested in 2008 by Jin classified roadways by comparing roadway and land use characteristics. More accurate AADT estimates were obtained using an unweighted k-nearest neighbor model than those obtained using a traditional non-cluster method (Jin et al., 2008). According to this method, the training set is used in order to assign an unclassified short-term count by comparing it to the most similar samples in the training set. Equation 2.9 and 2.10 are show below where:

$$D(X,Y) = \sqrt{\sum_{I=1}^{n} \left(x_i - y_i\right)^2} \qquad (2.9)$$

where:

X = $x_1, x_2, \ldots, x_n$, and

Y = $y_1, y_2, \ldots, y_n$ represent the *n* attributes value of two sample records (Jin et al., 2008).

And the attributes used in the analysis were normalized based on Equation 2.10:

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \qquad (2.10)$$

2.4.1 Discriminant Analysis

One potential statistical technique, suggested by Aunet (2000) to improve the assignment of short-term counts to SAFs, is the use of Discriminant Analysis (DA). DA compares the membership requirements of groups established by the ATR data to the characteristics of the short-term count data. The short-term counts represent the classified objects of the analysis and are assigned to a factor group based on a calculated probability of group membership.

The current methods of factor group assignment are subject to a great deal of inconsistency because of the heavy reliance on engineering judgment (Jin et al., 2008; Zhao et al., 2004). Aunet (2000) determined that the functional classification of a roadway does not have significant impact on seasonal traffic patterns, despite the fact that it is an easily identifiable component (Aunet, 2000).

Limited research efforts have been dedicated to the application of discriminant analysis in the AADT estimation process. On the other hand, DA has been used extensively in other scientific fields.

CHAPTER III

DESCRIPTION OF THE EMPIRICAL DATA SETTING

This chapter of the research study provides a description of the traffic count data used in the research. This data are provided by the Office of Innovation, Partnerships and Energy, Traffic Monitoring Section and are collected from:

- Continuous count, automatic traffic recorders (ATRs) and weigh-in-motion (WIM) stations; as well as
- Short-term, pneumatic tube count data.

The remaining section for this chapter includes descriptions of the continuous count and short-term count data, data cleaning and processing, future directions and a statistical comparison between the two directions of each station.

3.1 Continuous Count

The continuous count data provided in this study are based on ATR and WIM data collected by ODOT. Continuous data are used to classify and develop SAFs that are later used with the short-term data described in the next section. In this study, there are five traffic volume cards that are in service with ODOT. The five cards are:

- Vehicle volume (3-Cards);
- Vehicle classification (C-Cards);
- Weigh-in-motion data (C-Cards);
- 4-Cards; and
- S-Cards.

The data provided within this study includes the first three types of cards for each month of the year from 2002 to 2007. Table 3.1 shown below provides the number of ATRs and WIMs per card that is currently available in this research study.

Table 3.1. Number of ATRs and WIMs per type of data and year.

	ATR		WIM
	3-Card	C-Card	C-Card
2002	196	79	75
2003	202	89	61
2004	203	114	54
2005	202	56	51
2006	206	62	49
2007	178	-	111

3.1.1 3-Card Format

The 3-Card vehicle volume data are taken at 60-minute and 15-minute intervals and are formatted with the ODOT Modified 3-Cards. The initial format labeled "ODOT Modified" is used to reflect the minor differences between the TMG 3-Card specification and ODOT's version. The 60-minute 3-Card file format contains one record per line per lane for a 24-hour period, meaning a four-lane site contains four records per line within a daily file. The data given for each count includes the station number, the direction, the lane, the day of the week, the date, the hourly volume and the beginning and ending times. The 15-minute 3-Card format file contains one record per line per lane for an eight-hour segment of a given day. However, the data structure remains exactly the same as the 60-minute 3-Card. Volume data per lane are available only for the 2006 and 2007 years.

3.1.2 C-Card Format

The C-Card file format is available for both ATR and WIM sites. The 60-minute C-Card file format contains one record per line per lane for each hour of the day. The 15-minute C-Card file format maintains the same data structure as the 60-minute C-Card file. Each count contains the station number, the direction, the lane, the hour, the day, the month, the year, the total volume, the number of axles per functional class and the beginning and ending time of each count. For both formats, the classification and vehicle description are based upon the FHWA 13-classification scheme.

3.1.3 4-Card Format

An older file format included in this data set is in the process of being phased-out in the near future and exists for historical records. Along with the description of the format, a detailed relationship between the 60-minute C-Card and the 4-Card is given for the file conversion from the old type format to the new one. The *S*-Card format is not widely used. To date the researcher has not explored this data source.

3.1.4 Statistical Difference between the Two Traffic Directions of a Road

The analysis of the study, as stated in Chapter I, is conducted throughout the report for two types of seasonal adjustment factors: 1) SAFs estimated from two-way traffic volumes, which are calculated based on the sum of the two directions of the traffic; and 2) SAFs estimated for each direction of a roadway. In order to conduct the two analyses, it is important to examine first whether the traffic volumes of the two directions of a road are statistically different. The two populations are tested for statistical difference at a 95% confidence interval.

The first set of the t-tests was conducted for the two directions per station and the second set per functional class. From the first set it is found that the directions of 153 stations exhibit different traffic patterns, whereas 83 stations have similar traffic in both directions. The second set of tests results in 15 different directions for all functional classes and only 6 can be considered statistically the same. It can be concluded that the two analyses can be conducted separately, since the majority of the roads do not have similar traffic in both directions.

3.2 Short-Term Data

The short-term duration count data are usually 24-hour or 48-hour sampling durations. Initially, the short-term counts are divided by year, 2000-2007, the program type count, Highway Performance Monitoring System (HPMS), Requests, Regular, the type of data, volume or classification and by county. Both volume and axle classification data are consistent with AASHTO recommendations and their format is similar to that of the ATRs data structure. There are 20,923 short-term counts from 2000 to 2007 within the 88 counties of Ohio's transportation network system.

3.3 Historical Count Locations Information

Historical, geographical and general information for both permanent and portable counters are given in a MS-Access database file which consists of three tables. Table 3.2 contains location information and other characteristics for the continuous count stations.

Table 3.2. Permanent count locations information.

Table	Characteristics
Permanent Count Locations	Site, Direction, District, County, Route, Log Point, Functional Class, Lanes, Program, Type, Location, Equipment, Phone, Company, ACPower, City, Pavement Type, Median Type, Current Status, HPMS, NLFID, Start Date, End Date, Longitude, Latitude, Gen_Comments, Gen_Location, s_Collineage, s_Generation, s_Guide, s_Lineage

Geographical information is given for each site such as district, county, city, route, functional class of the roadway on which they have been installed, direction, exact mile-point on the roadway, longitude and latitude. Moreover, the number of lanes, the program and the type of each counter, the type of the pavement, the median and the type of the equipment are included in the database. General information such as condition of each station, beginning and ending date of their performance is also available. Table 3.3, provides a description of the short-term data locations and the fourth table, Table 3.4, provide supplementary descriptive information for the type of each count.

Table 3.3. Short-term count locations.

Table	Characteristics
Short-Term Count Locations	County, Route, Log_Beg, Station, Location, City_Town, Functional Class, Type_CNT, NLFID
Short-Term Count Type Description	Type Count, Description

Table 3.4. Short-term count type description.

Type Count	Description
C	48-Hour Vehicle Volume
D	48-Hour Vehicle Classification
E	24-Hour Vehicle Volume
F	24-Hour Vehicle Classification
G	Rail Road Crossing
H	Speed Monitoring Location
I	Volume Special Request
J	Classification Special Request
K	MPO Count
L	24-Hour Manual Turning Movement Count
Q	Inactive 48 Hour Vehicle Volume
R	Inactive 48 Hour Vehicle Classification
S	Inactive 24 Hour Vehicle Volume
T	Inactive 24 Hour Vehicle Classification

The utilization of these data sets in each examined method is described in more detail throughout the remaining chapters of this report. The data cleaning process, different types of errors and the final form of the data which are used to develop seasonal adjustment factors are presented in Chapter IV.

CHAPTER IV

DEVELOPMENT OF SEASONAL ADJUSTMENT FACTORS

4.1 Introduction

The development of seasonal adjustment factors (SAFs) for cars and trucks are based on a series of data aggregation steps in concert with multiple mathematic calculations. Chapter IV describes the methodology used for developing SAFs for the State of Ohio. A series of nine steps are developed to create seasonal adjustment factors. These nine steps are:

- Step One – Importing the "Raw Data File",
- Step Two – Cleaning the data set,
- Step Three – The aggregation of the empirical setting,
- Step Four – The estimation of the average traffic volumes,
- Step Five – The estimation of the annual average daily traffic volumes,
- Step Six – The creation of SAF methodology,
- Step Seven – "Ground Truth" evaluation of the newly developed SAFs,
- Step Eight – The development of structured query language (SQL) code which is used for the creation of data tables, and
- Step Nine – The quality control and data validation checks.

In total, this research study developed more than 1,600 adjustment factors for the years 2002 through 2007. The remaining portion of this chapter describes in more detail these nine steps used in the development of SAFs that are evaluated within this research study.

4.2 Step One: The initial importing of the “Raw Data Files”

The data files are collected from the 88 counties within Ohio and are consistent with Federal Highway Administration (FHWA) and Traffic Monitoring Guide (TMG) recommendations. Figure 4.1 shown below is a flow diagram illustrating the procedural process used in the development of SAFs.

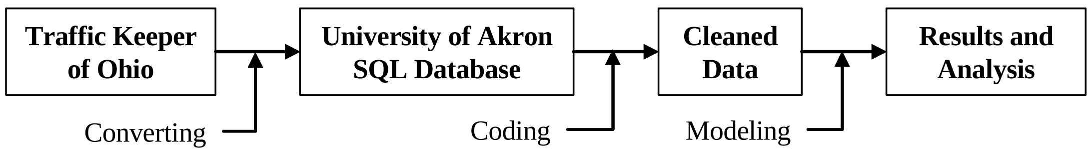

Figure 4.1. Flow diagram of the data provided by the OTS.

The data are initially provided within this research as “.txt” files from the “Traffic Keeper of Ohio” (TKO) database platform. From this initial source, the “.txt” files are downloaded as “raw files” onto the IBM server and the “raw files” are then imported into Microsoft SQL Server 2005 Enterprise Edition. This software platform is specifically selected for its scalability and the flexibility required for this research study. From this point forward the data files are located within the Microsoft platform. Once the data are on the server, the hard drives are mirrored which means that all data currently on the server are duplicated continuously. This back-up is the first form of data protection on the server.   The second form of data back-up is the creation of both the initial “raw format” files and “clean format” files. With the correct numerical format, the “clean format” data are considered prepared for future analysis. Figure 4.2, below, illustrates the current data structure provided within the SQL platform.

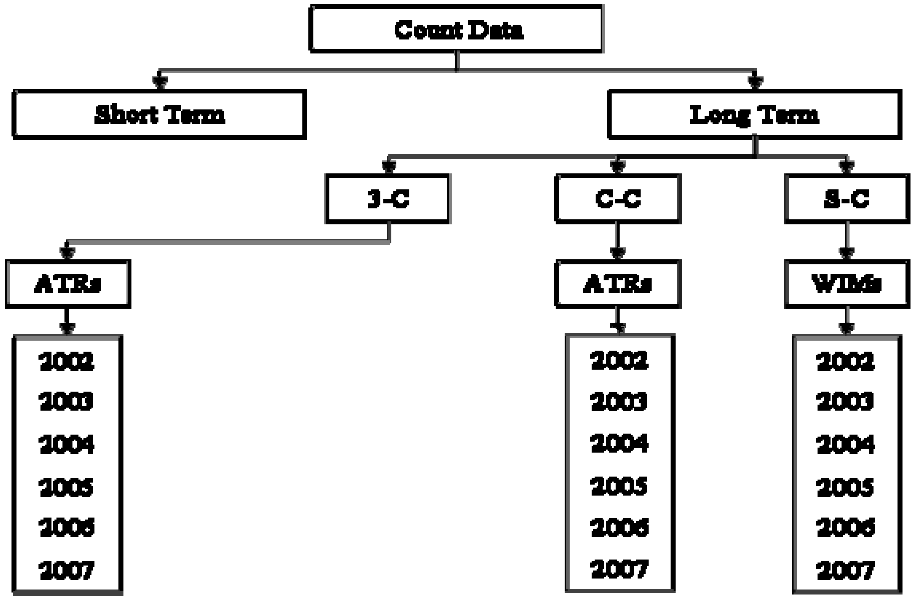

Figure 4.2. Long-term data structure provided within the SQL platform.

In this structure the data are separated first by the long-term and short-tem counts. The long-term counts are then divided into total volume data, 3-Cards, and classification data, C-Cards, per year. This initial structure allows this research study the most flexibility for data analysis. The data may still be grouped by location for multiple years or geographical areas within the state, or the data may be grouped by volumes or by nlf_id records. The nlf_id records are unique records that are combined with ODOT roadway inventory (RI) files. These files provide additional geometric information including the lane width, shoulder width and type of horizontal or vertical curve. This information may be evaluated as needed in future periods of the research.

4.3 Step Two: The Initial Cleaning of the Data Set

The second step for the development of SAFs is to clean the “raw data” files. In the cleaning stage there are two primary tasks. The first task is to convert the data from character to numeric values, for example “01” becomes “1”. This task is important for future calculations including summations, averages and standard deviations. The second task is the identification of possible errors or inconsistencies within the “raw data set”. As a result of the number of records obtained in this research study, data from time-to-time are corrupt and unusable. In these cases, these data points are identified through a control process developed within SQL Server platform and, when necessary, are discarded from the final analysis if the data are determined to be corrupt. In the remaining portion of step two, three errors or inconsistencies, as well as the approximate number of data points associated with each inconsistency, are described in further detail.

4.3.1 Total Duplicate Records

The first check of the raw data is to determine the total number of duplicate records per year for either the Automatic Traffic Recorder (ATR) or the Weigh-in-Motion (WIM) sites. In most cases this check is required to prevent duplicate records that may bias the total number of vehicles per site. When duplicate records are found, only one of the records is deleted, while the other record remains in the final data set.

4.3.2 Partial Duplicate Records

Partial duplicate records are the second most common data inconsistency. Partial duplicate records occur when the locations of the counts are not consistent with the volume of vehicles records. For example, station one may have three lanes per direction that are collecting data. In the data set, each lane will have an individual row. In some cases there may be three rows all containing information about lane one for the same time period. In this example, it may be assumed that probably lane two and lane three are not recording the correct data. This occurs as a result of the data collected from the site indicates three different volumes for lane one instead of one volume for lane one, one volume for lane two and one volume for lane three.

4.3.3 Total Volume Inconsistencies

The third common inconsistency within the data set is defined as the total volume error. In this case, the total volume error varies between the total volume of vehicles and the summation of the individual vehicle classes. A total volume error occurs when the difference between the values does not equal zero. It is important to mention that as a result of the initial data structure, the 3-Card ATR data are unable to be tested for this inconsistency.

As a result of this task, the data sets are cleaned and may be used as input in the analysis that follows. In case the original data set is desired, an easy and simple modification to the code allows the activation or inactivation of the previously described columns.

4.4 Step Three: Aggregation of the Empirical Setting

The aggregation of the empirical setting is the third step in the development of SAFs. In this step of the research study there are three main categories for aggregating the empirical setting, the vehicle type, the functional classification of the roadway and the direction of travel along the roadway. Each of these aggregation categories are developed for all combinations of methods in the final analysis. For example, four vehicle groupings are developed for all functional classifications for both total, as well as per direction. An extensive number of SAFs are developed and evaluated under ground truth conditions as a direct result of incorporating all these aggregation levels.

4.4.1 Vehicle Type

The first level of aggregation is performed on the vehicle classification. In this study, as described earlier, there are two main data collection devices: ATRs and WIMS. For these pieces of equipment, there are 13 individual vehicle classes for ATR data and 15 individual vehicle classes for WIM stations. These vehicle descriptions are consistent with the FHWA classification system. In addition to the individual vehicle classifications, this research study evaluates the performance of grouping vehicles with similar characteristics. The grouping of vehicle classes provides additional information on vehicle travel important for many design and operational-based decisions. Other added benefits include the improved performance of several vehicle classes, for example vehicle class 12 is uncommon on the state highway system. These criteria are:

- One Vehicle Group – The 13 or 15 vehicle classes are combined into one class of total volume which is then used in the development of the seasonal adjustment factors;
- Two Vehicle Groups – The vehicle groupings are developed for two classification sets. The first set is for light-duty vehicles Class 1 through Class 3, and the second set is for heavy-duty vehicles, Class 4 through 13 for ATRs or 4 through 15 for WIMS. In this set two SAFs are developed;
- Three Vehicle Groups – The vehicle groupings are developed for three classification sets. The first group remains light-duty vehicles, Class 1 through Class 3. The second group includes all the single unit trucks, Class 4 through Class 7 and the third group combines the single and the multi-trailer truck classes Class 8 through Class 13 for ATRs and WIMs and an additional Class 8 through Class 15 for WIMs; and
- Four Vehicle Groups – The vehicle groupings are developed for four classification sets. The first group remains light-duty vehicles, Class 1 through Class 3. The second group includes all the single unit trucks, Class 4 through Class 7. The third group includes single trailer truck Class 8 through Class 10, and the fourth group includes the remaining multi-trailer trucks Class 11 through Class 13 for ATRs and WIMs and an additional Class 11 through Class 15 for WIMs.

This study developed four grouping criteria for analysis. Table 4.14 shown below summarizes the final vehicle groupings.

Table 4.1. Examined Groups.

Groups Examined	Vehicle Classes
One Group	Class 1 - Class 13
Two Groups	Class 1-Class 3, Class 4-Class 13
Three Groups	Class 1-Class 3, Class 4-Class 7, Class 8-Class 13
Four Groups	Class 1-Class 3, Class 4-Class 7, Class 8-Class 10, Class 11-Class 13

4.4.2 Functional Class

The functional class of the roadway is the second most common way of aggregating the data. Although the development of the SAFs is based on the individual locations of the ATRs and WIMs, the final analysis may group the data based on the functional classification of the roadway. In this research study, groups are developed for roadway functional classes 1, 2, 6, 7, 8, 9, 11, 12 and 14.

4.4.3 Direction

The final aggregation step within this research study is the analysis of both the total volumes versus the directional volumes. In directional aggregation, the data are divided based on the individual lane number scheme per ATR and WIM location. One example of this aggregation may be for a WIM site that has six lanes. The first three lanes are for the eastbound direction and the second three lanes are for the westbound direction. In the first task, the SAFs are developed for the total six lanes of travel, which in-turn provides an overall description of the volume traveling over one roadway segment. In some cases, however, additional information is needed to analyze the directional flow of travel. If this level of resolution is required, SAFs are developed based on the direction of travel. In the example above, lanes one through three are one group, while lanes four through six are a second group. The research study is then able to evaluate which techniques are the most effective for directional analysis.

Once the empirical aggregation is complete, SAFs are developed for each combination described above. The final results of this data aggregation create more than 1,600 adjustment factors that are compared and evaluated against ground truth performance measures.

4.5 Step Four: Estimation of the Average Traffic Volumes

In step four, there are seven methods that are developed to estimate the average traffic volumes per ATR and WIM station. These seven methods include: average half daily traffic (AHDT), average daily traffic (ADT), monthly average weekday traffic (MAWDT), Method A: monthly average daily traffic (MADTa), Method B: monthly average daily traffic (MADTb) and the day of the week annual average daily traffic (WAADT). The remaining portion of step four describes in more detail each of these seven average traffic volume estimates.

4.5.1 Average Half Daily Traffic (AHDT)

The average half daily traffic represents the 730 half ADTs per station per year of data. The half days are divided based on time of day with midnight to noon as the first half and noon to midnight as the second half. With the exception of the division of the day, the only remaining calculation is the summation of each hourly count.

4.5.2 Average Daily Traffic (ADT)

The average daily traffic represents the 365 ADTs for each station per year of data. Similar to the average half daily traffic, the only calculation is the summation of the full day hourly counts. In this research study, 18 hours is the minimum required number of hours per day to calculate ADT.

4.5.3 Weekly Average Daily Traffic (WADTs)

The third average traffic volume is the weekly WADT which is based on the average of the seven days of the week. The WADT is acceptable only if it has derived from at least 31 average weekly volumes. In this case, as described by Equation 4.1, the final results produce 52 or 53 estimates and these estimates correspond to one estimate per station per week.

$$WADT = \frac{\sum_{j=1}^{S} ADT_j}{S} \tag{4.1}$$

where:

ADT_j = is the average daily traffic, and

S = the number of available ADTs per week.

4.5.4 Monthly Average Weekday Daily Traffic (MAWDT)

The fourth estimate is the weekday MAWDT. In this method, as shown by Equation 4.2, the MAWDTs are the average volumes for all the Mondays, Tuesdays, Wednesdays, etc. for each month. In total this method produces 84 MAWDT, seven days multiplied by twelve months, per station per year. Three ADTs of the same weekday in a month are required in order to estimate the MAWDT as described in the following equation:

$$MAWDT_d = \frac{1}{n}\sum_{g=1}^{n} ADT_{dg} \tag{4.2}$$

where:

ADT_{dg} = the average daily traffic for day d,

d = day of week; Sunday is the first day (d=1) and Saturday is the last day of the week (d=7),

g = the occurrence of that day of the week in a month, for example g = 1 represents the first occurrence of the month, and

n = the number of days of that particular day of the week during that month, for example the number of Thursdays in the month of June.

4.5.5 Method A: Monthly Average Daily Traffic (MADTa)

The MADTa is the simple average of the 30 or 31 ADTs for each month and the MADTa is described by Equation 4.3:

$$MADTa = \frac{\sum_{j=1}^{k} ADT_j}{k} \qquad (4.3)$$

where:

ADT_j = average daily traffic for month j and

k = the number of days per month.

The final result from MADTa produces 12 estimates per station per year. Twenty one available average daily volumes is the minimum required number (k) to estimate the MADTa.

4.5.6 Method B: Monthly Average Daily Traffic (MADTb)

The MADTb as described by Equation 4.4 estimates the average of the average Mondays, Tuesdays, Wednesdays, Thursdays, Fridays, Saturdays and Sundays per month per station per year. Equation 4.4 is described by:

$$MADTb = \frac{1}{7}\sum_{d=1}^{7}\left(\frac{1}{n}\sum_{g=1}^{n} ADT_{dg}\right) \qquad (4.4)$$

where:

ADT_{dg} = the average daily traffic for day d,

d = day of week; Sunday is the first day (d=1) and Saturday is the last day of the week (d=7),

g = the occurrence of that day of the week in a month, for example g = 1 represents the first occurrence of the month, and

n = the number of days of that particular day of the week during that month, for example the number of Thursdays in the month of June.

4.5.7 Day of the Week Annual Average Daily Traffic (WAADT)

The final estimate of the average daily traffic is the WAADT. In this estimate, the annual average Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday are estimated for each year. WAADT is based on the average of a particular week over the duration of the year. This estimation is defined by the following equation:

$$WAADT = \frac{1}{7}\sum_{d=1}^{7}\left(\frac{1}{v}\sum_{j=1}^{v} ADT_j\right) \tag{4.5}$$

where:

d = day of week; Sunday is the first day (d=1) and Saturday is the last day of the week (d=7), and

v = number of available ADTs per year for each day-of-week.

4.6 Step Five: Estimation of the Annual Average Daily Traffic Volumes

The estimation of the annual average daily traffic may begin after the completion of the seven methods used to determine the average daily traffic. Step five of the data methodology is the estimation of AADT values using one of five methods. These five methods include: the simple average, WADT, MADTa, MADTb, and finally WAADT. The remaining portion of step five describes the five methods used in the estimation of the annual average daily traffic volumes.

4.6.1 Simple Average

The first approach for estimating AADT is the simple average of ADTs throughout a year. As shown in Equation 4.6, the numerator is the summation of all the individual ADTs. This summation may be used for both the half days as well as the full days. The denominator is the number of days with data. Equation 4.6 is defined as:

$$AADTa = \frac{\sum_{j=1}^{n} ADT_j}{n} \tag{4.6}$$

where:

AADTa = the annual average daily traffic (vehicles) using the first method,

ADT = the average daily traffic (vehicles), and

n = the number of available daily volumes (ADTs) during a year.

4.6.2 Average of the WADTs

In the second method the AADT is calculated as the average of the available WADTs during a year. Equation 4.7 estimates 52 or 53 average annual daily traffic volumes if there are no missing data in the data set. Equation 4.7 is defined by:

$$AADTb = \frac{\sum_{j=1}^{w} WADT_j}{w} \tag{4.7}$$

where:

AADTb = the annual average daily traffic (vehicles) using the second method,

WADT = the weekly average daily traffic (vehicles), and

w = number of available weeks during a year.

4.6.3 Average of the MADTa

The third method for estimating the annual average daily traffic is developed for the monthly average daily traffic. In this case, the AADTc is defined in Equation 4.8 as:

$$AADTc = \frac{1}{12}\sum_{i=1}^{12} MADTa_i = \frac{1}{12}\sum_{i=1}^{12}\left(\frac{1}{k}\sum_{j=1}^{k} ADT_{ij}\right) \qquad (4.8)$$

where:

$AADTc$ = the third estimation of the annual average daily traffic (vehicles),

$MADTa_i$= the monthly average daily traffic (vehicles) for month i estimated by using a simple average of daily volumes using Method A,

ADT_{ij} = the average daily traffic (vehicles), and

k = the number of available daily volumes (ADTs) during month i.

4.6.4 Average of MADTb

The AADTd is estimated as the average of 12 MADTb for a year and is described by the following equation:

$$AADTd = \frac{1}{12}\sum_{i=1}^{12} MADTb_i = \frac{1}{12}\sum_{i=1}^{12}\left(\frac{1}{7}\sum_{d=1}^{7}\left(\frac{1}{l}\sum_{g=1}^{n} ADT_{gdi}\right)\right) \qquad (4.9)$$

where:

$AADTd$ = the fourth estimation of the annual average daily traffic (vehicles),

$MADT_{bi}$= the monthly average daily traffic (vehicles) of month i estimated by using a simple average of daily volumes Method B,

ADT_{gdi} = the average daily traffic (vehicles),

g = the number of available volumes (ADTs) for each day-of-week of a month,

d = day of week; Sunday is the first day (d=1) and Saturday is the last day of the week (d=7), and

i = the month of the year.

4.6.5 Average of Seven Annual Average Day-of-Week Volumes – AASHTO (WAADT)

The final method is recommend by AASHTO (1992) and Section 2 of the TMG. In this method, shown in Equation 4.10, the WAADT is estimated by first computing average monthly days of the week (12 months by 7 days = 84 values) and then averaging the values to calculate the seven annual average days of the week. Finally, these seven days are averaged to yield the AADT. Equation 4.10 is defined as:

$$AADTe = \frac{1}{7}\sum_{i=1}^{7}\left[\frac{1}{12}\sum_{j=1}^{12}\left(\frac{1}{n}\sum_{k=1}^{n} VOL_{ijk}\right)\right] \qquad (4.10)$$

where:

$AADTe$ = the fifth estimation of the annual average daily traffic (vehicles),

VOL_{ijk} = the daily traffic for day k, of day-of-week i and month of the year j,

k = the occurrence of a particular day of the week in a month, for example k =1 represents the first occurrence, and

n = the number of days of that day of the week during that month.

4.7 Step Six: Development of Seasonal Adjustment Factors

Step six applies the results from steps four and five and develops the adjustment factors. In this section seven adjustment factors are developed. These seven factors include: partial day, daily factors for each day of the year, weekly, monthly average weekday, Method A: monthly average, Method B:

monthly average and the weekday annual average factor. These seven factors are selected and developed based on research by Cambridge Systematics (1994) and suggestions within the TMG Section Three (2001). The remaining portion of this section describes in more detail the seven calculated factor groupings.

4.7.1 Partial Day Factors (F_{AHDT})

The first factor grouping is for partial days, or 12 hours per day. The partial day estimates are based on midnight to noon and noon to midnight for each day of the year. In other words, the first factor is a midnight-to-noon factor and the second factor a noon-to-midnight factor. Equation 4.11 describes the relationship between the two factors. Equation 4.11 is defined as:

$$AADT = AAHDT_1 + AAHDT_2 \qquad (4.11)$$

where:

$AAHDT_1$ = the annual average half daily traffic from midnight-to-noon,

$AAHDT_2$ = the annual average half daily traffic from noon-to-midnight, and

$AADT$ = annual average daily traffic estimated from continuous data.

As a result of dividing the day into two partial days, the factors groupings are described by Equation 4.12 for the midnight-to-noon period and Equation 4.13 for the noon-to-midnight time period.

$$F_{AHDT1} = \frac{AAHDT_1}{AHDT_1} \qquad (4.12)$$

where:

$AAHDT_1$ = the annual average half daily traffic from midnight-to-noon,

$AHDT_1$ = the average half daily traffic from midnight-to-noon, and

F_{AHDT1} = the midnight-to-noon factor for each day of a year.

In the second half daily factor, Equation 4.13 represents the noon-to-midnight portion of the day, Equation 4.13 may be defined as:

$$F_{AHDT2} = \frac{AAHDT_2}{AHDT_2} \tag{4.13}$$

where:

$AAHDT_2$ = the annual average half daily traffic from noon-to-midnight,

$AHDT_2$ = the average half daily traffic from noon-to-midnight, and

F_{AHDT2} = the noon-to-midnight factor for each day of a year.

4.7.2 Daily Factors for Each Day of the Year (F_{ADT})

The second factor grouping creates an adjustment factor for every full day of this year or 365 factors. This factor methodology is described by Equation 4.14. Equation 4.14 is defined as:

$$F_{ADT} = \frac{AADT}{ADT} \tag{4.14}$$

where:

$AADT$ = the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,

ADT = the average daily traffic, and

F_{ADT} = the average daily traffic factor.

4.7.3 Weekly Factors (F_{WADT})

The third factor grouping is developed for each week of the year, with week one representing the first week of the year. For example, if January 1 is a Wednesday, the first factor grouping consists of Wednesday through Saturday. Similarly if the final week of the year is incomplete, the factor grouping would end on December 31 regardless of the actual day of the week. As a result of these criteria associated with these factor groupings, there are 52 or 53 factors generated per year. Equation 4.15 is defined below:

$$F_{WADT} = \frac{AADT}{WADT} \tag{4.15}$$

where:

$AADT$ = the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,

$WADT$ = the weekly average daily traffic, and

F_{WADT} = the weekly average daily traffic factor.

4.7.4 Monthly Average Weekday Factors (F_{WADT})

The fourth factor grouping is a set of seven day-of-week factors for each month, with a total 7 days a week multiplied by 12 months, equal to 84 factors per year. These factor groupings, for example, represent the average factor for the Mondays in March and are created based on Equation 4.16. In Equation 4.16 the variables include:

$$F_{MAWDT} = \frac{AADT}{MAWDT} \tag{4.16}$$

where:

$AADT$ = the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,

$MAWDT$ = the monthly average weekday daily traffic, and

F_{MAWDT} = the monthly average weekday daily traffic factor.

4.7.5 Method A: Monthly Average Factor (F_{MADT1})

The MADTa which is the first monthly estimate, is a simple average of the available days of a month. In method A, the denominator is the MADTa and is described in Equation 4.17.

$$F_{MADT1} = \frac{AADT}{MADTa} \tag{4.17}$$

where:

$AADT$ = the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,

$MADTa$ = the average monthly traffic as defined by Equation 4.3, and

F_{MADT1} = the first monthly average traffic factor.

4.7.6 Method B: Monthly Average Factor (F_{MADT2})

The MADTb is the second monthly estimate and this estimate is the average of the average days of the week of a month. In method B, the MADTb is used in the calculation of the factor F_{MADT2} as described in Equation 4.18:

$$F_{MADT2} = \frac{AADT}{MADTb} \tag{4.18}$$

where:

$AADT$ = the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,

$MADTb$ = the average monthly traffic as defined by Equation 4.4, and

F_{MADT2} = the second monthly average traffic factor.

4.7.7 Weekday Annual Average Factor (F_{WAADT})

Seven day-of-week factors are developed for each ATR and WIM (e.g. average Monday factor, Tuesday factor, etc., are developed for each year) as described in Equation 4.19:

$$F_{WAADT} = \frac{AADT}{WAADT} \tag{4.19}$$

where:

$AADT$ = the annual average daily traffic estimated from continuous data, all five methods for calculating AADTs are used in this equation,

$WAADT$ = the weekly annual average monthly traffic, and

F_{WAADT} = the weekly annual average monthly traffic factor.

4.8 Step Seven: Development of "Ground Truth" Performance Measures

The final step in the development of SAFs is the evaluation of the best methods to produce the most accurate SAFs. The successful completion of this task is based on the development of performance measures used to evaluate or provide "ground truth". These estimates are then able to answer questions such as:

- How effective are the SAFs when they are estimated for individual vehicle classes or combined?
- What is the impact of using multiple adjustment factors instead of one?
- What are the best months to collect truck data and how does seasonality affect the predicted AADT?
- What are the impacts of sample duration on the short-term count duration and timing on AADT estimates?
- What are the impacts of total direction versus both directions individually?

The development of ground truth estimates are based on the AADT predictions described previously in steps four through six and the actual observations recorded by the ATR and WIM sites. For example, AADT predictions for year 2004 are then evaluated with actual AADT observations for 2005. The values determined from the comparison of the two years are consistent with research studies developed by Thomas (1997), Erhunmwunsee (1991), Lingras (2000), Sharma (1999), Tang (2003), Lam (2000), Zhong (2006). The evaluations of the predicted values with the actual values in this study are developed from the mean absolute error (MAE), standard deviation and coefficient of variation. The MAE is defined below in the following equation:

$$MAE = \frac{\left| AADT_{pred} - AADT_{obs} \right|}{AADT_{obs}} * 100 \tag{4.20}$$

where:

MAE	=	mean absolute error defined as a percent,
$AADT_{pred}$	=	the AADT predicted from year one, and
$AADT_{obs}$	=	the AADT results from the following year.

The analysis of the ground truth data is based on the temporal selection of the days of the week as well as various sample durations of the short-term counts. In this research study, the mean absolute errors and standard deviations are developed for all combinations as defined in Table 4.2.

Table 4.2. The temporal selection of ground truth examples.

Sample Duration	Days of the Week Sampled
24 Hours	Mon, Tue, Wed, Thur, Fri
48 Hours	Mon-Tue, Tue-Wed, Wed-Thur, Thur-Fri,
72 Hours	Mon-Wed, Tue-Thur, Wed-Fri
96 Hours	Mon-Thur, Tue-Fri

4.9 Step Eight: The Development and Implementation of SQL Code

Step eight describes the software coding required to complete all data aggregation and mathematical calculations described in tasks two through seven. The development and implementation of the SQL code are created for three aggregation procedures. The first procedure is the development of artificially created variables that help the user later with grouping the data. These artificial variables are based on criteria such as time of day, day of week, and week of the year. The second SQL procedure is used to organize the data, create new tables, all mathematical calculations and to summarize the final results. The third procedure is used to analyze the ground truth.

4.9.1 Artificial Data Creation

The first series of SQL codes are developed to create indices in the form of data columns to be used for future analysis. In general, these data columns are created to identify temporal similarities between tables. Some of the artificial updates include the day of the week, week of the year, the error codes and the functional roadway classifications.

4.9.2 Development of Adjustment Groupings

The second series of code is more extensive. This SQL code is developed to create new data formats that are required within this study. The overall process is similar for the ATRs and the WIMs. Figure 4.3 shown below provides flow diagram for the steps required in the overall development of the most accurate SAFs. As shown in the Figure 4.3, there are six SQL tasks that are developed for each of the ATR and WIM data sets. The first two tasks have already been described in step two of this chapter.

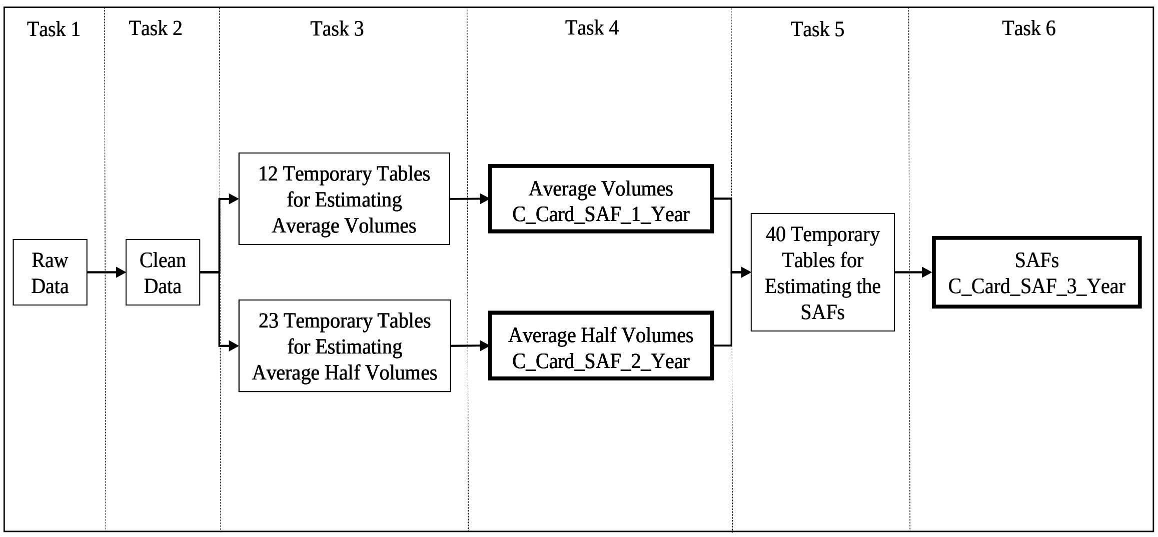

Figure 4.3. Development of SAFs.

SQL code is used to develop two main temporary table templates in the third task. These temporary tables are created for calculation purposes. Once the results are finalized, these tables are no longer required and are discarded. The first series of temporary tables consists of 12 tables that are used for the estimation of the average volumes. The first 11 tables store the calculations used to develop ADT, WADT, MAWDT, MADTa, MADTb, WAADT, AADTa, AADTb, AADTc, AADTd and AADTe. The 12th temporary table is used to estimate the hourly volumes by direction. This table allows the addition of volumes for each lane, creating the directional as well as the total volume. The second part of task three is the creation of 23 additional temporary tables. The structure of these temporary tables is similar to the first set of temporary tables with one exception; the data are divided into two factors per day. One factor is for 12:00 AM to 12:00 PM and the second is 12:00 PM to 12:00 AM. The 23rd table is then used to estimate the volumes by direction.

In task four of the SQL process, two summary tables are created that contain the average volumes that are developed within task three. These tables are used later to estimate the SAFs as well as the "ground truth". In task five, 40 additional temporary tables are created based on the results of eight factor groupings in combination with the five AADTs. In task six, the SQL code is developed to create a summary of the findings. This summary table, along with the tables developed in tasks two and four, are then used in the ground truth data analysis.

4.9.3 SQL Code Used with the Development of Ground Truth Analysis

The third main area for the development of SQL code is the establishment of ground truth between the actual and the predicted values. Figure 4.4 shown on the following page illustrates the overall direction of SQL coding required for this task. Similar to Figure 4.3, there are six tasks that are required for the ground truth component. In task seven, the three main tables are developed from task six. In task eight, the SQL code separates the data into 43 temporary tables. The first temporary table is created to predict the new AADTs for each day of the year. The SAFs are then applied to the ADTs of the following year in this data structure. By using the new AADTs from this table, the remaining 42 tables are created. The results of these temporary tables are then stored in one table corresponding to each short-term count.

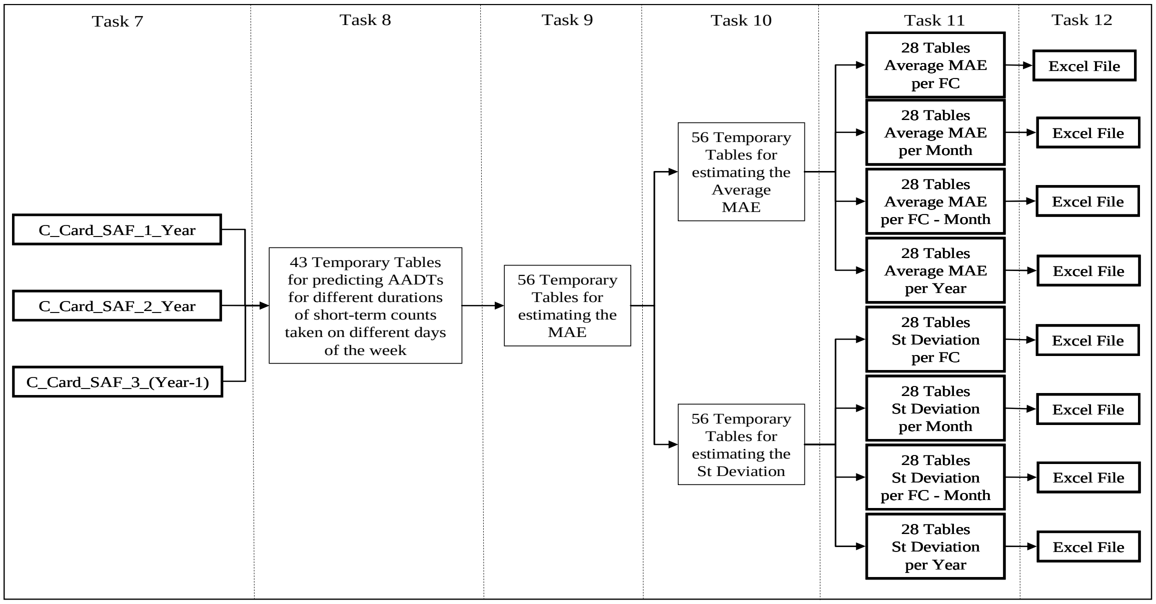

Figure 4.4. Ground truth flow diagram.

In task nine, the mean absolute errors are developed based on the description provided in step seven, Equation 4.20. In task ten, two sets of 56 tables are created based on day of the week and the length of hourly sampling. In task ten, the top set of tables are estimates of the mean absolute error, while the bottom set of tables summarize the corresponding standard deviations of the mean absolute error. Other research studies do not provide information on the standard deviations, in most cases, however, standard deviation calculations provide greater flexibility and more in-depth analysis that may be required in future work.

In task eleven, the SQL code is developed to summarize the findings from task ten. In this case, there are 112 temporary tables developed for both the mean absolute errors as well as the corresponding standard deviations. The four sets of summary data are based on the functional class, month, month combined with functional class and per year. In the final task, task twelve, the summary of results are exported from SQL and imported into an Excel format.

4.10 Step Nine: The Quality Control and Data Validation Checks

One of the most important components of data analysis is validating the results in Figure 4.4 using a different method. This ensures that the procedural methodology is correct and accurate. The objective of this section is to describe the methods used with the data validation. These methods are divided into the following sections:

- Data importation and calculations;
- Data validation; and
- Conclusions.

Two software platforms are used in the data validation. The first platform is Microsoft SQL Server Management Studio Express. The second software platform is Microsoft Excel 2007. In this data validation procedure as shown in Figure 4.5, the data are initially exported from the SQL platform and imported into Excel.

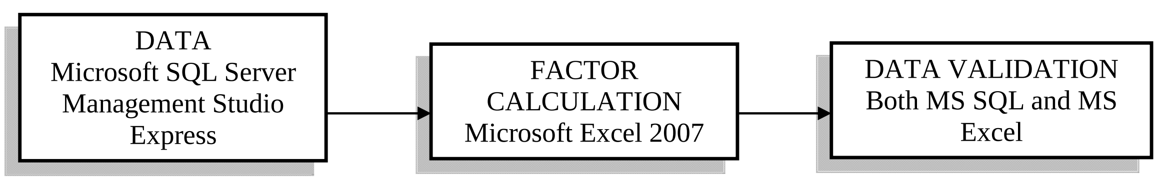

Figure 4.5. Data validation procedure using Microsoft SQL and Microsoft Excel.

Manual calculations are performed on the data and final values are determined once in Excel. These values are compared with the SQL tables developed from the SQL code described in the step eight. In the final spot check, the results from the manual calculation should match the SQL performed operation. If there is a match, the SQL code is validated and the results are implemented. Conversely, if the data does not match, both the manual calculations as well as the SQL code are reevaluated until both procedures produce the same results. The remaining portion of this section describes the overall process of quality analysis, quality control (QA/QC) procedures in more detail.

4.10.1 Data Importation and Calculations

The first task in the data validation process is to obtain the clean data from Microsoft SQL. A query may be written to obtain data for specific stations, directions and months. An example of this type of query in SQL code is shown below:

*Select **

From [3_Card_Clean_Atr_2002 N]

Where [Station Number] = 727 and [Direction] = 1

In this particular query, the user would like to see all data which corresponds to station number 727 and is located in direction 1. The results of this query are displayed in a temporary table similar to Figure 4.6 shown below.

Results | Messages

	3	39	FC	Station Number	Direction	Lane	Year	Month	Day	Day of Week	Week of Year	Vol 001 to 100	Vol 101 to 200	Vol 201 to
1	3	39	12	727	1	0	2	4	1	2	14	390	300	190
2	3	39	12	727	1	0	2	4	2	3	14	440	320	250
3	3	39	12	727	1	0	2	4	3	4	14	440	320	230
4	3	39	12	727	1	0	2	4	4	5	14	420	320	230
5	3	39	12	727	1	0	2	4	5	6	14	510	340	270
6	3	39	12	727	1	0	2	4	6	7	14	590	400	310
7	3	39	12	727	1	0	2	4	7	1	15	700	480	350
8	3	39	12	727	1	0	2	4	8	2	15	380	260	210
9	3	39	12	727	1	0	2	4	9	3	15	300	220	210
10	3	39	12	727	1	0	2	4	10	4	15	260	260	220
11	3	39	12	727	1	0	2	4	11	5	15	300	240	230
12	3	39	12	727	1	0	2	4	12	6	15	310	250	250
13	3	39	12	727	1	0	2	4	13	7	15	350	230	210
14	3	39	12	727	1	0	2	4	14	1	16	310	200	160
15	3	39	12	727	1	0	2	4	15	2	16	260	190	190
16	3	39	12	727	1	0	2	4	16	3	16	300	210	210
17	3	39	12	727	1	0	2	4	17	4	16	280	230	220

Query executed successfully. | THE-9B06C1A44E5\SQLEXPRESS (9.0 SP2) | THE-9B06C1A44E5\Administrator (52) | Ohio_SAFs | 00:00:02 | 363 rows

Figure 4.6. Temporary table in Microsoft SQL showing the results of the query.

As may be seen in Figure 4.6, information is retrieved pertaining to the FC (functional class), station number, direction, lane, year, month, day, day of week, week of year and hourly volume counts. This entire table is then imported into Excel for further data manipulation. Once the data are imported into Excel, they are analyzed to calculate traffic factors such as WADT, MADT and AADT. Figure 4.7 below displays this data after being imported into Excel.

D	E	F	G	H	I	J	K	L	M	N	O	P
FC	Station	Direction	Lane	Year	[mm]	Day	[dd]	[wk]	Vol 001 to 100	Vol 101 to 200	Vol 201 to 300	Vol 301 to 400
12	727	1	0	2	4	1	2	14	390	300	190	180
12	727	1	0	2	4	2	3	14	440	320	250	240
12	727	1	0	2	4	3	4	14	440	320	230	210
12	727	1	0	2	4	4	5	14	420	320	230	240
12	727	1	0	2	4	5	6	14	510	340	270	330
12	727	1	0	2	4	6	7	14	590	400	310	280
12	727	1	0	2	4	7	1	15	700	480	350	240
12	727	1	0	2	4	8	2	15	380	260	210	230
12	727	1	0	2	4	9	3	15	300	220	210	250
12	727	1	0	2	4	10	4	15	260	260	220	280
12	727	1	0	2	4	11	5	15	300	240	230	300
12	727	1	0	2	4	12	6	15	310	250	250	270

Figure 4.7. Data after being imported into Microsoft Excel.

In both Figures 4.6 and 4.7 the data structure is consistent. The main reason for this SQL table is the increased data storage capacity required in this study. The next task in the data validation process is the manual calculation of critical input parameters. The first key function is “AVERAGEIF” and the second function is “SUMIF”. The “AVERAGEIF” function, shown in Figure 4.8, is used to calculate average traffic volumes based on specific criteria, such as day of week and month.

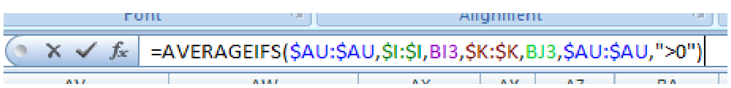

Figure 4.8. “AVERAGEIF” function used to calculate average traffic volumes.

As shown in Figure 4.8, several criteria may be entered at once, making the calculation of factors efficient for small data sets. For example, to calculate the average traffic on Mondays in June, the “AVERAGEIF” function is set to calculate the average of the daily volumes if the [mm], month column, is equal to 6 and the [dd], day of week column is equal to 1. Another extension of the “AVERAGEIF” function is the user’s desire to calculate the average traffic for the 25th week of the year. In this case, the

“AVERAGEIF” function is set to calculate the average of the daily volumes if the [wk], week of year, column is equal to 25.

BD	BE	BF	BG	BH	BI	BJ	BK	BL	BM	BN	BO	BP	BQ
WADT					WAMT					MADT s avg			
[wk]	# days	WADT	St. Dev.	C.V.	[mm]	[dd]	WAMT	St. Dev.	C.V.	[mm]	MADT	St. Dev.	C.V.
1	5	18,550	3834.606	20.672	1	1	14,270	393.022	2.754	1	18,088	2638.997	14.5
2	7	18,247	2572.967	14.101	1	2	18,395	469.077	2.550	2	18,752	2233.315	11.9
3	7	18,276	2749.720	15.046	1	3	17,526	2951.606	16.841	3	19,682	2405.956	12.2
4	7	18,529	2220.589	11.985	1	4	18,798	1263.950	6.724	4	22,362	2337.799	10.4
5	7	16,690	2021.278	12.111	1	5	18,626	2729.145	14.652	5	22,140	2252.540	10.1
6	7	18,389	2646.951	14.395	1	6	22,050	650.897	2.952	6	24,178	2569.200	10.6
7	7	19,037	2651.966	13.930	1	7	16,780	738.873	4.403	7	24,730	2162.684	8.7
8	7	19,450	1926.603	9.905	2	1	15,418	1506.749	9.773	8	25,211	2309.705	9.1
9	7	18,977	2372.915	12.504	2	2	19,288	1361.944	7.061	9	21,569	1768.612	8.2
10	7	19,347	2304.168	11.910	2	3	18,763	1185.338	6.318	10	21,405	1744.026	8.1
11	7	19,851	2178.344	10.973	2	4	18,883	493.719	2.615	11	20,406	2690.665	13.1
12	7	20,001	1983.250	9.916	2	5	20,170	847.467	4.202	12	20,295	2981.493	14.6
13	7	19,413	3432.656	17.682	2	6	21,650	2175.791	10.050				
14	6	24,373	2089.600	8.573	2	7	17,093	939.091	5.494				
15	7	22,649	2098.836	9.267	3	1	17,216	1426.457	8.286				
16	7	21,729	1698.288	7.816	3	2	18,813	1325.704	7.047				

Figure 4.9. Table in Microsoft Excel showing results of various “AVERAGEIF” functions.

The “SUMIF” function, Figure 4.10, calculates the total traffic for each day in the year and may be completed by setting the “SUMIF” criteria to MM (Month Column) = 1 and DD (Day Column) = 1, and then changing the values for each day in the year. For example, the criteria for calculating the total traffic on August 15 would be MM = 8 and DD = 15.

```
=SUMIFS($K:$K,$F:$F,AO3,$G:$G,AP3)
```

Figure 4.10. “SUMIF” function used to calculate total daily traffic.

In addition to the “AVERAGEIF” and “SUMIF” commands, a third series of manual calculations are the development of standard deviation and coefficient of variation associated with each of the factors.

4.10.2 Manual Validation for the Factor Groupings

The averages of each of these factors, the MADT and WADT, are then used to predict AADT. Once each of the AADT values are calculated, the adjustment factors may then be determined. Each of the average traffic factors is compared to each of the AADTs to determine the most appropriate adjustment factor. Figure 4.11 shown below shows the results in Excel from each of these calculations.

H	I	J	K	L	M	N	O	P
WADT								
[wk]	F_AADT_MADT_WAMT	F_AADT_MADT s avg	F_AADT_WAADT	F_AADT_WADT	F_AADT s avg	[mm]	[dd]	F_AADT_MADT_WAMT
1	1.162491015	1.162705778	1.163635904	1.163907319	1.163698737	1	1	1.511156856
2	1.181785472	1.1820038	1.182949363	1.183225283	1.183013239		2	1.1722864
3	1.179937922	1.180155908	1.181099994	1.181375482	1.181163769		3	1.230412435
4	1.163835454	1.164050465	1.164981667	1.165253395	1.165044572		4	1.147154396
5	1.292043639	1.292282336	1.293316119	1.293617781	1.293385954		5	1.157747682
6	1.172696227	1.172912876	1.173851167	1.174124964	1.173914551		6	0.977968632
7	1.132743947	1.132953214	1.133859539	1.134124009	1.133920764		7	1.285113727
8	1.108699657	1.108904483	1.109791569	1.110050425	1.109851495	2	1	1.398683855
9	1.136325341	1.136535271	1.137444461	1.137709767	1.137505879		2	1.118040614
10	1.114593948	1.114799862	1.115691665	1.115951897	1.115751909		3	1.149324895
11	1.086279925	1.086480608	1.087349757	1.087603378	1.08740847		4	1.142020831
12	1.078133407	1.078332586	1.079195216	1.079446935	1.079253489		5	1.069122872
13	1.110820946	1.111026163	1.111914947	1.112174298	1.111974987		6	0.996037336
14	0.884745966	0.884909417	0.885617315	0.885823883	0.885665136		7	1.261618156
15	0.95212223	0.952298129	0.953059935	0.953282234	0.953111398	3	1	1.252567863

Figure 4.11. Tables in Microsoft Excel showing results of factor calculations.

The clean data for the station numbers and directions are exported from SQL and imported into Excel, along with the automatic calculations provided by “AVERAGEIF” and the “SUMIF’ statements within Excel. This makes checking values for different stations efficient. A random selection of stations for spot checks serves the purpose of this supplement analysis. It is important to note, however, that because of the nature and size of the data set, it is not realistic to spot check all the stations and all the lanes of traffic.

The approach for C-Card data closely resembles the 3-Card data, but with one additional step. The added step for checking C-Card data is to verify the total daily traffic volume is correct for each station. This is done in Excel by using the “SUMIF” function, where the calculated sum of numbers based to certain criteria. Once the daily traffic is calculated, the average traffic factors are developed and are consistent in methodology as compared with the 3-Cards. The data are imported into Excel, and the

"AVERAGEIF" function is used to calculate the average traffic and corresponding adjustment factors. This analysis is done for the total volume, Class 2 and Class 9 volumes for the C-Cards.

4.10.3 Data Validation

Once the data are processed in Excel, they are compared to the results from the SQL platform to check for data integrity. Figure 4.12 shown below illustrates the AADT results from Station Number 727, Direction 1 for 3 Card ATR data.

BW	BX	BY	BZ	CA
AADT from MADT from WAMT	**AADT from MADT s AVG**	**AADT from WAADT**	**AADT from WADT**	**AADT s avg**
21,564	21,568	21,585	21,590	21,587
St. Dev.	St. Dev.	St. Dev.	St. Dev.	St. Dev.
2283.806	2288.968	1829.392	2334.870	3203.783
C.V.	C.V.	C.V.	C.V.	C.V.
10.591	10.613	8.475	10.814	14.842

Figure 4.12. Tables in Microsoft Excel showing results of AADT calculation methods.

A query may now be executed in SQL to obtain the results for these AADT values using the SQL code described in the previous section. The retrieval of the required data is provided by the SQL code shown below:

*Select * From [3_Card_Clean_ATR_2002 AADT from MADT from MAWDT per FC Dir1]*

Where [Station Number] = 727

Notice the "from" statement for retrieving data is from an alternative source [3_Card_Clean_ATR_2002 AADT from MADT from MAWDT per FC Dir1] as compared with [3_Card_Clean_Atr_2002 N].

Results | Messages

	FC	Station Number	Direction	AADT from MADT from WAMT	St Dev	CV	Number_Rows
1	12	727	1	21564	2283.823	10.591	12
2	12	727	5	21024	2144.291	10.199	12

Figure 4.13. Temporary table in Microsoft SQL showing results of the query.

These results may now be compared back to the Excel results to check for consistency. In Figures 4.12 and 4.13 above, the values of importance are highlighted in Excel produce the AADTb equal to 21,564 which is consistent with the values illustrated in Figure 4.13. Any discrepancies between SQL results and Excel results are likely to be due to rounding. At this point, the data sets are considered to be clean and the results are now ready for the ground truth evaluation.

CHAPTER V

ANALYSIS AND FINAL SELECTION OF THE MOST APPROPRIATE FACTORS

5.1 Introduction

The development of the 1,600 SAFs is based on the methodology that is documented in Chapter V of this report. In Chapter V, all 1,600 developed SAFs are evaluated using ground truth analysis. The results from the ground truth analysis provide guidance on the selection of the most accurate SAFs. In some cases there may be multiple SAFs that produce the same findings per condition. The remaining portion of the chapter is divided into eight steps. These eight steps include:

- Step One –Sensitivity analysis of the five methods developed to estimate AADT,
- Step Two –Temporal analysis of the mean absolute errors,
- Step Three –Directional analysis, two-way versus total volumes,
- Step Four –Average SAFs for vehicle class groupings based on roadway functional classification,
- Step Five –Vehicle class groupings based on roadway functional classification,
- Step Six –The development of multiple factor groupings,
- Step Seven –The impact of monthly parameters on short-term counts,
- Step Eight –The impact of day of week short-term counts.

As a result of the number of SAFs that are developed in this study it is not realistic to document all the findings. This results section highlights the most important findings.

5.2 Step One: Sensitivity Analysis of the AADT values

The first step in the overall selection of the SAFs is a sensitivity analysis that is performed on the five methods, described by Equations 4.6 through 4.10 in Chapter IV. These five methods for estimating AADT are then applied as the numerator in Equations 4.12 through 4.19. The final results from the

AADT sensitivity analysis for the ATR and WIM data sets are shown below in Figures 5.1 and 5.2. In both figures, the Y-axis is the mean absolute error and the X-axis is the five methods used in calculating AADT for each of the seven SAF calculations.

5.2.1 The AADT analysis of the ATR Data Set

The results for the five methods used to calculate the AADTs are relatively similar with less than a 10 percent mean absolute error across all seven factors. There are some slight trends in the results that suggest the AADTa, Equation 4.6, and the AADTd, Equation 4.9, perform slightly better, less than 1 percent, than the other methods.

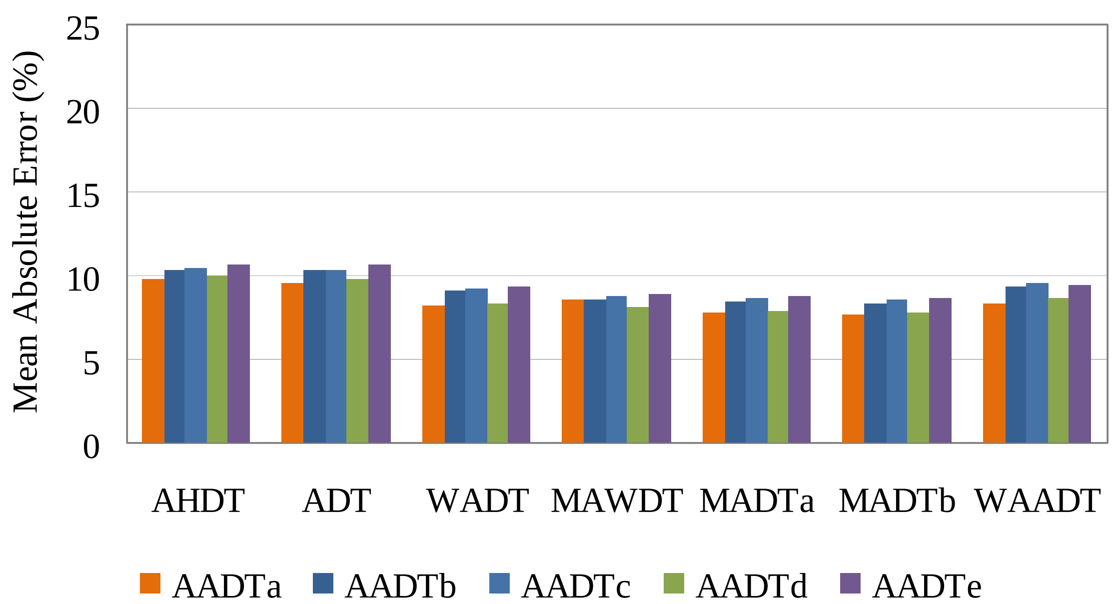

Figure 5.1. AADT sensitivity analysis using ATR data set.

5.2.2 The AADT analysis of the WIM Data Set

The results for the WIM data, shown in Figure 5.2, are similar to the results shown in Figure 5.1. In Figure 5.2, the five methods produce similar results showing mean absolute errors between 12 and 14 percent. The overall best results yield less than one percent improvement are the AADTa and the AADTc estimates.

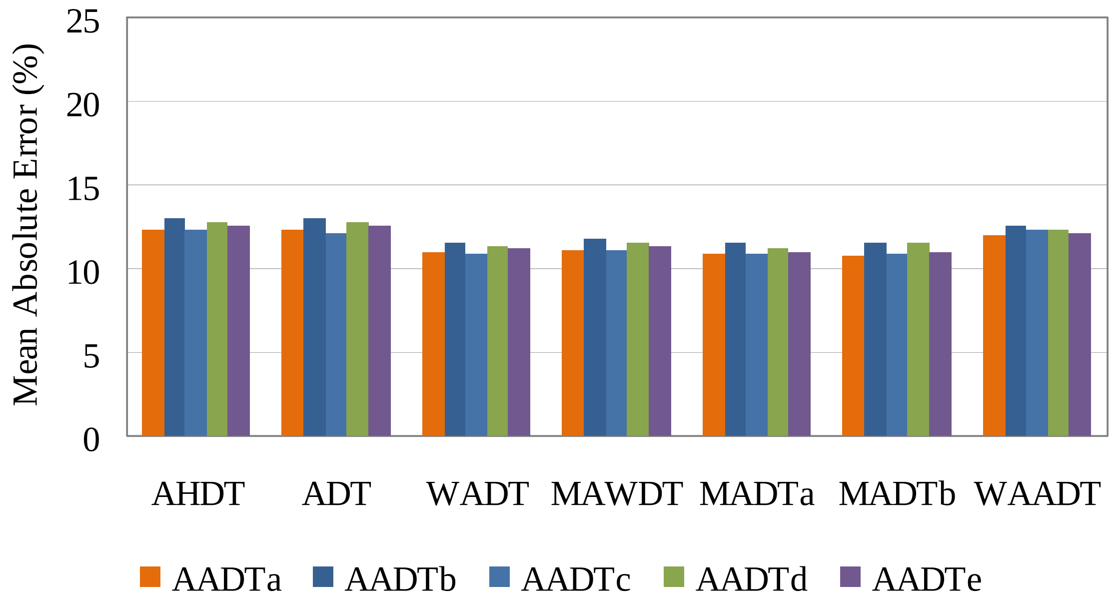

Figure 5.2. AADT sensitivity analysis using WIM data set.

5.2.3 Comparison and Summary of Findings for the AADT methods using the ATR and WIM Data Sets

The results from Figures 5.1 and 5.2 show that in most cases the five methods used for the calculation of the AADTs produce similar results across each of the seven methods used in the calculation of SAFs for the ATRs and WIMs. In both data sets, the first method, AADTa, Equation 4.6, produces slightly better results. As a result of this finding, the remaining sections of this chapter report results using this method AADTa for calculating AADT.

5.3 Step Two: Annual Temporal Sensitivity

The annual temporal sensitivity is evaluated in the second step of this research study. This analysis is important for multiple reasons. First, the data set developed in this project is based on multiple years of data. Second, the annual temporal sensitivity addresses the question of whether to or not to average multiple years worth of data. Third, each technique is evaluated over time. As a result of this temporal range, the stability within each year for each technique is compared with the ground truth in order to evaluate the change in the mean absolute errors over multiple years. For example, 2002 factors are used with 2003 ADTs, and 2003 factors are used with 2004 ADTs and these factors along with the actual volumes allow for the comparison of results using the mean absolute errors, Equation 4.20, for all the years of data. Figures 5.3 and 5.4 represent the overall temporal stability for the ATRs, while Figures 5.5 and 5.6 represent to the overall temporal stability for the WIMs. For both data sets, Figures 5.3 and 5.5 represent January, a winter month, while Figures 5.5 and 5.6 represent July, a summer month. In these figures, the Y-axis represents the mean absolute error and the X-axis represents the year of the short-term count. In these figures the results are based on the AHDT, ADT, WADT, MAWDT, MADTa, MADTb and WAADT.

5.3.1 ATR Annual Temporal Results

The annual ATR temporal results are shown below in Figures 5.3 and 5.4. The results for the month of January show the overall mean absolute error changes by 5 to 10 percent between 2003 and 2005.

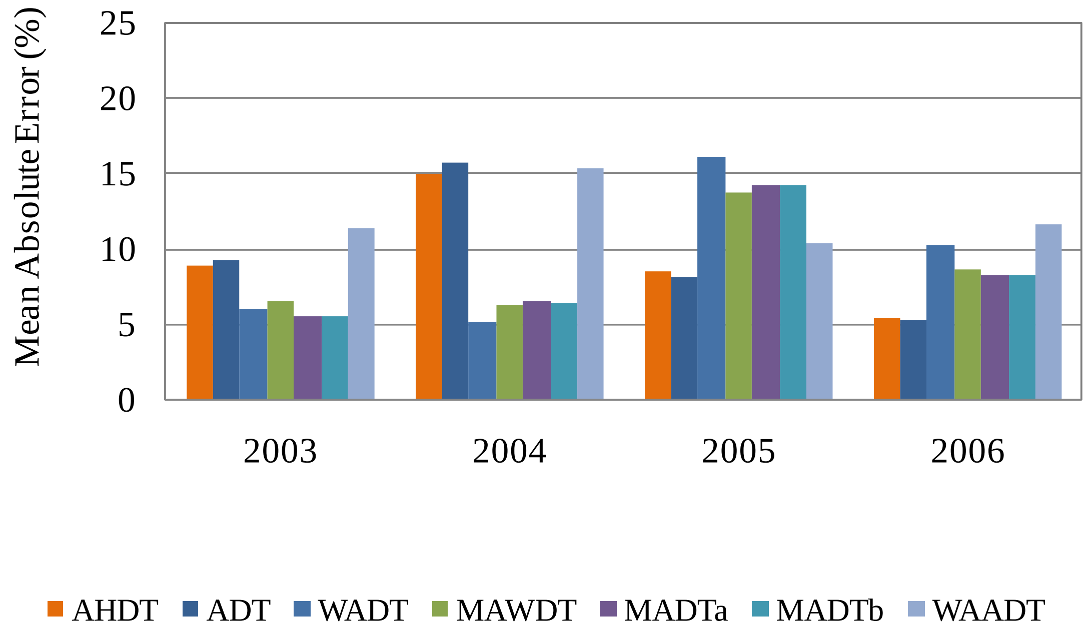

Figure 5.3. Annual temporal sensitivity for the ATR data set for the month of January.

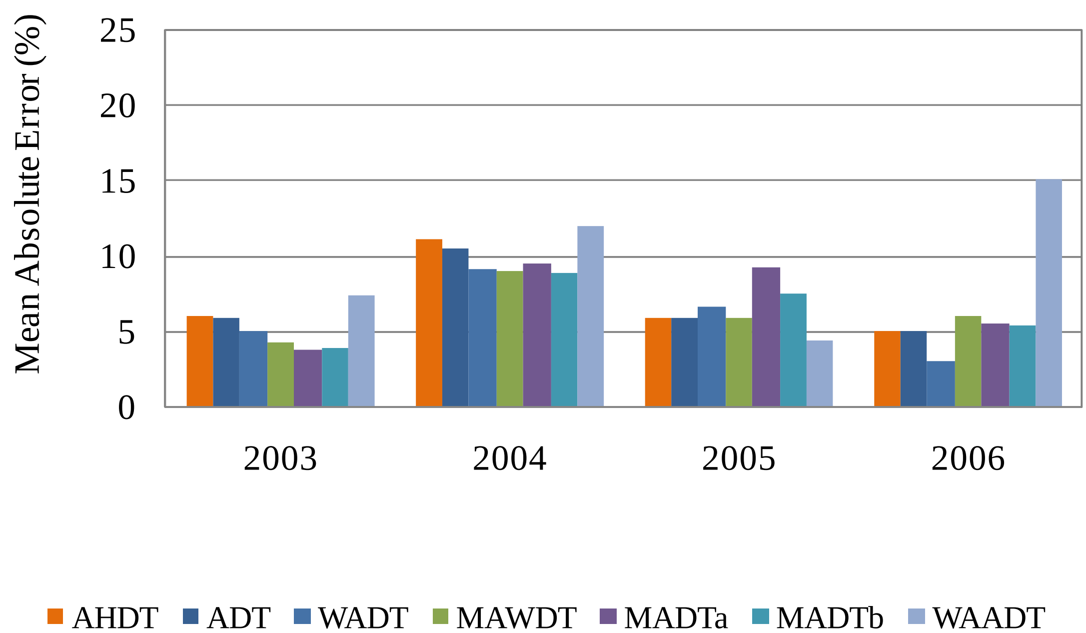

Figure 5.4. Annual temporal sensitivity for the ATR data set for the month of July.

The lowest mean absolute error occurs for the year 2003. The mean absolute error increases slightly for 2004 and 2005, and the trend in the mean absolute error begins to decrease for 2005. The results for the month of July are shown above in Figure 5.4. In Figure 5.4, the trend remains similar to Figure 5.3 with a low mean absolute error in 2003 followed by an increase in 2004 and 2005. The mean absolute error begins to decrease for 2006 with the exception of the WAADT. In comparing the two seasons, the results shown in Figure 5.4 are between 5 and 10 percent lower than the comparable winter month, Figure 5.3, and these findings may be the direct result of adverse conditions associated with the winter months.

5.3.2 WIM Annual Temporal Results

The annual temporal results for the WIM data set are shown in Figures 5.5 and 5.6. The WIM results are slightly different from the ATRs. In these figures, the overall trends show a decline in the mean absolute error from 2003 through 2005. In Figure 5.5, the WIM results are displayed for the month of January.

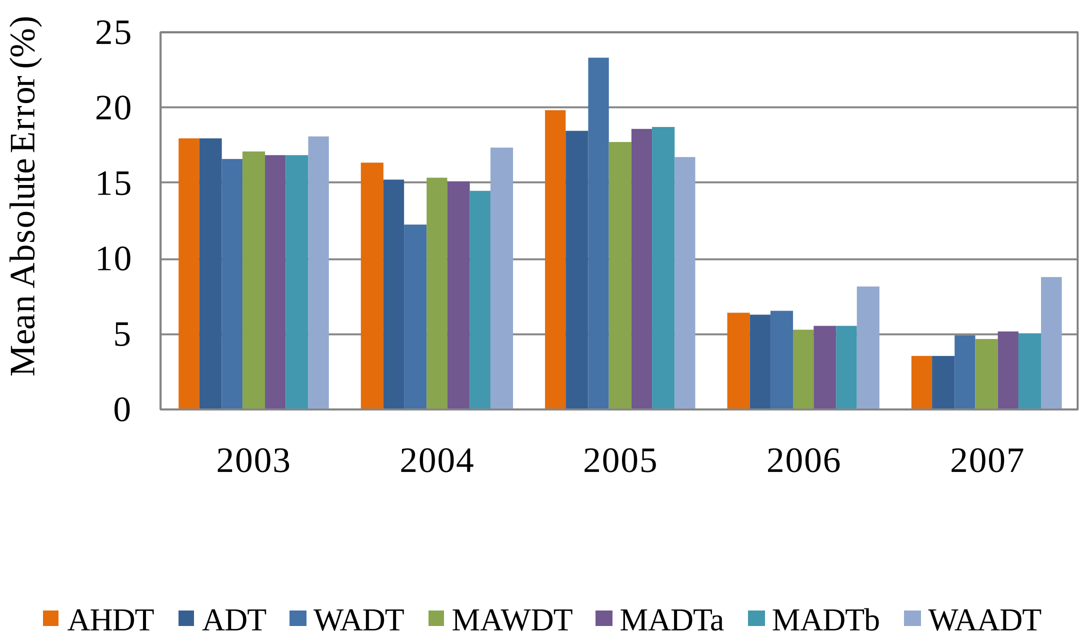

Figure 5.5. Annual temporal sensitivity for the WIM data set for the month of January.

These results in general show the seven methods for each year perform relatively similar with less than 5 percent mean absolute error difference between all seven methods. In general, 2005 has the highest overall mean absolute error. It is interesting to note that 2006 and 2007 mean absolute errors decrease by 10 percent over the previous three years. This decrease may be the direct result of a systematic improvement in the data collection over this same time period.

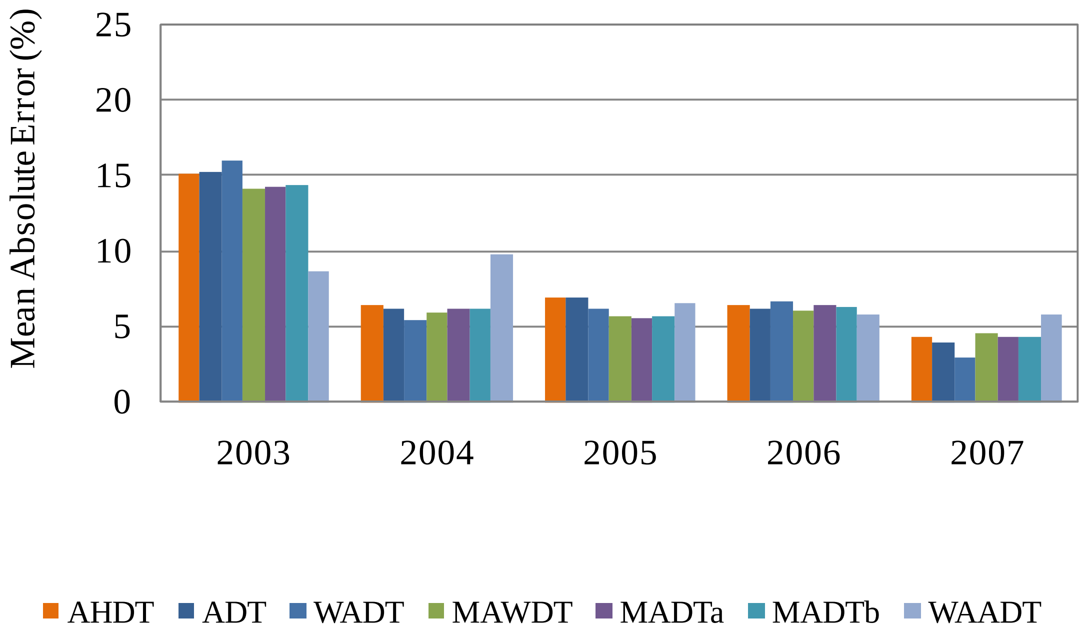

Figure 5.6. Annual temporal sensitivity for the WIM data set for the month of July.

The second set of results for the WIM shown in Figure 5.6 suggest 2003 produces the highest individual mean absolute errors. Other results show that in general, on a yearly average each of the seven methods produce similar mean absolute errors that are within 5 percent of each other. The data from 2004 through 2007 summer months are consistent with mean absolute error values between five and seven percent. In the comparison between winter and summer months it is interesting to see that the summer WIM produces lower and more consistent mean absolute errors. For example, for the 2004 and 2005 time period, there is a 10 percent difference between the winter and summer months. This difference may be the result of variability within the traffic, an increase in the number of WIMs or potentially another systematic change between summer and winter operations.

5.3.3 Comparison and Summary of Findings for the Temporal Stability using the ATR and WIM Data Sets

The temporal stabilities for each of the seven techniques are compared and in general there are some similarities between the ATR and WIM data sets. In most cases, the mean absolute errors are equal to or less than 15 percent with all seven techniques producing similar results for both the January and July sampling periods.

There are some differences, however, between the ATRs and the WIMs. In the case of the ATRs, the mean absolute error increases to a high in 2005 and then decreases in 2006 and 2007, while the WIM results are the highest in 2003 and 2004 and then the mean absolute error declines by 10 percent for all records following 2005. As a result of the voluminous amount of data collected and analyzed, the remaining results are developed based on the overall average results for the entire data collection period. In all cases, the results are analyzed on a per year basis as well as on the average basis. In general the yearly values display similar trends as the aggregated values.

5.4 Step Three: Directional Analysis

In the third step of analysis, the adjustment factors for the ATRs and the WIMs are developed for both the total and the directional volumes. In these cases, vehicles are aggregated based on the methodology described in Chapter IV. The results, shown in Figures 5.7 and 5.8, are developed for all roadway classifications for all years of data for MADTa. In these figures, the Y-axis is the mean absolute error and the X-axis is the number of vehicle groups.

5.4.1 ATR Directional Analysis Results

The results for the ATR directional analysis are shown in Figure 5.7. In this figure, the overall results compare the total adjustment factors with the directional adjustment factors. In this figure, there are two results. The first result shows the impact of the vehicle aggregation on the corresponding mean absolute error. In this finding for the ATR data set, the lowest mean absolute error occurs for the one group containing all the vehicle classes. The mean absolute error for both total and directional continue to increase as the number of groups increases.

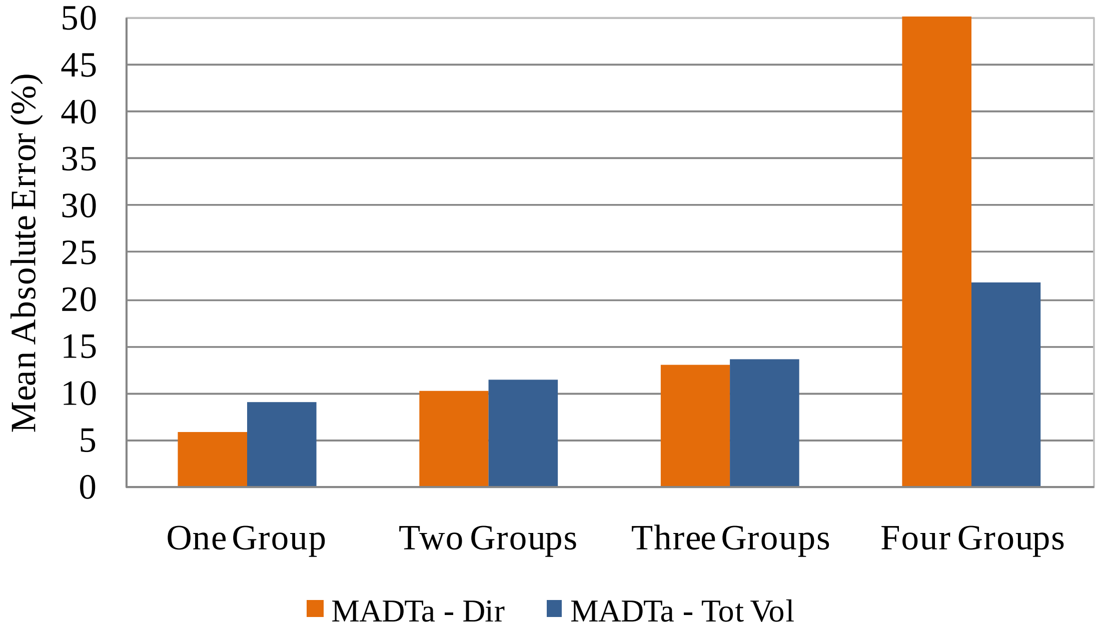

Figure 5.7. ATR directional analysis.

The second set of results compares the total analysis with the directional analysis. In general the methods produce similar mean absolute errors. In terms of the overall performance, the directional methods produces slightly lower mean absolute errors for one to three vehicle groupings, while the total directional method produces lower mean absolute error for more than three groups.

5.4.2 WIM Directional Analysis Results

The WIM analysis is performed in a similar manner as the ATR analysis. In these results, shown in Figure 5.8, there are two findings. The first finding shows that the mean absolute error for both the total and the directional is the lowest for one aggregate group. The mean absolute error increases with the addition of each group and the highest mean absolute error is associated with four vehicle groupings.

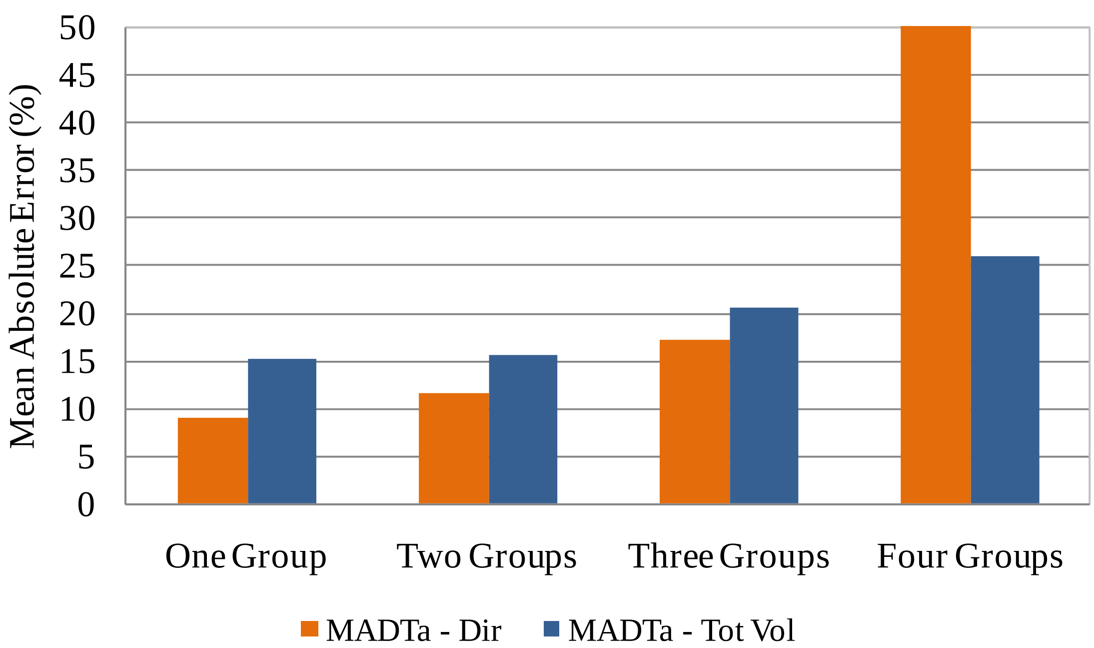

Figure 5.8. WIM directional analysis.

The second set of results is the direct comparison between the total and the per direction analysis. Similar to the ATR findings, the directional analysis produces slightly lower mean absolute errors when there are three or less vehicle groups. When the number of vehicle groups is greater than three, the total direction analysis should be used as it produces lower mean absolute errors.

5.4.3 Comparison and Summary of Findings for the Directional Analysis using the ATR and WIM Data Sets

In general the results for both the ATR and the WIM data sets produce similar findings. In the comparison between the total and the directional analysis, the directional analysis is slightly better for one to three groups, while the total direction produces slightly better results for more than three groups. One possible explanation is the impact of vehicle sample size as the number of aggregate groups increase. As a result of these findings and the volume of data provided within these data sets, the remaining analysis is developed on a per directional basis. Additional information used in the directional analysis are found in Appendix C.

5.5 Step Four: The Average SAFs for Vehicle Class Groupings based on Roadway Functional Classification

The fourth step of Chapter VI evaluates the average of the seven SAFs techniques for both individual and aggregated vehicle classification groupings for all the roadway functional classifications. The results are shown in Figures 5.9 and 5.10 for the ATR data set, while Figures 5.11 and 5.12 are the results for the WIM data set. In the following analysis, the Y-axis remains the mean absolute error, while the X-axis is the individual or aggregate vehicle classifications.

5.5.1 ATR Average Vehicle Classification and all Roadway Functional Classification Results

The results for the ATR data are shown in Figures 5.9 and 5.10. In the first figure, the total volume, which is an aggregate step for all the vehicles, produces the lowest mean absolute error. In terms of individual vehicle classes, vehicle class 2 and vehicle class 9 produce the lowest errors, while all the remaining individual vehicle classes produce mean absolute errors greater than 20 percent.

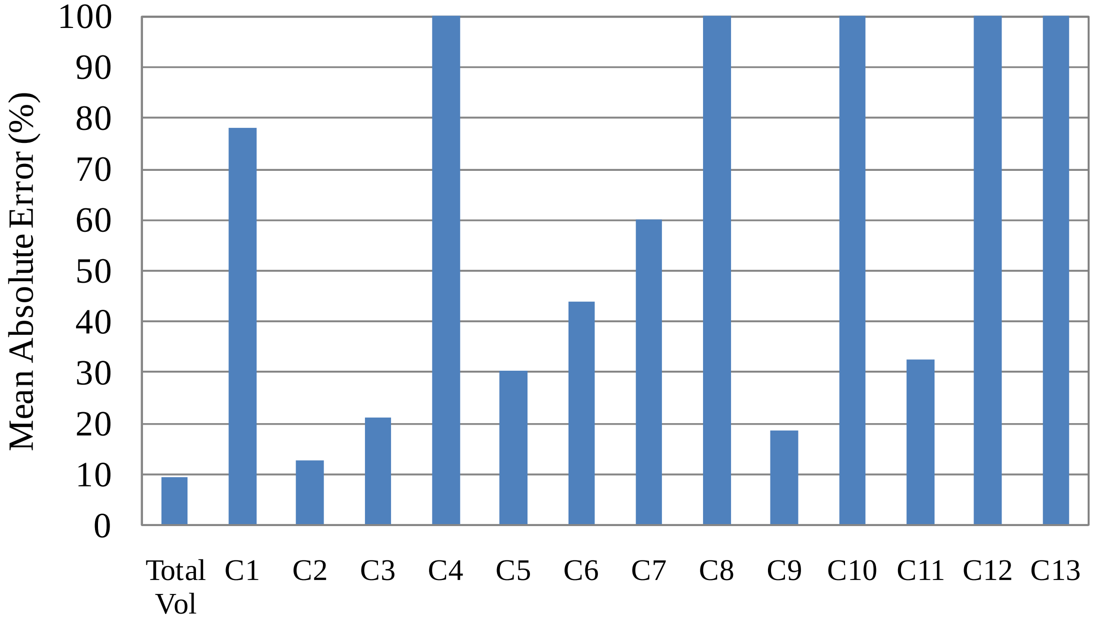

Figure 5.9. Average SAFs developed for all individual vehicle classes for all roadway functional classes using the ATR data set.

The vehicle classes with the highest mean absolute errors are vehicle classes 4, 8, 10, 12 and 13. In general, these results may be directly related to low sample sizes associated with these individual vehicle classes. One strategy that is suggested from the Traffic Monitoring Guide is to develop a series of groupings that are associated with the various heavy-duty vehicle classes. The groupings are based on the methodology that is described in Chapter IV. The mean absolute error results for these groupings are shown below in Figure 5.10.

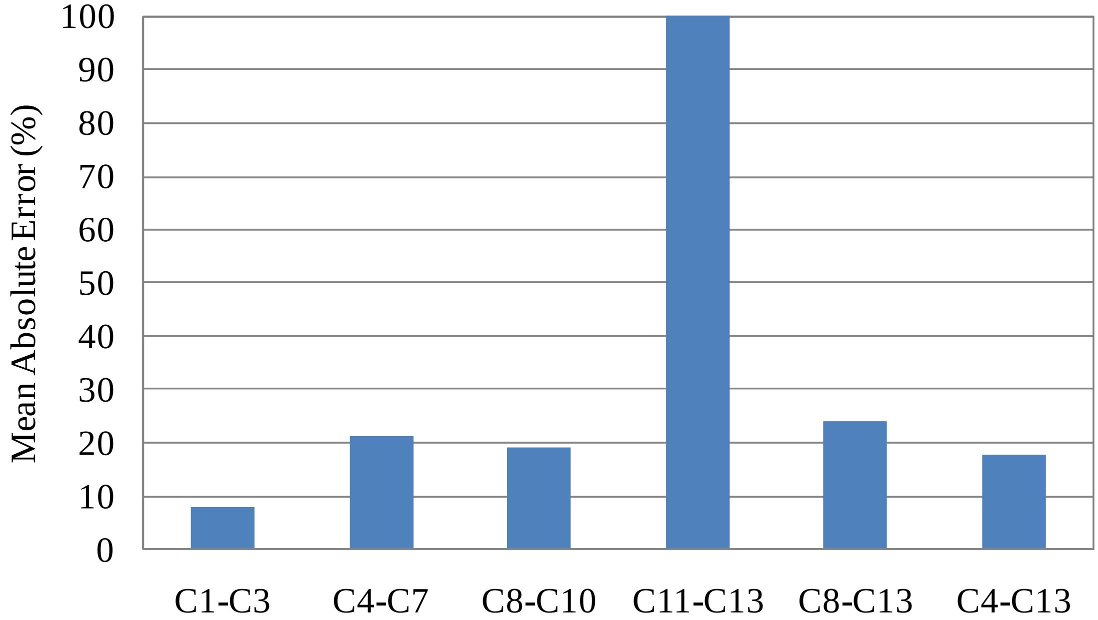

Figure 5.10. Average SAFs developed for aggregated vehicle classes for all roadway functional classes using the ATR data set.

In Figure 5.10, the individual vehicle groupings shown in column one include class 1 through 3, which represent motorcycles and passenger cars. This grouping produces the lowest average mean absolute errors. The second set of results is developed for both single trucks and trucks with trailers, and the final column, vehicle classes 4 through 13, is developed for all heavy-duty vehicles. The overall results show that grouping vehicle classes 11 through 13 together do not produce reliable results. In order to incorporate vehicle classes 11 through 13 into a group, two additional groups are developed for vehicle classes 8 through 13 and vehicle classes 4 through 13. Both aggregate groups produce more reliable results in terms of mean absolute errors. In general, the most accurate method for aggregating vehicle classes is to group separately the vehicle classes into one aggregate group for light-duty vehicles, classes 1 through 3, and a second group for heavy-duty vehicles, classes 4 through 13.

5.5.2 WIM Average Vehicle Classification and all Roadway Functional Classification Results

The second set of results is developed for the WIM data. The results from the WIM data are shown in Figures 5.11 and 5.12. In Figure 5.11, the results are developed for the individual vehicle classes. In Figure 5.11, the individual vehicle classes are grouped together as described in Chapter IV. The results for the individual classes show vehicle classes 2 and 3 are the only individual classes that produce mean absolute errors that are less than 20 percent. The lowest heavy-duty vehicles are classes 5, 8 and 9. In general, individual vehicle classes 1, 7, 10, 11, 12 and 13 are not stable as they produce mean absolute errors that are greater than 100 percent.

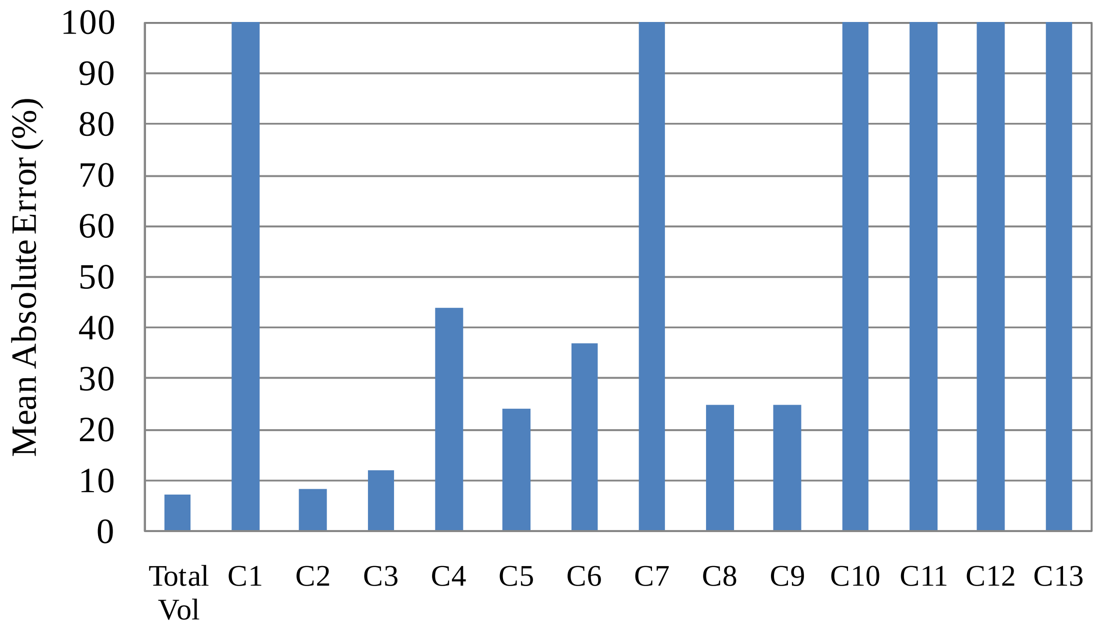

Figure 5.11. Average SAFs developed for all individual vehicle classes for all roadway functional classes using the WIM data set.

As a result of some of the high errors, which may be explained by the low sample size within each group, the vehicle classes are aggregated in a similar manner to those of the ATRs. The results for the nine vehicle class groupings are found in Figure 5.12. Similar to the ATRs, the light-duty vehicle classes produce the lowest mean absolute errors, while vehicle classes 11 through 13 and vehicle classes

11 through 15 have the overall highest error. In this set of results there is no added benefit for grouping vehicle classes 11 and greater together. In order to improve and lower the corresponding mean absolute errors, the higher vehicle classes need to be grouped with other vehicle classes. The best performing heavy-duty grouping is for vehicle classes 4 through 13. While this may be explained partially by the increase in sample size, it is interesting to note that the addition of vehicle classes 14 and 15 to the aggregated set increases the overall mean absolute error. This trend is also shown with vehicle classes 8 through 13 in comparison with vehicle classes 8 through 15. Based on these results, it is recommended that neither vehicle class 14 nor 15 be included in the most accurate heavy-duty aggregate data set.

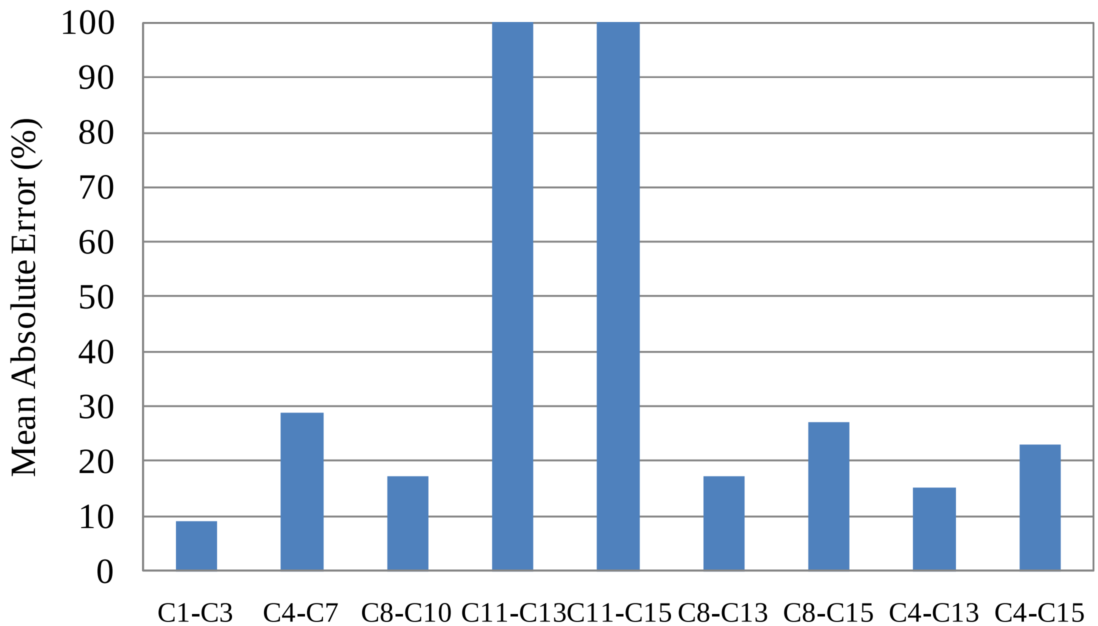

Figure 5.12. Average SAFs developed for aggregated vehicle classes for all roadway functional classes using the WIM data set.

5.5.3 Comparison and Summary of Findings for the Average Vehicle Classification for All Roadway Functional Classifications using the ATR and WIM Data Sets

The overall trends are similar in comparison between the ATR and WIM data sets. Individual vehicle classes with lower sample volumes do not perform as well as individual factor groupings. In these cases, the best groupings are developed for one light-duty grouping, vehicle classes 1 through 3 and a second heavy-duty grouping, vehicle classes 4 through 13. Other findings between the two groups show that the aggregated classes have slightly lower mean absolute errors for the WIM data set over the ATR data set.

5.6 Step Five: Individual SAFs for Vehicle Class Groupings per Roadway Functional Classification

In step five, the mean absolute errors are developed for each of the individual and aggregate vehicle classes for each roadway functional class. The results highlighted in step five of this chapter are developed for functional class 11 on a per direction basis. Figures 5.13 through 5.16 show the results for the ATRs and the WIMs. Figures 5.13 and 5.15 represent the individual vehicle classes, while Figures 5.14 and 5.16 represent vehicle class groupings. These groupings show the impact of dividing the results based on one of the seven methodologies used to develop SAFs. In each of these figures, the Y-axis is the mean absolute error and the X-axis represents the individual vehicle classes as described by FHWA. The results for each of these figures include the average mean absolute error associated with each of the seven groupings.

5.6.1 ATR Vehicle Class Grouping Results per Roadway Functional Classification

The results for the ATR data set are similar to the previous set of findings, Figure 5.9 and 5.10 with higher volume individual vehicle classes producing lower mean absolute errors. In this case, vehicle classes 2, 3, 8 and 9 all have mean absolute errors that are less than 20 percent, while other vehicle classes with lower volumes still have high mean absolute errors. Vehicle classes 1, 12, and 13 are greater than 100 percent mean absolute errors. Other findings of interest include roadway functional classification 11 produces lower mean absolute errors for vehicle classes 2, 3, 5, 8 and 9 when directly compared to the average of the seven methods for all roadways, as seen in Figure 5.9.

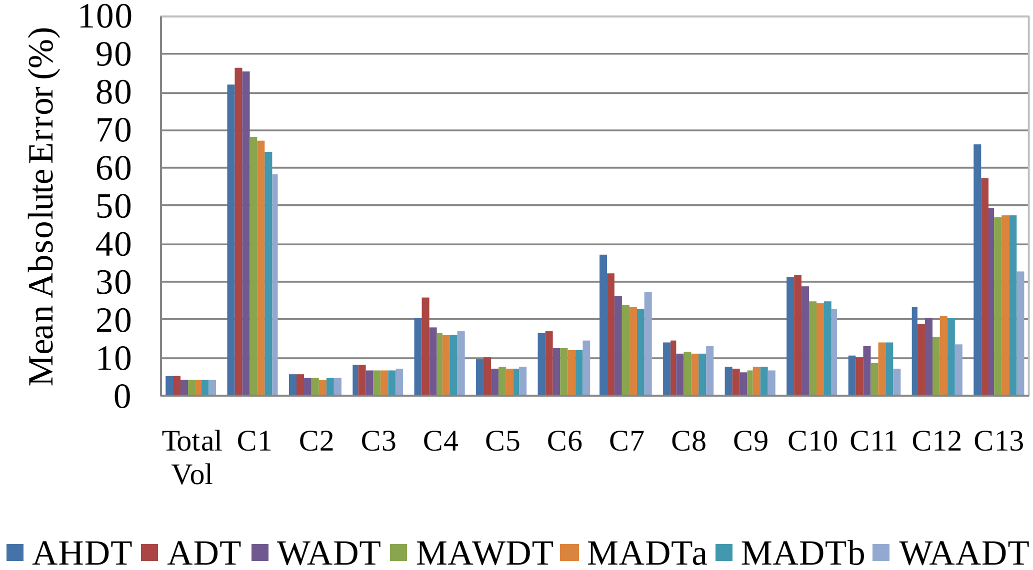

Figure 5.13. The individual SAFs developed for all individual vehicle classes for all roadway functional classes using the ATR data set.

This may be the direct result of the higher vehicle volumes or the product of more stable traffic throughout the analysis. In general, for the higher vehicle volumes, it seems the ADT method produces slightly higher mean absolute errors. A third findings of interest shows there is no single method that produces the overall lowest mean absolute errors across all 13 vehicle classes for all roadway functional classifications.

In the second set of analysis for the ATRs, the data are aggregated into multiple vehicle categories for both light-duty vehicle classes 1 through 3 and heavy-duty vehicle classes 4 through 13. The results for the aggregated vehicle classes are shown in Figure 5.14 for roadway functional class 11. In Figure 5.14, the light-duty vehicle grouping produces the lowest overall mean absolute error, less than 5 percent, while the vehicle class grouping for vehicles classes 11 through 13 has the highest mean absolute error. These results are similar to the overall findings shown in Figure 5.10.

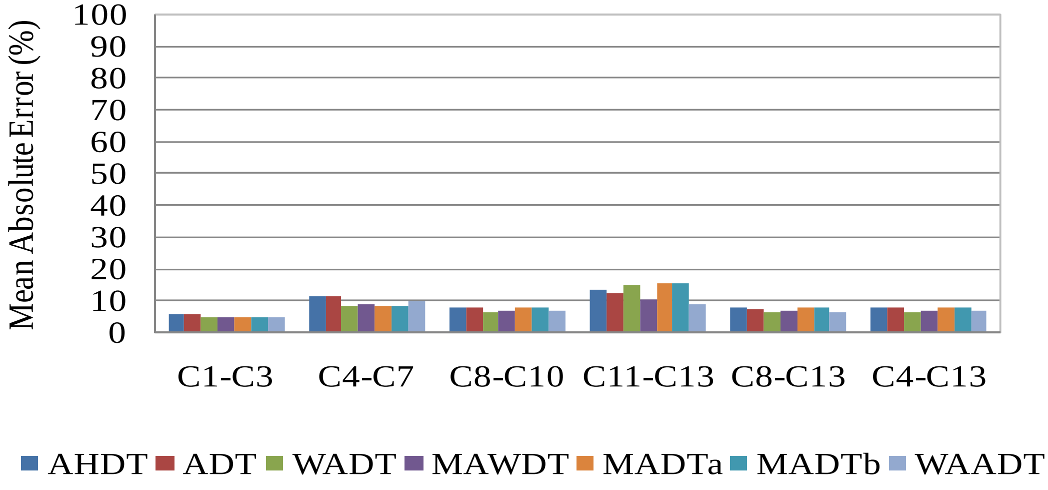

Figure 5.14. The individual SAFs developed for aggregated vehicle classes for all roadway functional classes using the ATR data set.

One additional result of interest is the comparison of the mean absolute errors between the average methods for all roadway functional classifications and the separation of the seven SAF methods in association with the individual roadway function classification, in this case functional class 11. In this comparison, the results in Figure 5.14 show the mean absolute error improves by 10 percent for the vehicle class groupings 8 through 10, 8 through 13 and 4 through 13, and vehicle classes 4 through 13 improve by approximately 5 percent.

5.6.2 WIM Vehicle Class Grouping Results per Roadway Functional Classification

The WIM results for the individual and the aggregate classes per roadway functional class are shown in Figures 5.15 and 5.16. These figures are developed in a similar manner as the preceding ATR results section. The results shown in Figure 5.15 are similar to the WIM results shown in Figure 5.11, with individual vehicle class 2 followed by vehicle class 9 producing the lowest mean absolute errors. In general, there is no one method that consistently produces the lowest mean absolute error. In the comparison of the results for the overall average of the seven methods for all roadway functional classes and the individual SAFs for roadway functional class 11, shown in Figure 5.15, the mean absolute errors are lower in Figure 5.15 as compared with Figure 5.11. In the case of the individual heavy-duty vehicle classes, there is significant improvement for vehicle classes 7, 10, 11 and 12.

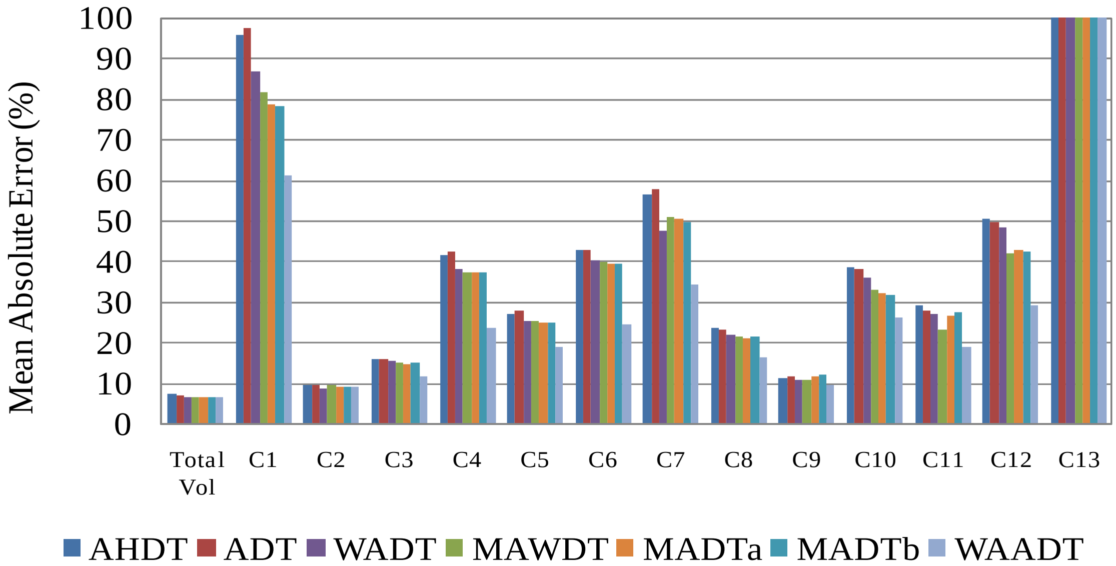

Figure 5.15. The individual SAFs developed for all individual vehicle classes for all roadway functional classes using the WIM data set.

In the second set of results, the vehicle classes are again aggregated based on light and heavy-duty vehicle classes in combination with the multiple factor groupings. Figure 5.16 shows the overall findings for the individual vehicle aggregate groupings for roadway functional class 11.

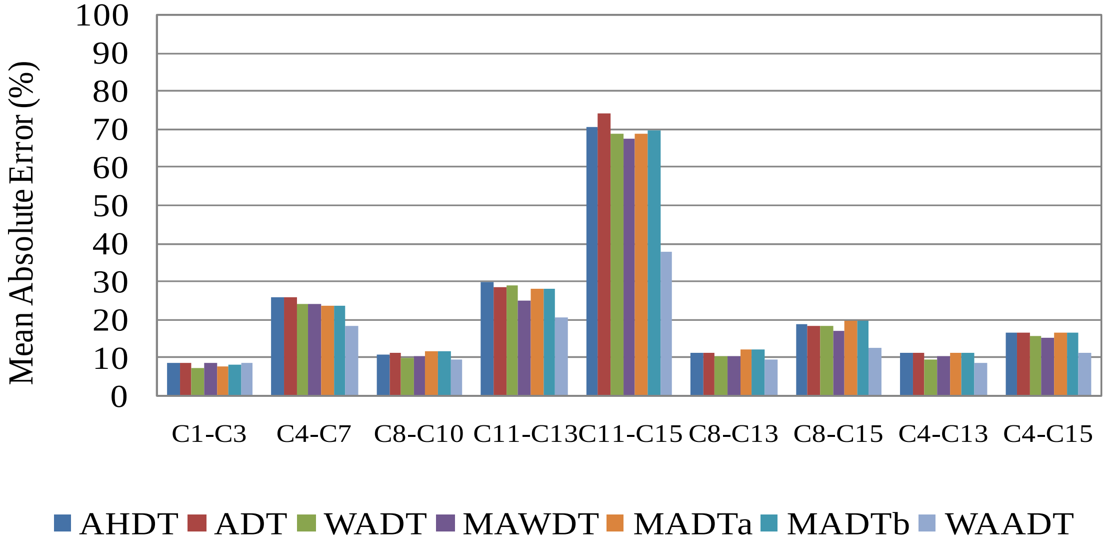

Figure 5.16. The individual SAFs developed for aggregated vehicle classes for all roadway functional classes using the WIM data set.

The results illustrated in Figure 5.16, with exception of vehicle class groupings 4 through 7 and 11 through 15, show that the seven methods produce similar mean absolute errors within 5 percent for each of the aggregated vehicle classes. Other findings are consistent with previous sections, which include the light-duty vehicles producing the lowest mean absolute errors. In terms of the heavy-duty vehicles, vehicle classes 8 through 10, 8 through 13 and 4 through 13 produce mean absolute errors around 10 percent. In general, the mean absolute errors increase with the addition of vehicle classes 14 and 15 within any aggregate group.

Other findings of interest are the direct comparison between the results shown in Figure 5.16 and Figure 5.12. In general, the mean absolute errors improve for all aggregate categories as the methods are divided in association with the selection of the individual roadway functional class. In Figure 5.12, the mean absolute error is greater than 100 percent for vehicle classes 11 through 13 and 11 through 15. The results shown in Figure 5.16 indicate that the mean absolute error improves to 30 percent for vehicle grouping 11 through 13, and vehicle grouping 11 through 15 improves to 70 percent. While these values are not ideal, the separation of the methods and the roadway functional classes produce better overall results for roadway classes with higher volumes.

5.6.3 Comparison and Summary of Findings for the Vehicle Class Groupings per Roadway Functional Classifications using the ATR and WIM Data Sets

The overall trends of the results are similar for both the ATRs and the WIM data sets for all functional classes. In these results, the individual vehicle classes have higher values of the mean absolute errors in comparison to vehicle groupings. Individual vehicle classes that perform relatively well are vehicle class 2, passenger cars, and vehicle class 9, standard semi-trucks. While other vehicles, such as vehicle class 1, motorcycles, have the largest mean absolute error. Other vehicles that do not perform well are vehicle classes 7, 10, 11, 13, 14 and 15. There are two potential explanations for these results. In all cases, these vehicles are less common and therefore the individual vehicle volumes are low. As a result of these low sample sizes, the mean absolute error increases substantially, especially when compared with more common vehicle types with high vehicle volumes. To increase the overall sample size, vehicle groupings should be considered to produce lower mean absolute errors. The results from these groupings, Figures 5.14 and 5.16, show that one vehicle grouping for trucks produces the lowest heavy-duty mean absolute error. In order to improve the overall mean absolute errors, it is recommended to aggregate the vehicle classes together. This recommendation is based on the trends found throughout all roadway functional classes.

5.7 Step Six: Selection of Multiple Factors

The development of multiple factor groupings, as seen in Tables 5.1 and 5.2 for the ATR and the WIM data sets, are based on the results from Figures 5.13 through 5.16 in combination with the corresponding standard deviations. The suggestions on the most effective SAFs are shown in Tables 5.1

and 5.2. In general, the factor groupings developed based on aggregated vehicle classes have lower mean absolute errors in comparison to the individual vehicle classes.

Table 5.1. SAFs for the ATR data set based on the lowest mean absolute errors and standard deviations per functional class.

ATR						
	FC1	FC2	FC7	FC11	FC12	FC14
Total Vol.	MAWDT MADTa	MAWDT MADTa	MAWDT MADTa	WADT MAWDT MADTa	WAADT	WADT MAWDT MADTa
Cars	MAWDT MADTa	MAWDT MADTa	MAWDT MADTa	WADT MAWDT MADTa	WAADT	WADT MAWDT MADTa
Trucks	WADT	MAWDT MADTa	WADT MAWDT MADTa	WADT MAWDT	WAADT	WAADT

Table 5.2. SAFs for the WIM data set based on the lowest mean absolute errors and standard deviations per functional class.

WIM						
	FC1	FC2	FC7	FC11	FC12	FC14
Total Vol.	WADT MAWDT MADTa	MADTa WAADT	WADT MAWDT MADTa	WADT MAWDT MADTa	MADTa WAADT	WADT MAWDT MADTa
Cars	WADT MADT WAADT	MADTa WAADT	WADT WAADT	WADT MAWDT MADTa	MADTa WAADT	WADT MAWDT MADTa
Trucks	WADT WAADT	WADT MADTa WAADT	WADT MAWDT MADTa	WADT MAWDT MADTa	MADTa WAADT	WAADT

In addition to the table results shown above, one final technique is developed within this section. The final technique is a multiple factor method which uses different adjustment factors for each functional class. The results for the directional analysis for both the ATR and the WIM data sets are shown in Tables 5.3 and 5.4. The purpose of the multiple factor method is to improve the overall mean absolute errors. The main disadvantages of using multiple SAFs versus a single SAF is the process of estimating AADT becomes more complicated and requires more computational time. The applicability of this approach is also limited since it may be combined with grouping permanent stations based on their functional classification. This approach, however, should be used cautiously if a combination of the two techniques, functional classification and clustering, is the next step of the analysis. The analysis described in this report is primarily focused on the factoring step of the traditional method of estimating AADT. Therefore the applicability and efficiency of the “multiple factor” approach should be examined in combination with the following steps of the analysis, “grouping” permanent stations and “assignment” of short-period counts to groups, with a thorough result-verification.

Table 5.3. Mean absolute error percent improvement for ATRs by using multiple factors instead of individual SAFs.

MAE Percent Improvement = MAE_i - $MAE_{MULTIIPLE\ FACTORS}$			
	MAE_{WADT} - $MAE_{M\ F.}$	MAE_{MAWDT} - $MAE_{M\ .F.}$	MAE_{MADT} - $MAE_{M.F.}$
One Group	0.772	0.472	0.341
Two Groups	2.585	2.211	1.990
Three Groups	3.927	3.367	3.025
Four Groups	>100	>100	<-100
Note: The column “Average Percent Reduction” is the average MAE percent difference between the examined groups for each scenario separately.			

The results for the ATRs are shown in Table 5.3. In Table 5.3, the more accurate AADT predictions are produced by applying different factors to each roadway functional classification. The analysis for the combined 13 vehicle classes, one group, results in the lowest errors in comparison to the other cases as expected. The improvement in mean absolute errors is higher when the number of groups increases. The results show improvement of 0.34 to 0.77 percent, one group, 1.99 to 2.58 percent, two groups and 3.02 to 3.92 percent, three groups.

The directional analysis using WIM data set yields similar results to the ATRs and is shown below in Table 5.4. The improvement of the AADT demonstrated by the mean absolute error is limited for the four types of vehicle groupings. The mean absolute error improves from 0.12 to 0.42 percent, one group, 0.29 to 0.92 percent, two groups and 0.04 to 0.75 percent, three groups.

Table 5.4. Mean absolute error percent improvement for WIMs by using multiple factors instead of individual SAFs.

MAE Percent Improvement = MAE_i - $MAE_{MULTIIPLE\ FACTORS}$			
	MAE_{WADT} - $MAE_{M.F.}$	MAE_{MAWDT} - $MAE_{M.F.}$	MAE_{MADT} - $MAE_{M.F.}$
One Group	0.125	0.424	0.242
Two Groups	0.292	0.913	0.928
Three Groups	0.751	0.455	0.041
Four Groups	>100	>100	>100
Notes: The column "Average Percent Reduction" is the average MAE percent difference between the examined groups for each scenario separately.			

It may be concluded that the use of multiple factors yields slightly lower errors than the use of one of the three individual factors, F_{WADT}, F_{MAWDT} and F_{MADT}. Potential classification of vehicle classes into four groups it is not recommended because the obtained errors do not allow for a precise estimation of AADT with errors greater than 100 percent.

5.8 Step Seven: The Impact of Monthly Parameters

In the seventh step, the mean absolute errors are developed based on the month in which the short-term count is collected. In Figures 5.17 and 5.18, the results are based on vehicle class grouping 4 through 13 on a per direction basis for roadway functional class 11. The results for the other vehicle groupings are similar. The purpose of this step is to define the optimum time of the year to collect short-term counts. In this set of results, the Y-axis remains the mean absolute error and the X-axis represents the month for the short-term data collection.

5.8.1 ATR Temporal Analysis for Monthly Short-Term Data Collection

Figure 5.17 shown below is developed for the ATR data set. The first result illustrates the influence of the individual roadway functional classes on mean absolute errors. In this case, roadway functional classes 12 and 14 produce the highest mean absolute errors throughout the year. The second set of results show for all roadway classifications, the months of November and December produce the highest estimates for the mean absolute errors. These high values may be the result of adverse weather in combination with holiday travel associated with Thanksgiving and the December holidays. The best months in terms of producing lower mean absolute errors include the months of March, May and July.

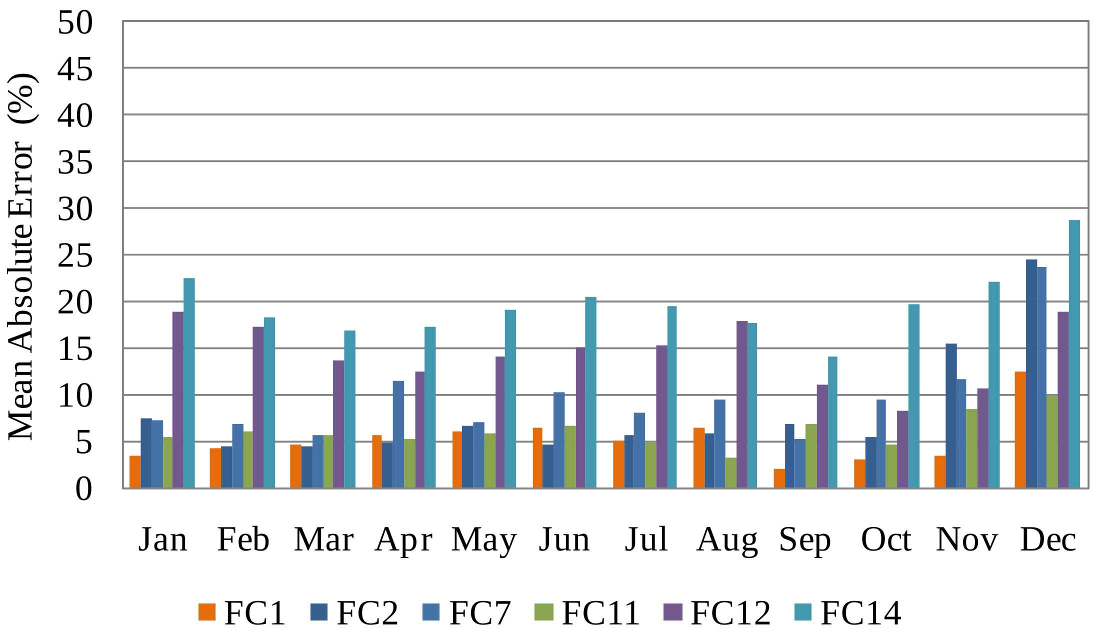

Figure 5.17. ATR temporal analysis for the monthly short-term data collection.

5.8.2 WIM Temporal Analysis for Monthly Short-Term Data Collection

In Figure 5.18, WIM results are the average for years 2003 to 2005. The results show roadway functional classifications 7 and 11 have the highest mean absolute errors, while roadway classes 1 and 12 in general have the lowest overall mean absolute errors. Other findings of significance show that the months of November and December, similar to the ATR data set, produce the highest mean absolute errors. Additional months with higher mean absolute errors include January and February. These results may be explained by the impact of adverse weather, holiday travel or another underlying trend. These results suggest truck SAFs should not be developed based on short-term sampling over the winter months.

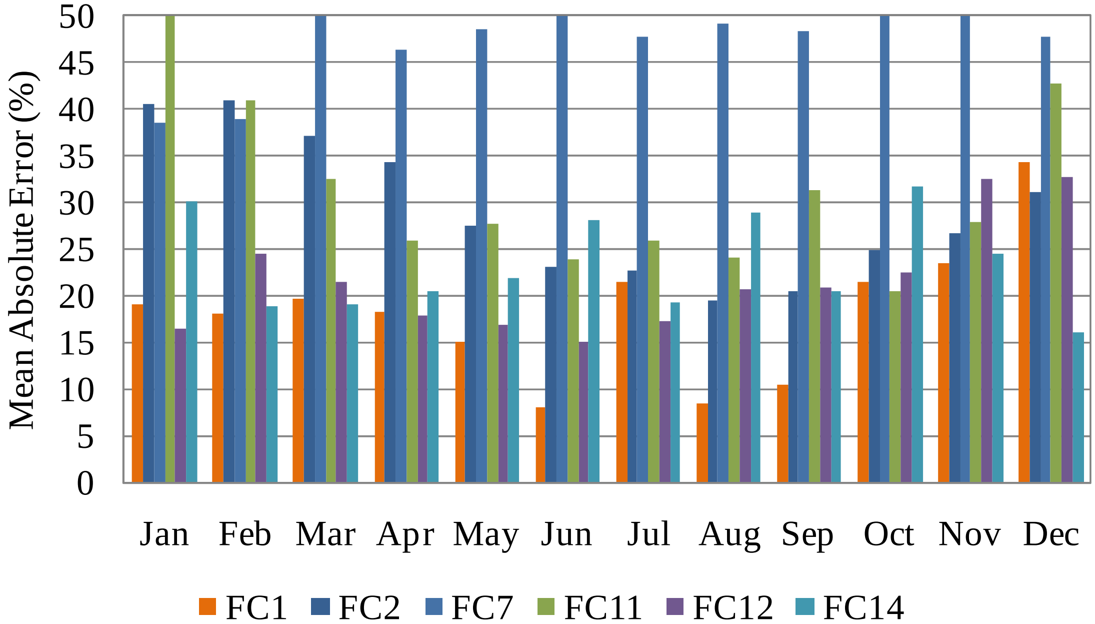

Figure 5.18. WIM temporal analysis for the monthly short-term data collection.

5.8.3 Comparison and Summary of Findings for the Temporal Analysis for Monthly Short-Term Data Collection using the ATR and WIM Data Sets

In the general, there are several comparisons that may be made between the ATR and the WIM data sets. The first comparison involves the selection of the highest and lowest producing mean absolute errors. In both cases, the worst months are November and December, while the summer months produce lower estimates for the mean absolute errors. Other comparisons show that there are no consistencies with the overall best individual roadway functional classification. This may be the result of the number of permanent stations or some other potential underlying trend within the data set. The final comparison is the magnitude of the mean absolute errors. The results show that the ATR data set in general produces mean absolute errors that are 20 percent less than the corresponding WIM data set.

5.9 Step Eight: The Impact of Day of the Week and Short-Term Duration

The second temporal analysis of the short-term counts is developed for the day of the week and the duration of the sample. In this step mean absolute errors are developed for Mondays through Thursdays as well as 24, 48, 72 and 96-hour sampling intervals. The vehicle groupings as well as the roadway functional classification remain consistent with previous sections. The results from this analysis are shown in Figures 5.19 and 5.20. In these figures, the Y-axis remains the mean absolute error and the X-axis represents the sampling duration and corresponding days of the week. The X-axis increases from short-term 24 hour duration on the left side of the figures to a 96-hour duration on the right side of the figures. The results are then separated by roadway functional class and the average of all functional classes.

5.9.1 ATR Temporal Analysis for Day of the Week and Sampling Duration for the Short-Term Data Collection

Figure 5.19 shows the results for the ATR data set. There are several findings of interest within this figure. The first finding suggests that roadway functional classes 12 and 14 regardless of sampling day and duration have the highest overall mean absolute error, greater than 15 percent. The second result is the overall comparison between the sampling days. In this result, the highest mean absolute errors occur for the 24-hour sampling duration on Monday, while the other three 24-hour sampling durations appear to have similar results.

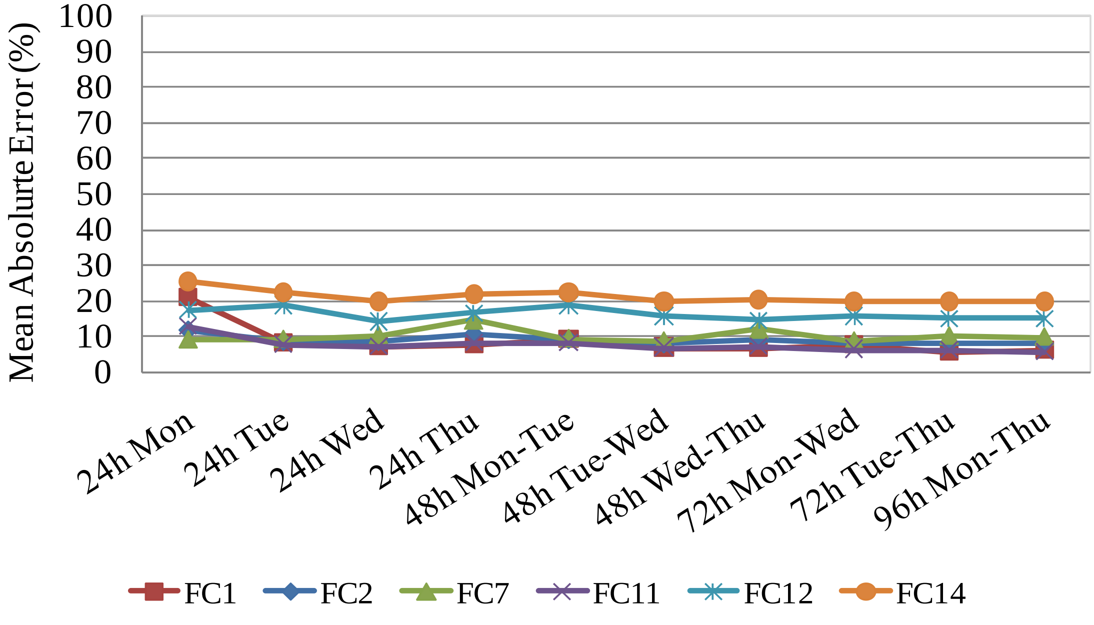

Figure 5.19. ATR temporal analysis for day of the week and sampling duration.

In terms of the day of the week selection for the 48-hour duration, the results show the 48-hour counts using Mondays have the overall highest mean absolute errors, while the other two 48-hour counts sample intervals are relatively similar in magnitude. For the 72-hour sampling duration, the results show that both sampling intervals produce the same values and, therefore, there is no adverse impact from sampling on Mondays. The overall findings within Figure 5.19 suggest when using Monday counts, the most optimal short-term sampling duration should be 72 hours in length. The final results from Figure 5.19 are the comparison of the overall sampling lengths. These results compare the overall impact of 24-hour counts versus 48, 72 and 96-hour counts. The lowest producing mean absolute error sampling interval occurs for the 96-hour sampling interval.

5.9.2 WIM Temporal Analysis for Day of the Week and Sampling Duration for the Short-Term Data Collection

The results for the WIM day of the week and duration of the sampling are shown below in Figure 5.20. The results show, with the exception of roadway functional classification 8, Mondays have the highest 24-hour mean absolute errors. Tuesdays and Thursdays have slightly lower mean absolute errors and Wednesdays have the lowest errors for the 24-hour duration. Similar to the ATR results, the 48 hour sampling duration with Mondays included has the highest mean absolute error associated with that particular sampling interval. When the sampling interval is increased to 72 hours, there are no adverse effects from sampling on a Monday. In comparing the 24, 48, 72 and 96 sampling duration, the 24-hour samples in general have the highest mean absolute errors followed by the other durations. In these results there seems to be no significant benefit in sampling longer than 48 hours in duration.

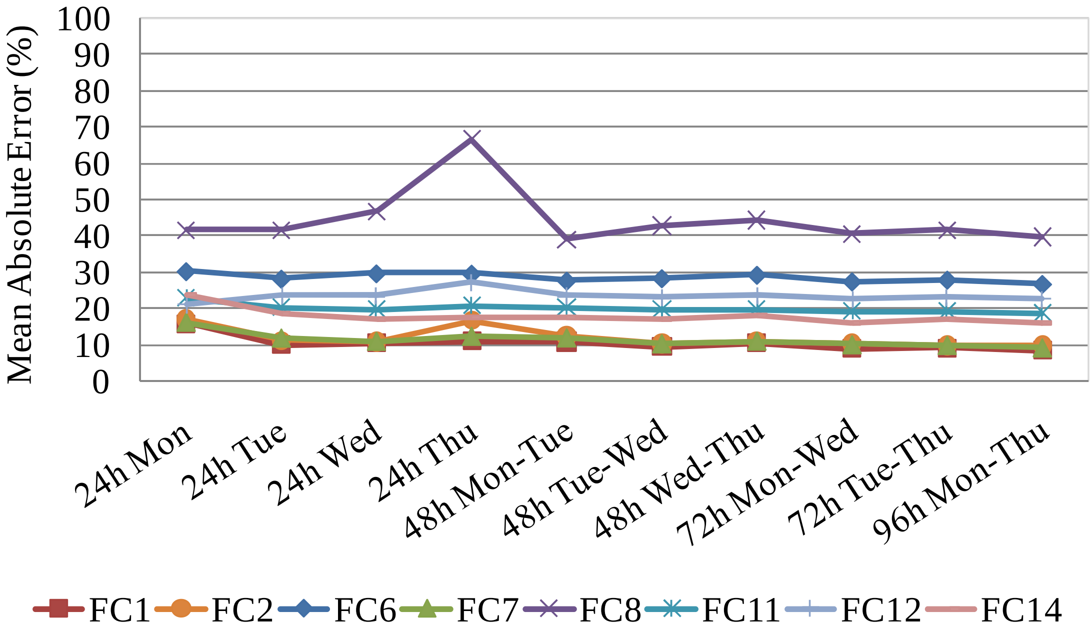

Figure 5.20. WIM temporal analysis for day of the week and sampling duration.

5.9.3 Comparison and Summary of Findings for the Day of the Week and Sampling Duration for the Short-Term Data Collection using the ATR and WIM Data Sets

The overall results from this analysis show the 24-hour durations produce the highest mean absolute errors, followed by 48-hour and then 72-hour sampling durations. In general, the largest change in the mean absolute error occurs between the 24 and the 48-hour counts. Comparing the 48-hour counts and the longer durations, there is little improvement in the mean absolute errors. In addition to the sampling duration, the day of the week also influences the increase or decrease of the mean absolute error. The overall findings from this show that Mondays, in general, produce the highest mean absolute errors. Tuesdays and Thursdays have slightly lower mean absolute errors and Wednesdays have the lowest errors of the week. The above findings are consistent with past research results. Thomas (1997) studied temporal and spatial variations in vehicle composition and truck volumes. He concluded that truck volume and truck type distribution vary temporarily and spatially from one location to another. Moreover, temporal patterns of total traffic are significantly different than the corresponding patterns of truck volumes. In 2002, Sharma investigated the reliability of daily truck estimates in conjunction with frequency, timing and duration of short-term counts. One of the findings is that longer counts are subject to smaller variations in traffic volume; therefore, they are likely to produce more accurate AADTs. It was also found that longer counts don’t necessarily result in better estimates than carefully selected schedules of shorter counts. Erhunmwunsee (1991) in a similar study found that the best period to begin a short-term count is the period that has its midpoint centered at 3 P.M. It was also indicated that longer length of counts results in more accurate estimates.

5.10 Summary of Results

This section presents the findings from the previous analysis conducted for the seasonal adjustment factors.

5.10.1 Five AADTs

Five methods are used for the calculation of the AADTs. According to the findings, all five methods produce similar results across each of the seven SAFs for both the ATR and WIM data sets. The first method, AADTa, produces slightly better results for both ATR and WIM data sets.

5.10.2 Temporal Stability

The temporal analysis, conducted for each of the seven techniques, reveals similarities between the ATR and WIM data sets. In most cases, with the exception of two factors, F_{AHDT} and F_{WADT}, the remaining mean absolute errors are similar for both the January and July sampling periods.

5.10.3 Directional Analysis versus Total Volume

The comparison between the directional and the total volume analysis show the directional analysis is slightly better when one or three vehicle groups are examined, while the total direction produces slightly better results for four vehicle groupings. One possible explanation is the impact of vehicle sample size. As the number of aggregate groups increases the sample size decreases and the total volume analysis can reflect better the traffic variation.

5.10.4 Vehicle Class Groupings per Roadway Functional Classifications

The overall vehicle class groupings per roadway functional classification are similar for both the ATR and the WIM data sets for all functional classes. In these results, the individual vehicle classes have higher values of the mean absolute errors in comparison to aggregate vehicle classes. Relatively accurate AADT predictions are obtained by applying SAFs to vehicle class 2, passenger cars, and vehicle class 9, standard semi-trucks, while other vehicles, such as class 1, motorcycles, result in the largest mean absolute errors. Other vehicles that did not perform well are vehicle classes 7, 10, 11, 13, 14 and 15. There are two potential explanations for these results. In all cases, these vehicle classes carry less traffic than the other heavy traffic classes and therefore the individual vehicle volumes are low. The small sample size usually results in an increased mean absolute error especially when compared with more common vehicle types with larger sample sizes. This indicates the vehicle groupings with higher traffic volume should be considered in order to produce lower mean absolute errors. The results from the analysis show that one vehicle grouping for trucks produces the lowest heavy-duty mean absolute error.

5.10.5 Multiple Factors

According to the results, the use of multiple factors yields slightly lower errors than the use of the three individual factors, F_{WADT}, F_{MAWDT} and F_{MADT}. The mean absolute error increases when the number of the examined groups increases and the potential classification of vehicle classes into four groups is not recommended for directional analysis.

5.10.6 Temporal Analysis for Monthly Short-Term Data Collection

There are several temporal comparisons that may be made between the ATR and the WIM data sets. The first comparison involves the selection of the highest and lowest producing mean absolute errors. In both cases, the worst months are November and December, while summer months produce lower estimates for the mean absolute errors. Other comparisons show that there are no consistencies with the overall best individual roadway functional classification. This may be the result of the number of permanent stations or some other potential underlying trend within the data set. The final comparison is the magnitude of the mean absolute errors. The results show that the ATR data set in general produces mean absolute errors that are 20 percent less than the corresponding WIM data set.

5.10.7 Day of the Week and Sampling Duration for the Short-Term Data Collection

The overall results from the day of the week and duration of the short-term data collection analysis show 24 hour durations produce the highest mean absolute errors, followed by 48-hour and then 72-hour sampling durations. In general, the largest change in the mean absolute error occurs between the 24 and the 48-hour counts. When comparing the 48-hour counts to the longer durations, there is little improvement in the mean absolute errors. In addition to the sampling duration, the day of the week also influences the increase or decrease of the mean absolute error. The overall findings show Mondays, in general, produce the highest mean absolute errors Followed by Tuesdays and Thursdays. Wednesdays have the lowest errors of the week.

CHAPTER VI

DEVELOPMENT OF FACTOR GROUPINGS

6.1 Introduction

Chapter VI of this research report describes the methodology used in the third step of the traditional method for estimating AADTs for both the ATR and WIM data. The main objective within this chapter is the development of eight methods for grouping/clustering the individual seasonal adjustment factors. There are several ways of grouping the SAFs. The most traditional way of grouping the data is by roadway functional classification or geographical location. In addition to these techniques the TMG (Section 4, 2001) recommends the use of cluster analysis. Cluster analysis is a statistical technique that groups data with similar pattern variations. More sophisticated cluster techniques include incorporating geographical or roadway functional class. To account for the various methods for grouping the data, eight methods are developed for the ATR and WIM stations for each year individually. The first four methods are the more traditional ways for grouping data, while Methods Five through Eight are more sophisticated using cluster analysis in concert with roadway, geographical, or both in the case of Method Eight. These methods include:

- Method One: Functional Classification (12 FCs);
- Method Two: Functional Classification based on new HPMS guidance;
- Method Three: Geographical Classification:
    - North / South;
    - East/ West;
    - Northeast / Northwest / Southeast / Southwestern / Central;
    - Urban / Rural;
- Method Four: Functional and Geographical Classification;
- Method Five: Cluster Analysis;

- Method Six: Functional Classification with Cluster Analysis;
- Method Seven: Geographical Classification with Cluster Analysis; and
- Method Eight: Functional, Geographical Classification with Cluster Analysis.

6.1.1 Division of the Data

The data provided and used within the eight methods is initially divided into three categories which is consistent with previous chapters. These categories include vehicle classification, direction of travel and temporally on an annual basis. The division of the vehicle classification is subdivided into total vehicle volumes for 3-Cards, total vehicle volumes for C-Cards, vehicle classes 1 through 3, light-duty and vehicle classes 4 through 13, heavy-duty. The second division of the data is directionally, total directional volumes and per directional volumes. The division of the data provides a comprehensive data set that will highlight the strengths and weakness associated with each option.

6.2 Method One: Functional Classification

The first method is the most traditional method, grouping the data based on stations with the same roadway functional classification. This method is currently used by ODOT as well as many other DOTs. There is one main challenge with this method. The number of full-time continuous counters is limited for some roadway functional classes, for example local roads. As a result of these limitations there may be some difficulty in populating some of these groupings. The groupings in Method One are based on the following functional classes:

- FC 01 – Principal Arterial Interstate (Rural);
- FC 02 – Principal Arterial - Other (Rural);
- FC 06 – Minor Arterial (Rural);
- FC 07 – Major Collector (Rural);
- FC 08 – Minor Collector (Rural);

- FC 09 – Local (Rural);
- FC 11 – Principal Arterial – Interstate (Urban);
- FC 12 – Principal Arterial – Other Freeways and Expressway (Urban);
- FC 14 – Principal Arterial – Other (Urban);
- FC 16 – Minor Arterial (Urban);
- FC 17 – Collector (Urban); and
- FC 19 – Local (Urban).

6.3 Method Two: Functional Classification based on new HPMS guidance

In the second method, the new HPMS guidance on merging the rural/urban classifications is implemented. The new functional classes according to HPMS are defined as follows:

- FC 01 – Interstate;
- FC 02 – Other Freeways and Expressways;
- FC 03 – Other Principal Arterial;
- FC 04 – Minor Arterial;
- FC 05 – Major Collector;
- FC 06 – Minor Collector; and
- FC 07 – Local.

6.4 Method Three: Geographical Classification

The third method groups the data geographically/spatially. One of the strengths or rationales for dividing the data geographically is the ability to capture driver related patterns that are associated with local driver characteristics. The final selection of the borders is based on the US census information. In all cases the division of the data occurs at the county line. Additional geographical classifications may be based on latitude/longitude values or roadways. These methods of grouping data are not explored within this study. The final distribution of sites includes:

- North and south;
- East and west;
- Northeast, northwest, southeast, southwest, central; and
- Urban and rural.

The results from this stratification of the data are shown in Figures 6.1 through 6.4.

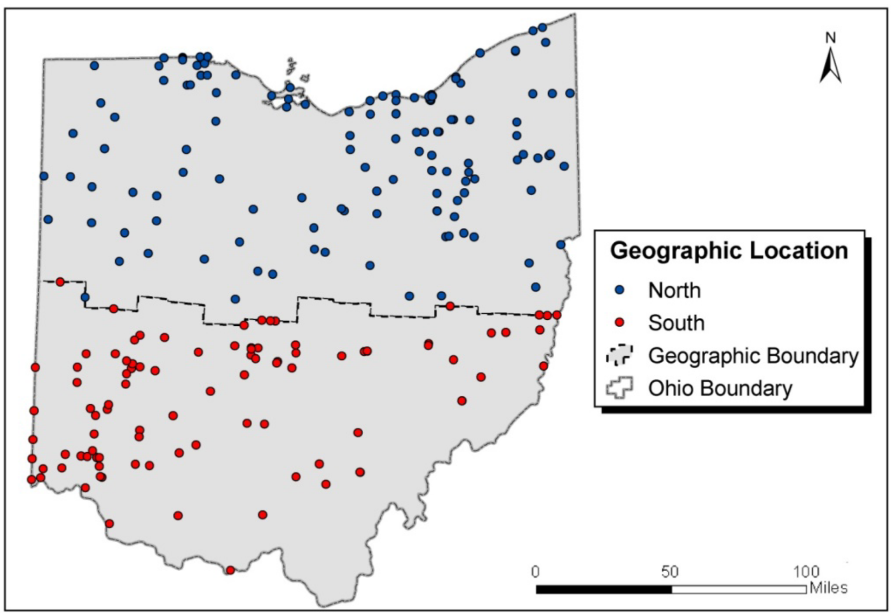

Figure 6.1. North and south geographical areas.

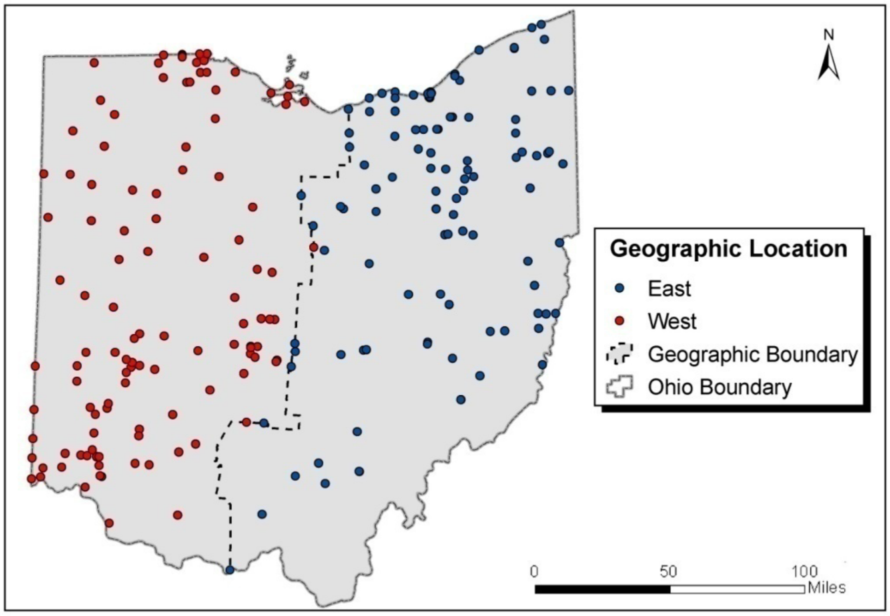

Figure 6.2. East and west geographical areas.

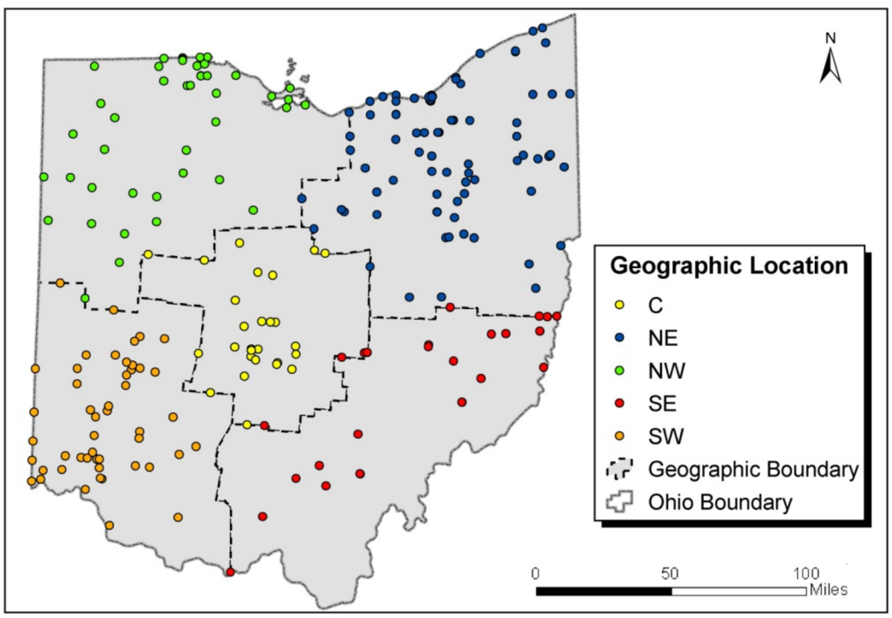

Figure 6.3. Northeast, northwest, southeast, southwest and central geographical areas.

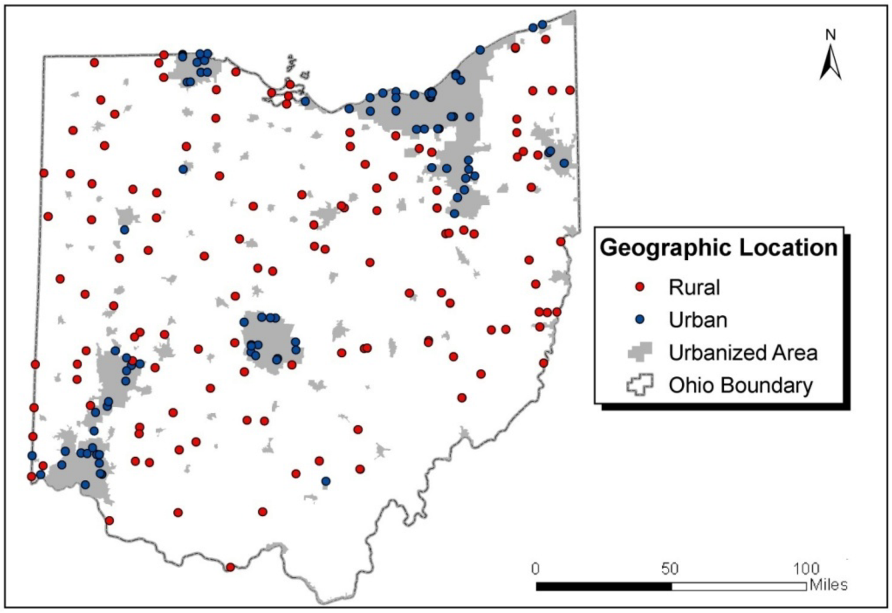

Figure 6.4. Urban and rural geographical areas.

6.5 Method Four: Functional and Geographical Classification

The fourth method for grouping, shown in Figure 6.5, is the combination of both the roadway functional classification and the geographical location.

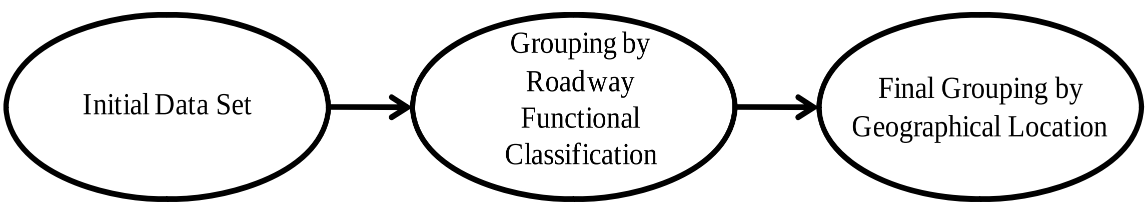

Figure 6.5. Flowchart used with Method Four.

In this method, each group is initially divided into one of the roadway functional classes described in Method One. Once divided, the groups are further subdivided into geographical areas as described in Method Three. For example, all roadway functional class one data are grouped together, next the data are separated again into two subgroups, one for northern and the second for southern Ohio. In Method

Four there are 12 roadway classes, four geographical areas, four vehicle groupings and two directional inputs. In this method, all combinations are included which corresponds to 384 data points per year.

6.6 Method Five: Cluster Analysis

Method Five is the first method that involves clustering as a means of grouping the volume data. In this method the data are clustered solely based on volume patterns. Clustering includes a number of algorithms and methods. It mainly consists of hierarchical and partition clustering (Eisen et al., 1998). Hierarchical clustering may include a number of algorithms such as Ward's, the average linkage, the complete linkage algorithm and the centroid algorithm (Faghri et al., 1995). Partition clustering uses the *k*-means cluster algorithm, is shown in Equation 6.1. The software program SPSS 16.0 is used with the *k*-means cluster algorithm to create groups of permanent stations. Equation 6.1 is shown below:

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} \left(x_j - \mu_i \right)^2 \qquad (6.1)$$

where:

J = intra-cluster variance,

k = total number of clusters produced from cluster analysis,

S_i = i= 1, 2, ….., k,

x_j = data point,

μ_i = centroid of all the points $x_j \in S_i$, and

$\left(x_j - \mu_i \right)^2$ = is a distance measure (Hartigan et al., 1979).

This algorithm attempts to identify relatively homogeneous clusters of stations based on the twelve monthly average factors. The *k*-means algorithm assigns each ATR to a cluster whose center is the nearest. The algorithm starts with *k* number of clusters and then moves factors between clusters. The optimal goal is to minimize variability within clusters and maximize variability between clusters. The *k*-means algorithm attempts to move the factor data into and out of clusters in order to get the most significant ANOVA results. The cluster membership, distance information, analysis of variance, F statistics and final cluster centers are then saved as an output. The algorithm forms clusters and the estimated statistics provide information about each variable's contribution to the discrimination of the clusters.

6.7 Method Six: Cluster Analysis with Roadway Functional Classification

The sixth method, shown in Figure 6.6, is similar to Method Five with one additional step. Unlike Method Five which clusters the entire state, the data are initially divided based on the roadway functional classification. Once the data are divided, the cluster algorithm is performed per roadway functional classification, Method One.

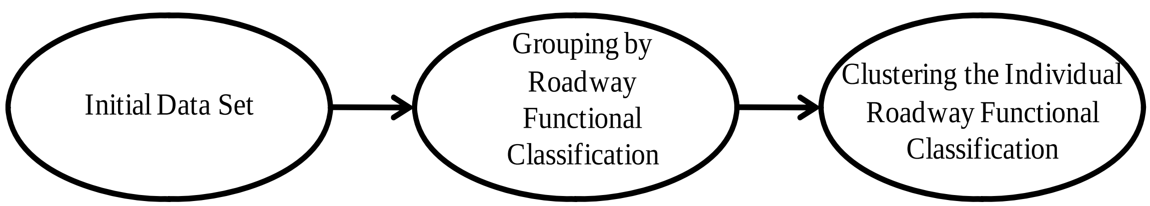

Figure 6.6. Flowchart used with Method Six.

One of the advantages of this technique is the potential simplification for assigning short-term counts to each cluster group. There is one main disadvantage for this method. In some cases there is limited amount of stations and therefore it may be difficult to adequately populate each group.

6.8 Method Seven: Cluster Analysis with Geographical Classification

The seventh method for clustering the data is similar to Method Five with one additional step for the geographical/spatial location. In Method Seven, Figure 6.7, the clustering is based on one of the five geographical locations that are described in Method Three.

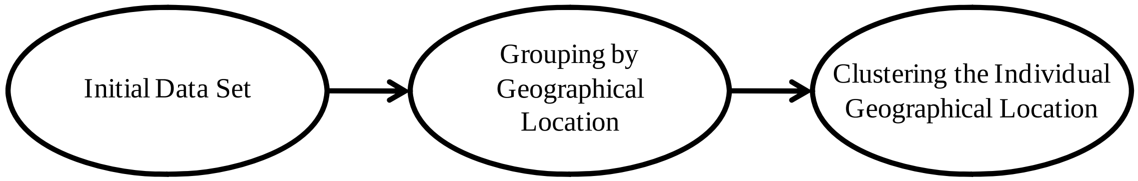

Figure 6.7. Flowchart used with Method Seven.

This method is selected to provide additional statistical evaluation and clustering of the regional driving behaviors across the state. Similar to Method Six, in some cases there is limited data and some groups are too small to be accurately populated.

6.9 Method Eight: Cluster Analysis with Roadway Functional and Geographical Classifications

Method Eight is the final cluster method. In this method, as shown in Figure 6.8, the clustering is based on dividing the data first by roadway functional class, Method One, and then by geographical/spatial location, Method Three, and lastly clustering within the subset of the data.

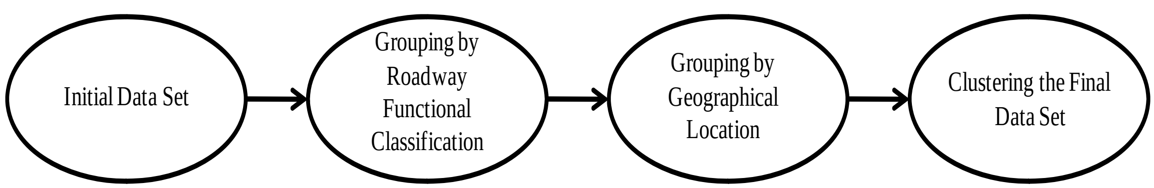

Figure 6.8. Flowchart used with Method Eight.

These results show these clustering groups provide both regional and roadway influences. Similar to Methods Six and Seven, the stratification of the data both geographically as well as roadway functional class limits the overall sample size of the clustering.

6.10 Evaluation of the Methods

Once the data are grouped using one of the eight methods described previously, the next step is to develop a series of statistical performance measures to evaluate the effectiveness of each method. Based on previous research (Faghri et al., 1995; Erhunmwunsee, 1991; French et al., 2001; Zhao et al., 2004), this study compares the variance, Equation 6.2, the standard deviation, Equation 6.3, and the weighted coefficient of variation, Equation 6.4. The average variance is defined as

$$AVar = \frac{\dfrac{\sum_{m=1}^{12}\left(x_{i,m,c} - \bar{x}_{m,c}\right)^2}{n_{m,c} - 1} \times n_{m,c}}{\sum_{m=1}^{12} n_{m,c}} \tag{6.2}$$

the average standard deviation is defined as

$$AStD = \frac{\sqrt{\dfrac{\sum_{m=1}^{12}\left(x_{i,m,c} - \bar{x}_{m,c}\right)^2}{n_{m,c} - 1}} \times n_{m,c}}{\sum_{m=1}^{12} n_{m,c}} \tag{6.3}$$

and the weighted coefficient of variation is defined as

$$ACoV = \frac{\left(\sqrt{\frac{\sum_{m=1}^{12}\left(x_{i,m,c} - \bar{x}_{m,c}\right)^2}{n_{m,c} - 1}} \times 100 \times n_{m,c}\right) \times \frac{1}{\bar{x}_{m,c}}}{\sum_{m=1}^{12} n_{m,c}} \qquad (6.4)$$

where:

m = month of year. January is the first (m=1) and December the last month (m=12),

c = number of sample groups for all eight methods,

$x_{i,m,c}$ = factor for station *i,* month *m* and groups *c,*

$\bar{x}_{m,c}$ = mean factor for month *m* and groups *c,* and

$n_{m,c}$ = number of factors in month *m* and groups *c.*

The monthly weekday factors are dimensionless as are the variance and the coefficient of variation.

6.11 Selection of the Optimum Number of Clusters

The difficulty in determining the optimum number of clusters is one of the main disadvantages of cluster analysis (TMG, 2001) and there is limited research in this area. The methodology proposed in this study is based upon the following criteria, derived from recommendations and findings of past research:

- Criterion One: Each cluster should contain five to eight ATRs, ideally (TMG, 2001);
- Criterion Two: A maximum precision of 10% with 95% confidence for each individual cluster is recommended (TMG, 2001); and
- Criterion Three: New cluster groupings should be determined on a yearly basis, creating stability within each group over time (Zhao et al., 2004; Zhao et al., 2008).

Selecting the optimum number of factor groupings within each cluster is required for Methods Five through Eight and the overall approach is the same. The recommended approach to determine the optimum number of clusters is illustrated in Figure 6.9 and includes the following steps.

6.11.1 Step One

In the first step the data set is grouped geographically and/or functionally into *m* subsets in order to take into consideration the underlying characteristics associated with a geographical area of a roadway functional class.

6.11.2 Step Two

In the second step the cluster analysis algorithm is implemented for each subset of the data. Initially, all ATRs are placed into one group, and then two clusters are created. The maximum number of clusters increases sequentially until a maximum number of clusters is reached. The maximum number is set equal to *n/5* where *n* is the number of ATRs in a data set. The number five is selected as the denominator based on the first criterion stated above. As a result, *n/5* analyses are conducted for each data set and the j^{th} analysis includes *j* clusters. For example if a data set consists of 40 ATRs, the first cluster analysis (j=1) consists of 1 cluster, the second analysis consists of two clusters (j=2), whereas the eighth and last analysis (j=40/5=8) forms eight clusters.

6.11.3 Step Three

Afterwards, a minimum number *k* ATRs within a cluster is established for all analyses, allowing consistency within the methodology. Each ATR in the clusters, having fewer stations than the minimum, typically two to three ATRs, are then relocated to other groups of the same analysis-type. For example if the first cluster of the eighth analysis includes two ATRs then the cluster is deleted by moving each ATR to one of the remaining seven clusters of the analysis. The relocation of the ATRs is based on the following three steps.

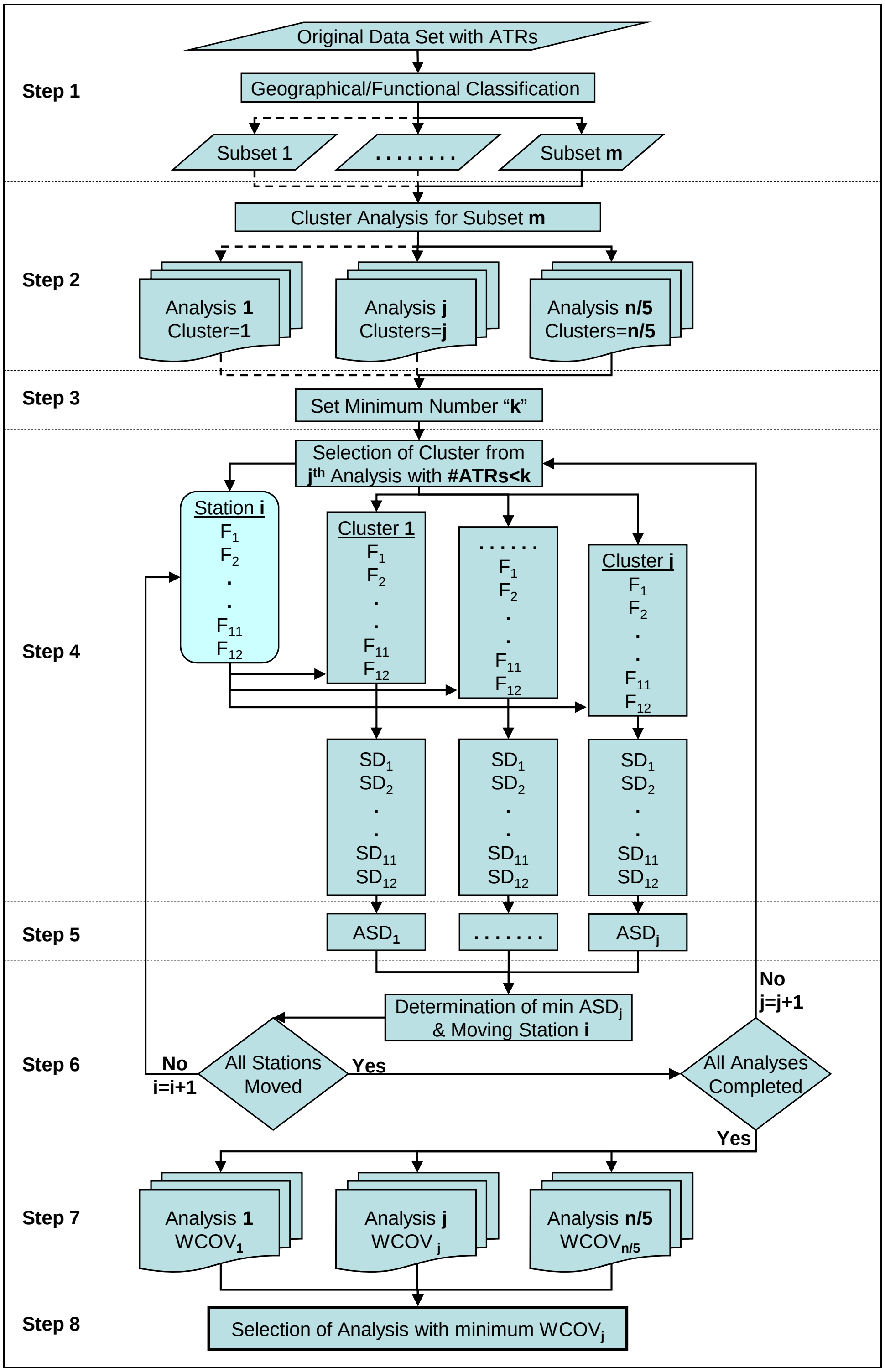

Figure 6.9. Illustration of the process for selecting the optimum number of clusters.

6.11.4 Step Four

In step four, the individual ATRs are compared with each of the cluster groups. The objective within step four is to create as many clusters as possible with low standard deviations within each individual clusters. The standard deviation (SD) used within step four is shown below in Equation 6.5.

$$SD_{i,m,c,j} = \left(\sqrt{\frac{\left(F_{i,m,j} - \overline{F}_{m,c,j}\right)^2}{2}} \right) \tag{6.5}$$

where:

$SD_{i,m,c,j}$ = standard deviation for month *m* between station *i* and cluster *c* of the j^{th} analysis,

$F_{i,m,,j}$ = monthly factor for station *i* and month *m* of the j^{th} analysis, and

$\overline{F}_{m,c,j}$ = group mean factor for month *m* and cluster *c* of the j^{th} analysis.

6.11.5 Step Five

In the fifth step the Average Standard Deviation (AStD), Equation 6.3, for all 12 monthly standard deviations is calculated by moving the ATR into and out of each of the clusters. The AStD captures the percent difference of the annual traffic between an ATR and a cluster. All clusters in step five, regardless of whether they meet or do not meet the requirement set in step three, are compared through moving the individual ATRs. The main goal behind this methodology is to increase the likelihood of assigning an ATR to a group with similar daily traffic patterns.

6.11.6 Step Six

In step six, the individual ATRs of a cluster that do not meet the requirements set in step three are assigned to a different cluster based upon of the same analysis with the minimum AStD. The remaining clusters of the j^{th} analysis are examined and their stations are moved if the clusters still do not have at least k ATRs within a cluster. After allocating all the ATRs, the j^{th} analysis may have fewer clusters than originally included. The clusters of the $(j+1)^{th}$ analysis are checked after all clusters of the j^{th} analysis are modified. Step six is complete when all the analyses are checked and each of the cluster groups includes at least k ATRs.

6.11.7 Step Seven

In step seven, the overall variation of the clusters included in j analysis is expressed through the weighted coefficient of variation (WCOV) a measurement of the level of homogeneity within the individual clusters. The WCOV is shown in Equation 6.6:

$$WCOV_j = \sum_{c=1}^{j}\left(\sum_{m=1}^{12}\left(\frac{\sqrt{\dfrac{\left(F_{i,m}-\overline{F}_{m,c}\right)^2}{n_{m,c,j}}}}{\overline{F}_{m,c,j}}\right)\right)\times\frac{100}{\sum_{c=1}^{j}\left(\sum_{m=1}^{12}\left(n_{m,c,j}\right)\right)\times n_{c.j}} \qquad (6.6)$$

where:

$n_{m,c,j}$ = number of factors in month m, cluster c of the j^{th} analysis, and

$n_{c,j}$ = final number of clusters of the j^{th} analysis after the allocation of the continuous sites.

6.11.8 Step Eight

In the eighth and last step of the analysis, the clusters of the analysis j, having the minimum WCOV, are selected as the final factor groupings. Further changes of the groups based on other user’s needs are left at the analyst’s discretion. The results from the grouping of the individual factors are shown in Chapter VII.

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CHAPTER VII

FACTOR GROUPINGS RESULTS

7.1 Introduction

Chapter VII describes the final results from the eight methods described in Chapter VI. There are two objectives within this chapter. These objectives are:

- Objective One: determine the best individual grouping strategy per method; and
- Objective Two: determine the best overall method for grouping ATR and WIM stations.

The overall assessment of each method is based upon the standard deviation, coefficient of variation and the variance for each method, on an annual basis. The results provided within this chapter are based on the directional analysis. In all cases, the final results for the total direction per method are similar to the directional results. The remaining results are grouped based on vehicle classes total, light-duty and heavy-duty with all corresponding statistics. The order of the vehicle groups is 3-Card total volume, C-Card total volume, C-Card vehicle classes 1 through 3 and C-card vehicle classes 4 through 13.

7.2 Individual Method Results

Eight methods are used to evaluate the effectiveness of grouping data together. In Methods One through Four the data are grouped into a series of bins. The standard deviation, the coefficient of variation and the variance are calculated and compared within the individual groups. In some cases the options are obvious as it is shown in Method One, while other methods, such as Method Three, there are four ways of grouping the data. The individual results that perform the best from each method are then compared against the other seven methods. When applicable, the individual results are documented for 3-Card total volumes, C-Card total volumes, C-Card vehicle classes 1 through 3 and C-Card vehicle classes 4 through 13 for directional, as well as total direction for all years of data. Due to the extensive amount of data, the results obtained from the 3-Card total volume per direction are described in this section. The results from the C-Card data are consistent with the trends provided in the individual results section.

7.2.1 Method One

The first method groups the data according to roadway functional classification. The results are based upon data collected from 2002 through the end of 2006. There is no additional way to subdivide the data within this task. The results of the first method are shown in Figure 7.1 through 7.3. The high errors produced within functional class 7 and functional class 9 for the 2006 and the 2006 data set respectively, are due to the small number of continuous stations within the two data sets.

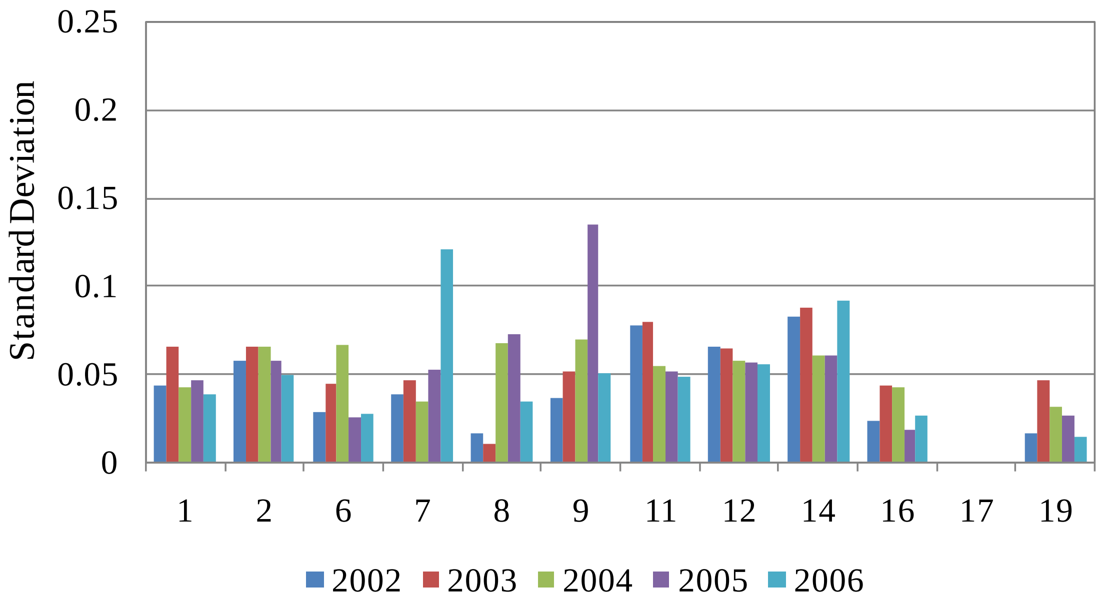

Figure 7.1. Method One SD for 3-Card directional volume.

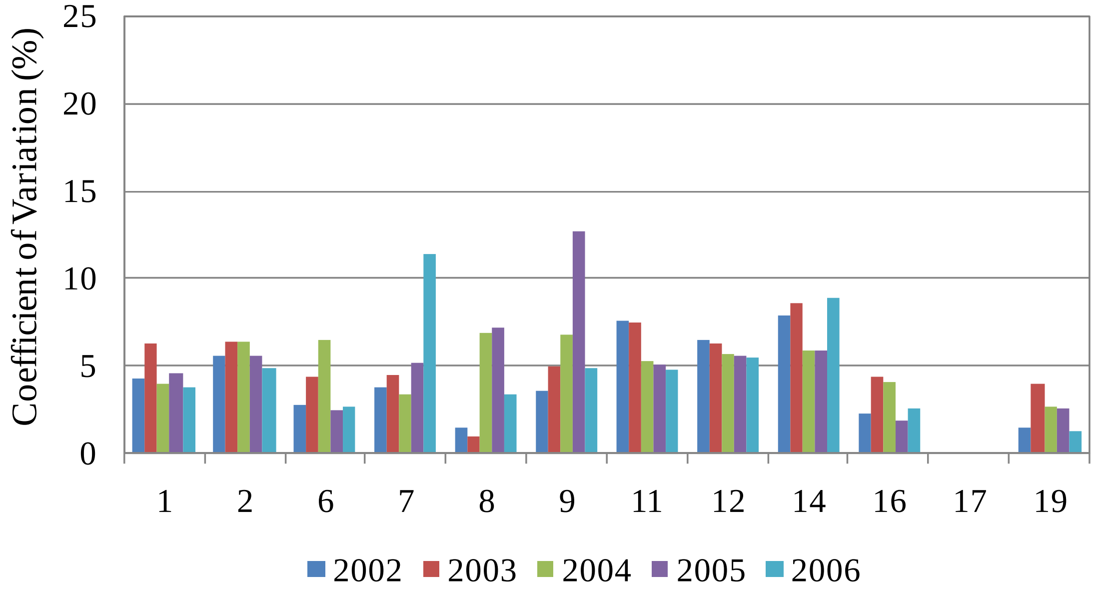

Figure 7.2. Method One COV for 3-Card directional volume.

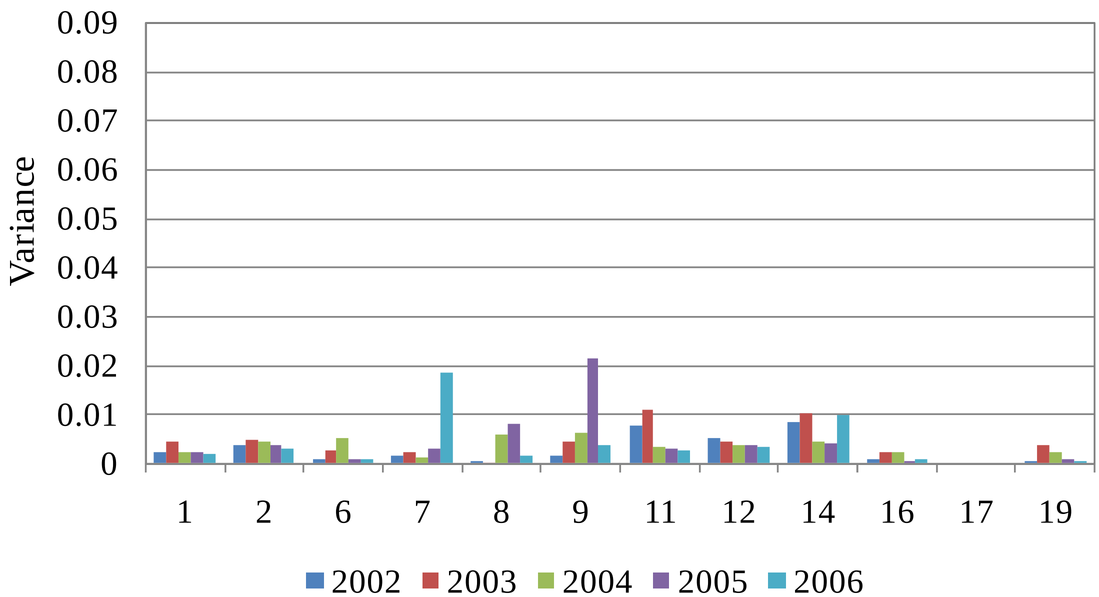

Figure 7.3. Method One variance for 3-Card directional volume.

7.2.3 Method Two

The second method is similar in approach to Method One but is updated with the new HPMS roadway classifications. The results of method two are shown in Figures 7.4 through 7.6. In general, with the exception of category 7, local roads, the standard deviation, the coefficient of variation and the variance remain similar. In Method Two there are no additional methods to segregate the data any further. The high errors produced in 2003 within functional class 7 are due to the small number of ATRs included in the data.

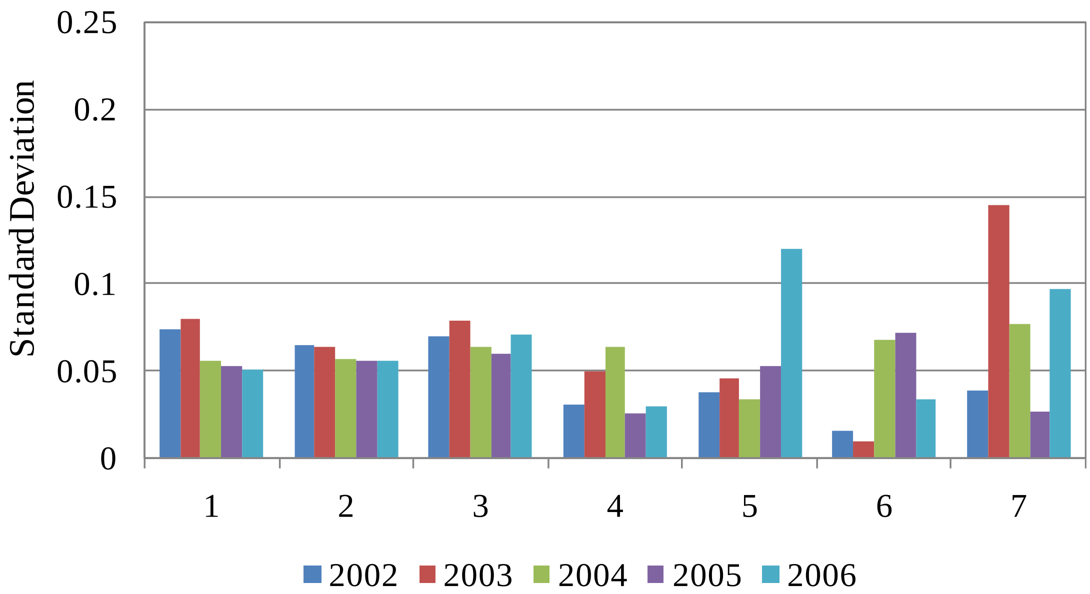

Figure 7.4. Method Two SD for 3-Card directional volume.

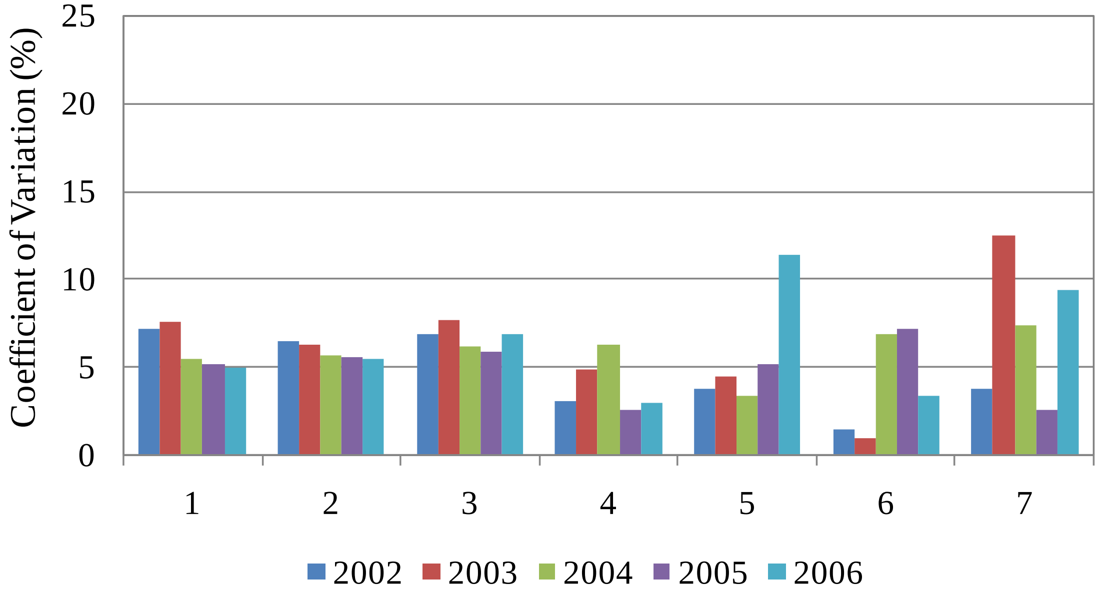

Figure 7.5. Method Two COV for 3-Card directional volume.

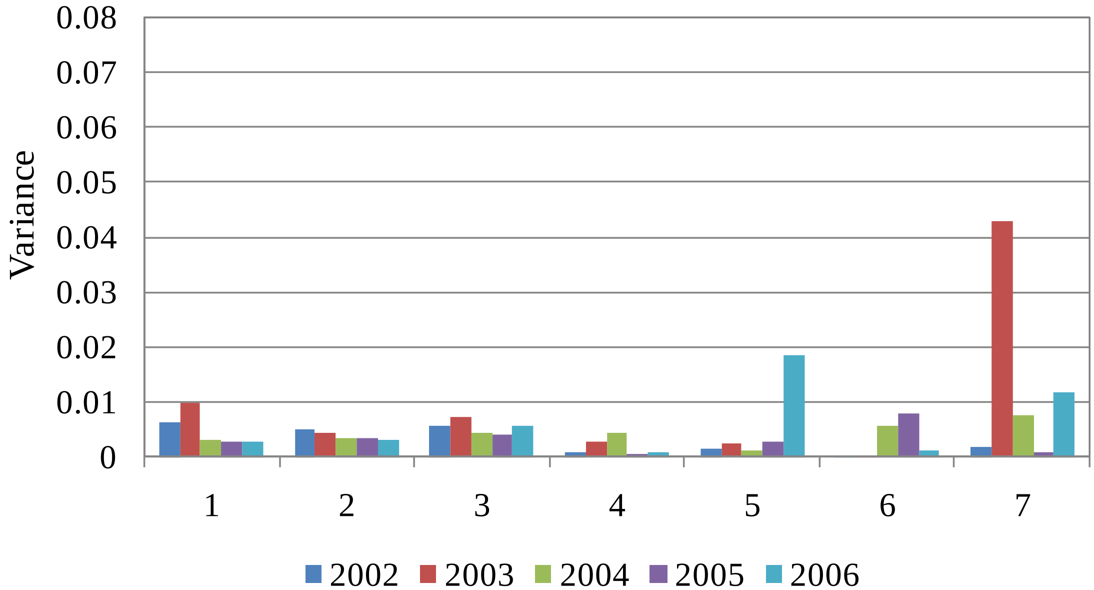

Figure 7.6. Method Two variance for 3-Card directional volume.

7.2.4 Method Three

The third method divides the data based on geographical/spatial separation. The final categories are based on urban and rural classification. The final results are shown in Figures 7.7 through 7.9. In general the overall standard deviation, the coefficient of variation and the variance remain similar between each division of the data. This suggests, from a statistical perspective, there is no overwhelming impact by grouping the data geographically. One potential suggestion is grouping the data using the five geographical regions because of the ease in assigning the short-term data within the smaller regions. From an engineering judgment perspective it seems more reasonable to group a short-term count located near Columbus with a continuous group from Columbus. Additionally, results of this analysis method show that the data are not significantly different between the geographical areas and the urban versus rural at a 95% confidence interval.

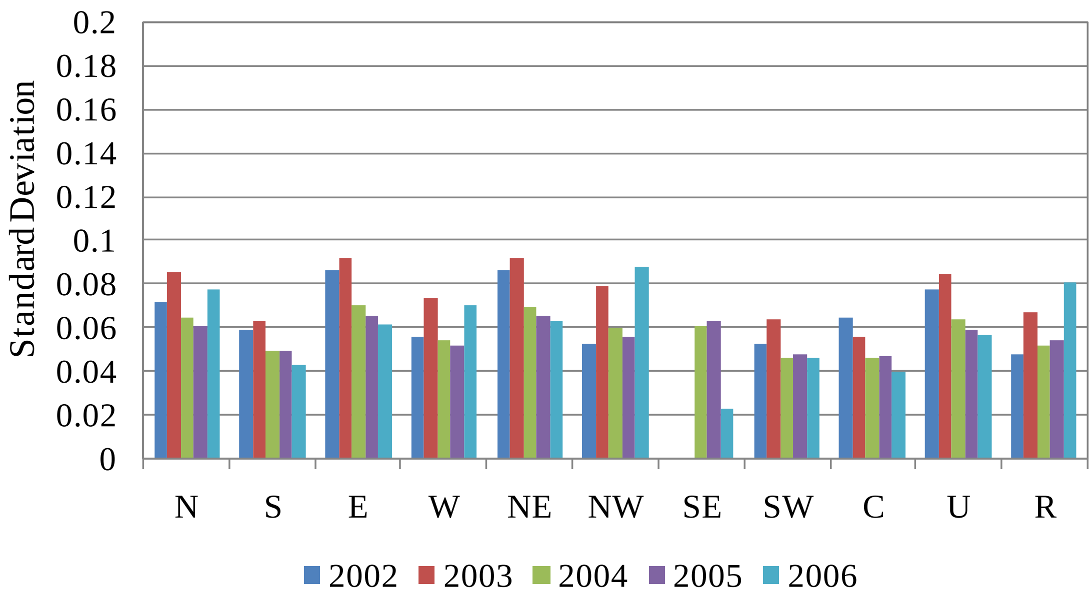

Figure 7.7. Method Three SD for 3-Card directional volume.

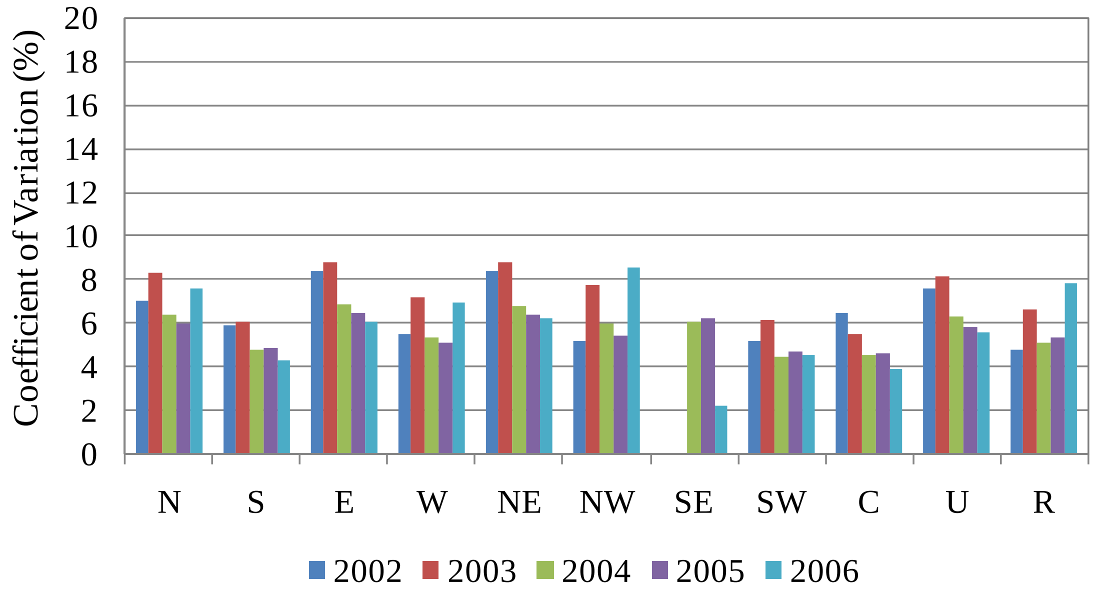

Figure 7.8. Method Three COV for 3-Card directional volume.

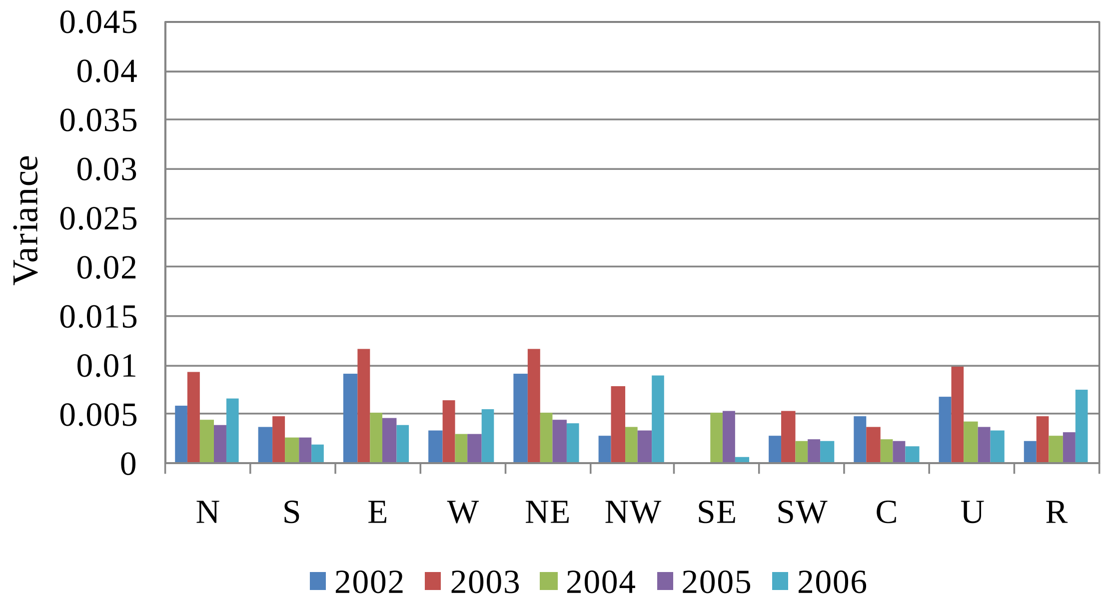

Figure 7.9. Method Three variance for 3-Card directional volume.

7.2.5 Method Four

The fourth method of grouping the data divides the data both geographically and by roadway functional class, creating up to 60 groups. Figures 7.10 through 7.12 shown below provide the statistical results for separating the data geographically in association with roadway functional class 11. One disadvantage to this method is that Method Four requires more stations to populate each group compared with Methods One through Three. Many of the roadway classifications, for example local roads, do not produce the appropriate statistical values as a result of the increase in data needs. The results are similar to Method Three and there is little added benefit for the additional data separation step. The second set of results show the standard deviation, the coefficient of variation and the variance all remain relatively consistent on a per annual basis.

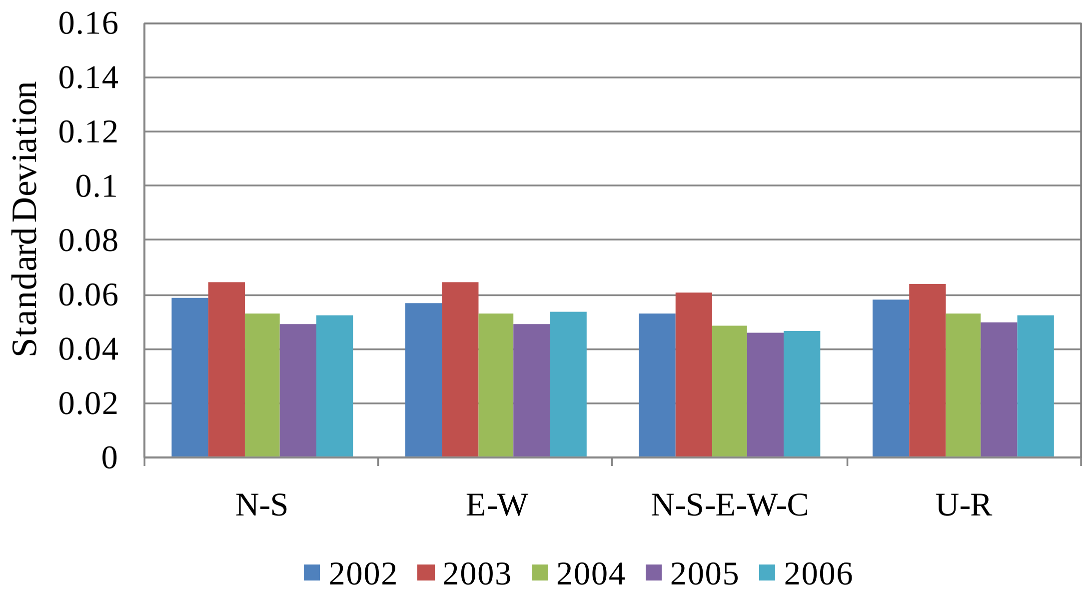

Figure 7.10. Method Four SD for 3-Card directional volume.

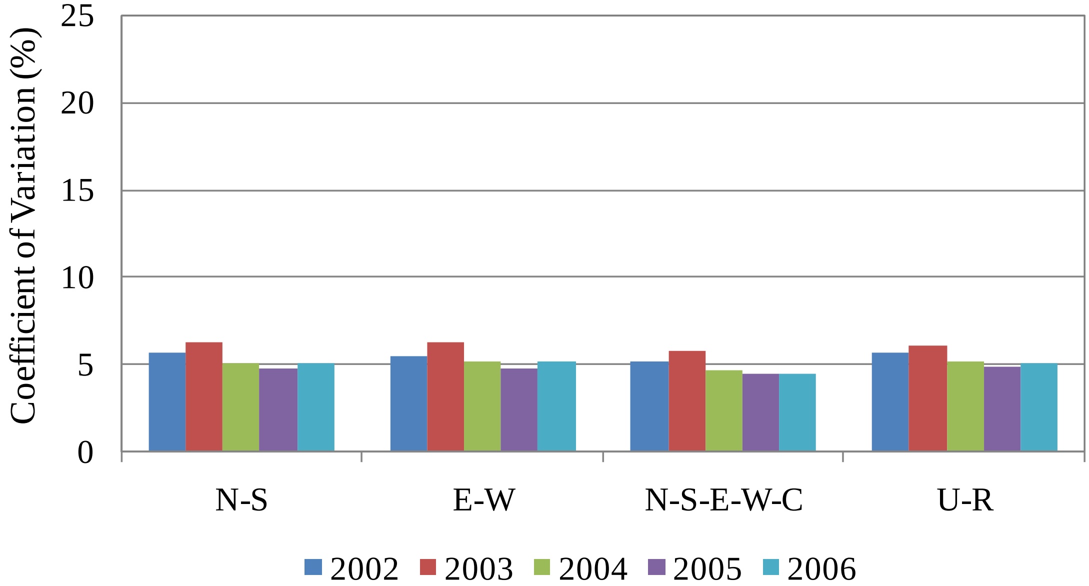

Figure 7.11. Method Four COV for 3-Card directional volume.

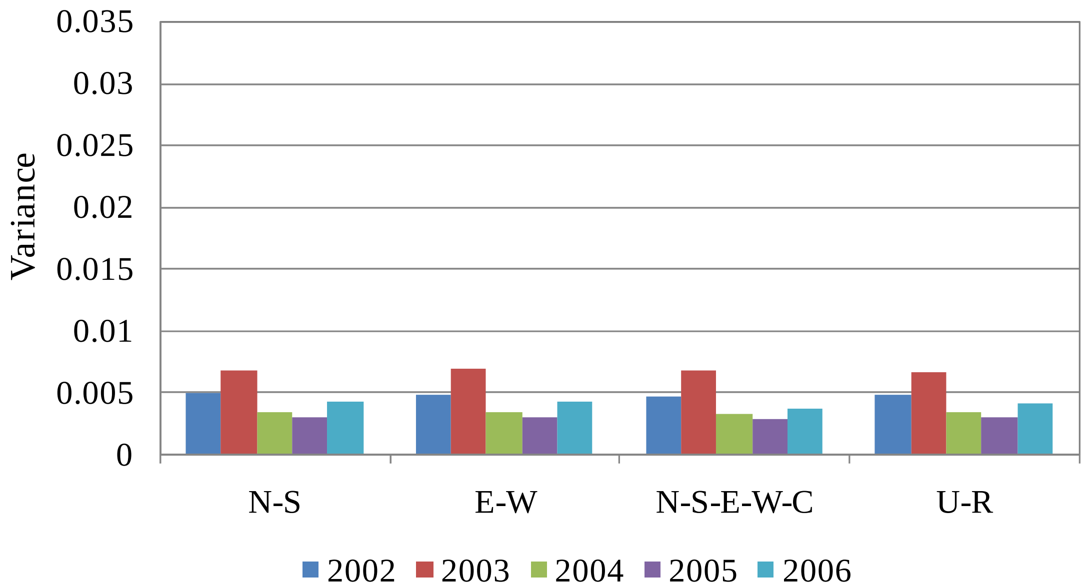

Figure 7.12. Method Four variance for 3-Card directional volume.

7.3 Discussion of Cluster Analysis

The suggestion to develop alternative methods in lieu of engineering judgment has been debated in many professional organizations including the TMG. One popular suggestion is the use of a statistical technique called cluster analysis, described previously in Chapter VI. There are many positive aspects to this approach, with the two most prominent advantages being grouping the data based on statistics instead of engineering judgment, and two new underlying trends may be discovered. The main disadvantage is the temporal stability within each group, creating a need to cluster each group on a yearly basis (Zhao et al., 2004; Zhao et al., 2008). Within the cluster analysis section there are two fundamental questions that need to be answered. These questions are:

- How many cluster groupings does the State of Ohio need to meet the recommendations provided within the TMG?
- Where does the State of Ohio need to add permanent continuous stations and where may the state remove continuous stations?

The evaluation of question one is described in detail within the next four sections, Methods Five through Eight. The results of the cluster analysis are shown in Figures 7.13 through 7.24. The "Stability of the Clusters" section evaluates the challenges of question two and provides preliminary evaluation of the temporal stability with clustering these stations.

The first question is relatively straight forward, how many cluster groupings are needed to meet recommendations provided within the TMG? The optimum number of clusters is based on two criteria. The first criterion is the overall statistical performance of the cluster. This is expressed through the standard deviation, the coefficient of variation and the variance of the cluster. The directional analysis results are shown in Figures 7.13 through 7.24 and the total directional results, not shown, are similar to Figures 7.13 through 7.24.

The second question requires engineering judgment. In the second criterion the individual number of stations is evaluated for each of the clusters. As an example, ten clusters is the optimum number of clusters required to meet the statistical performance measures required by the TMG. In this case the TMG recommends five to ten stations per cluster. In most cases within this research the number of stations per cluster is not equivalent, with some clusters holding 80 to 90 stations while other clusters may have one or two stations. In such situations, engineering judgment should be used to distribute a small quantity of the less populated clusters into more populated clusters.

7.3.1 Method Five

The first set of individual cluster results is developed, statewide, for Method Five. These results are developed annually and final results illustrate the impact of the number of clusters on the standard deviation, coefficient of variation, and the variance. Results provided within Method Five are developed for the direction cluster groupings for all vehicle classes and results for the total direction are similar. One of the strengths of the directional analysis over the total direction is the number of sites double. This in-turn allows for a greater number of clusters and the statistical performance measures are approximately one half the values of the total direction statistics. The overall results presented in Figures 7.13 through 7.24 are generally consistent over the five years of data. Other findings display the overall sensitivity or improvement diminishes past 10 cluster groupings when creating new clusters. Although it may be possible to populate additional clusters, the overall performance based on the amount of additional effort is not necessarily justifiable.

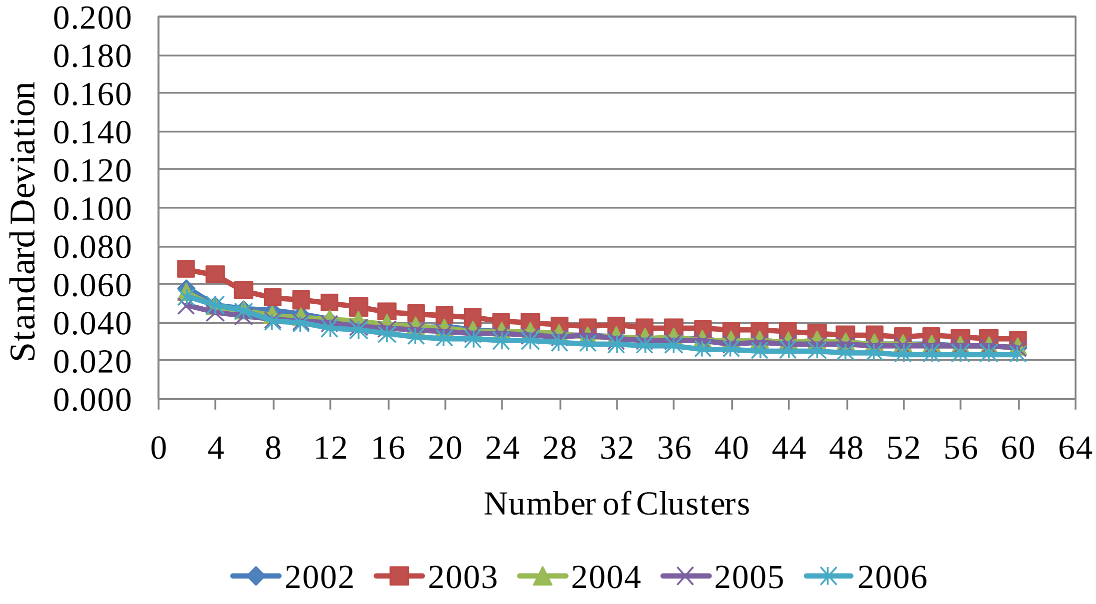

Figure 7.13. Method Five SD for 3-Card directional volume.

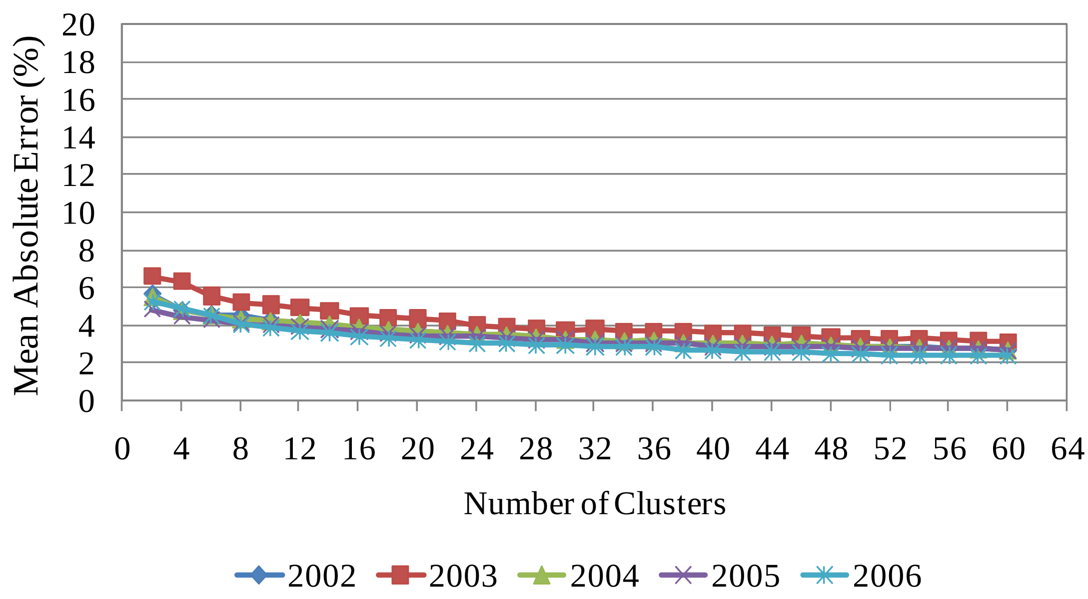

Figure 7.14. Method Five COV for 3-Card directional volume.

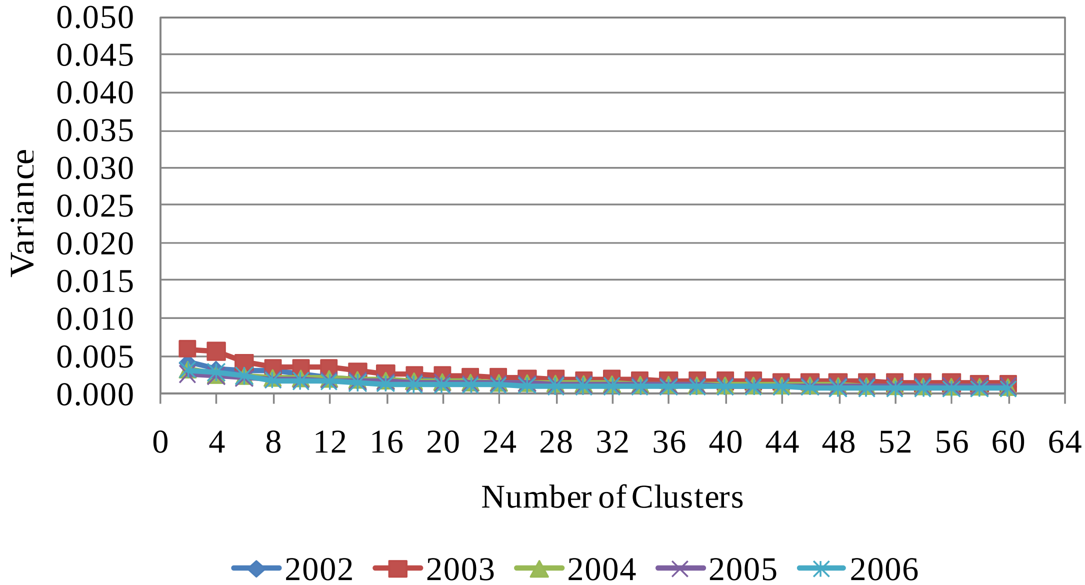

Figure 7.15. Method Five variance for 3-Card directional volume.

7.3.2 Method Six

The results for Method Six are developed for the combination of clustering and roadway classification. The results are based on the directional analysis for the 3-card total volumes. Generally, the overall results of Method Six analysis are similar to Method Five. But unlike Method Five where clusters are based solely on station patterns, Method Six subdivides the data first into roadway classifications. The number of potential clusters decreases to less than 20 clusters for the entire method as a result of the initial division of the data. Similar to the findings in Method Five, the directional approach creates more groups. This allows for an increase in data points to populate each cluster.

The results from Method Six are shown in Figures 7.16 through 7.18. The optimum number of clusters, using Method Six, remains consistent throughout the five years. The overall trends shown in Figures 7.16 through 7.18 are consistent for 3-card total volumes, vehicle classes 1 through 3 and vehicle classes 4 through 13.

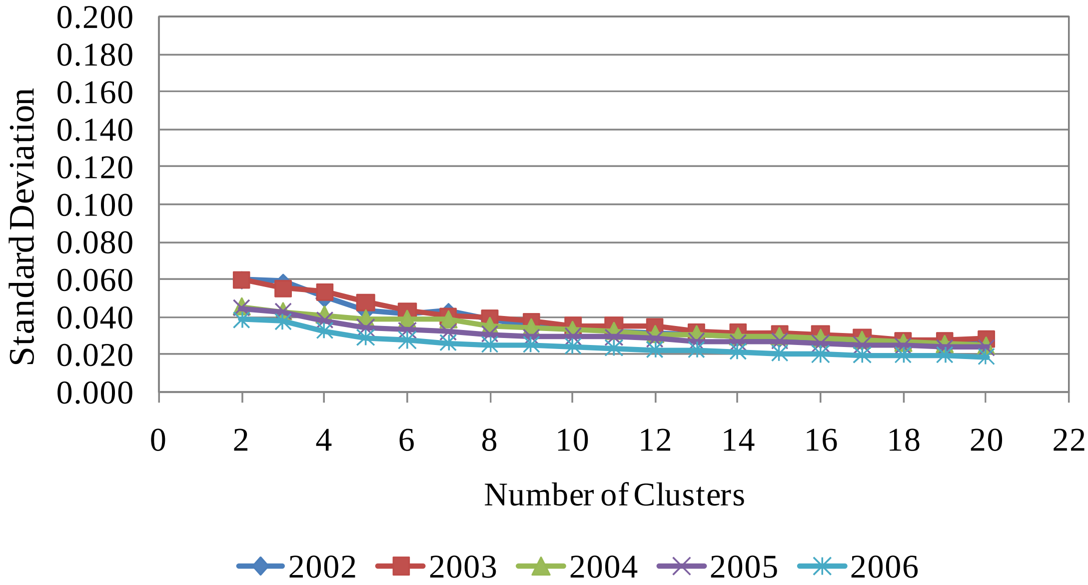

Figure 7.16. Method Six SD for 3-Card directional volume for roadway functional class 11.

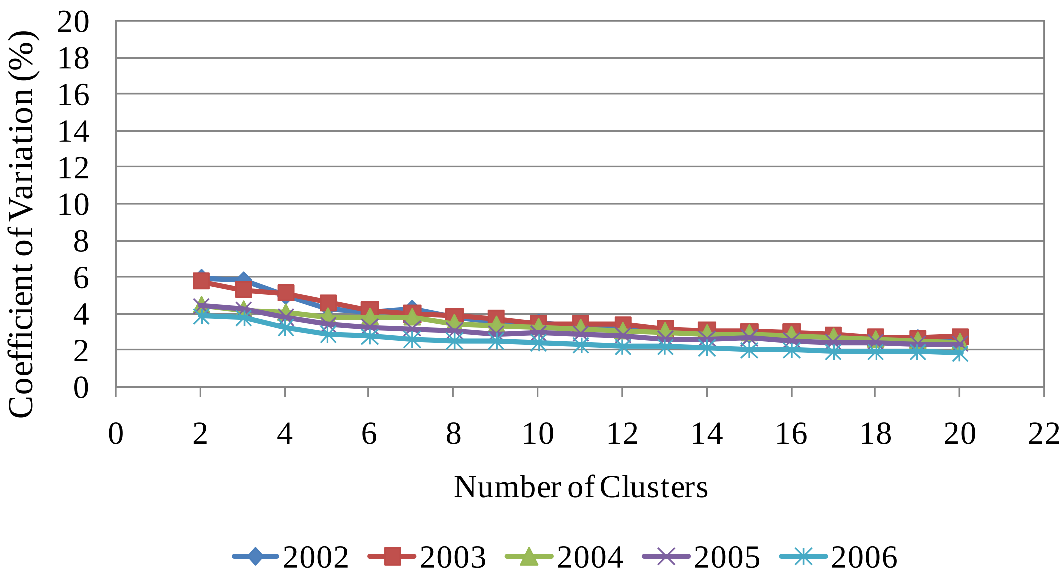

Figure 7.17. Method Six COV for 3-Card directional volume for roadway functional class 11.

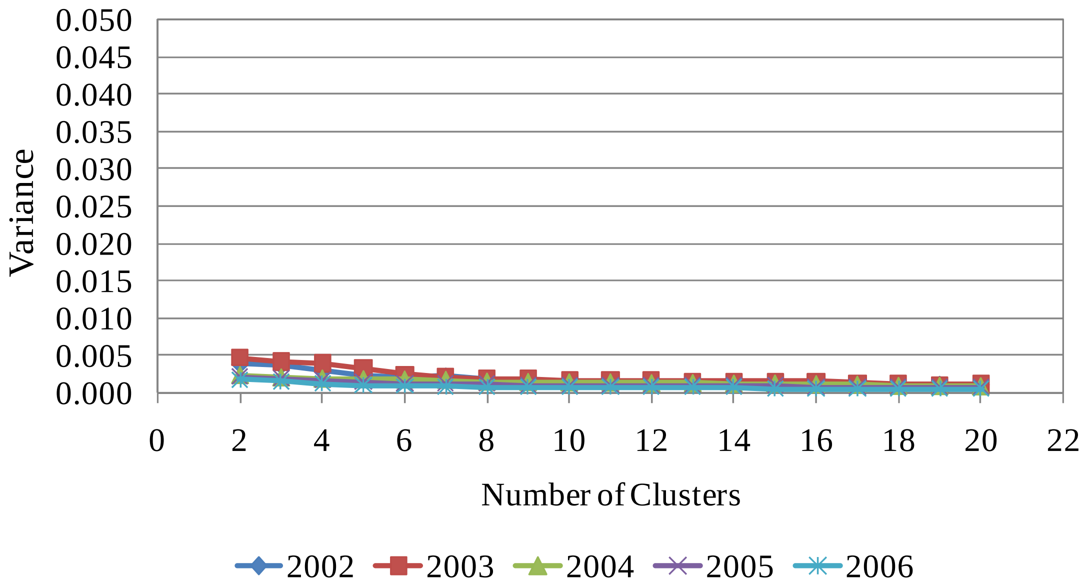

Figure 7.18. Method Six variance for 3-Card directional volume for roadway functional class 11.

7.3.3 Method Seven

The seventh method continues to have the same overall trends as Methods Five and Six and is shown in Figures 7.19 through 7.21. The main challenge with Method Seven is the ability to populate the number of individual clusters. The results remain similar with Method Six, less than 20 total clusters. The final optimal number of clusters remains between eight and twelve. Similar with the other methods, the final results are consistent between each year.

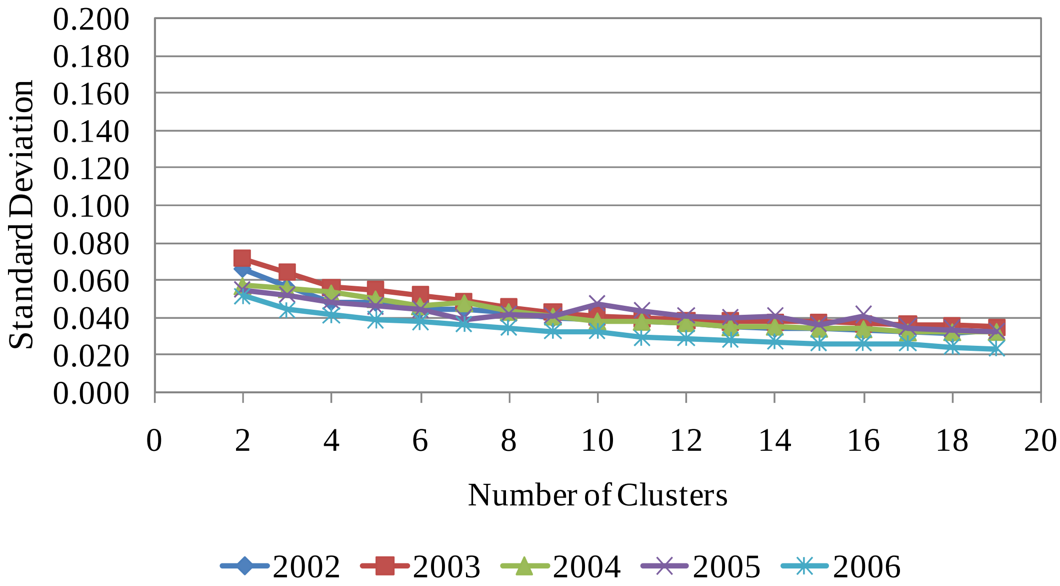

Figure 7.19. Method Seven SD 3-Card directional volume for northeast Ohio.

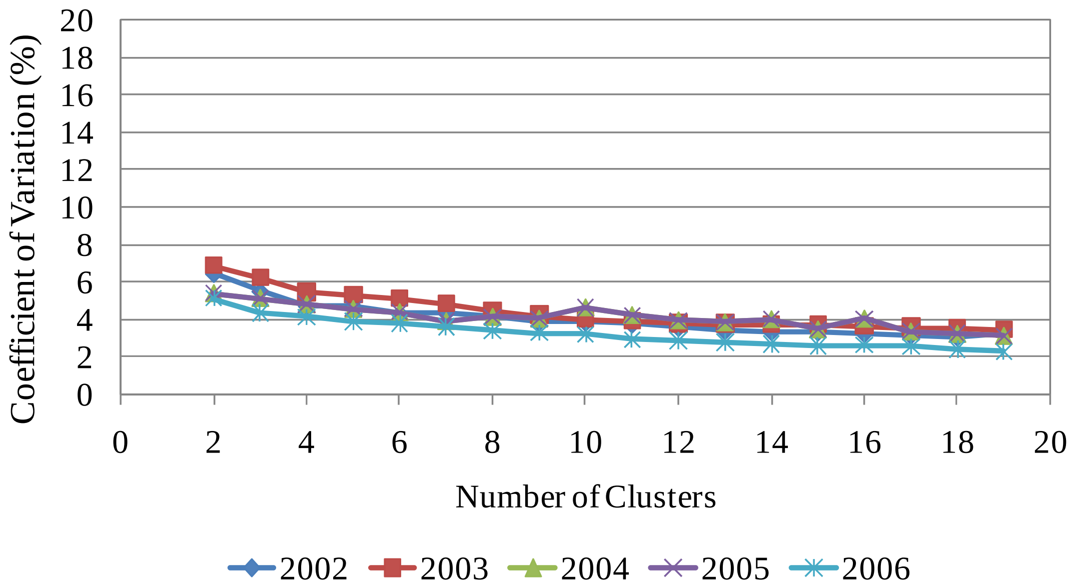

Figure 7.20. Method Seven COV 3-Card directional volume for northeast Ohio.

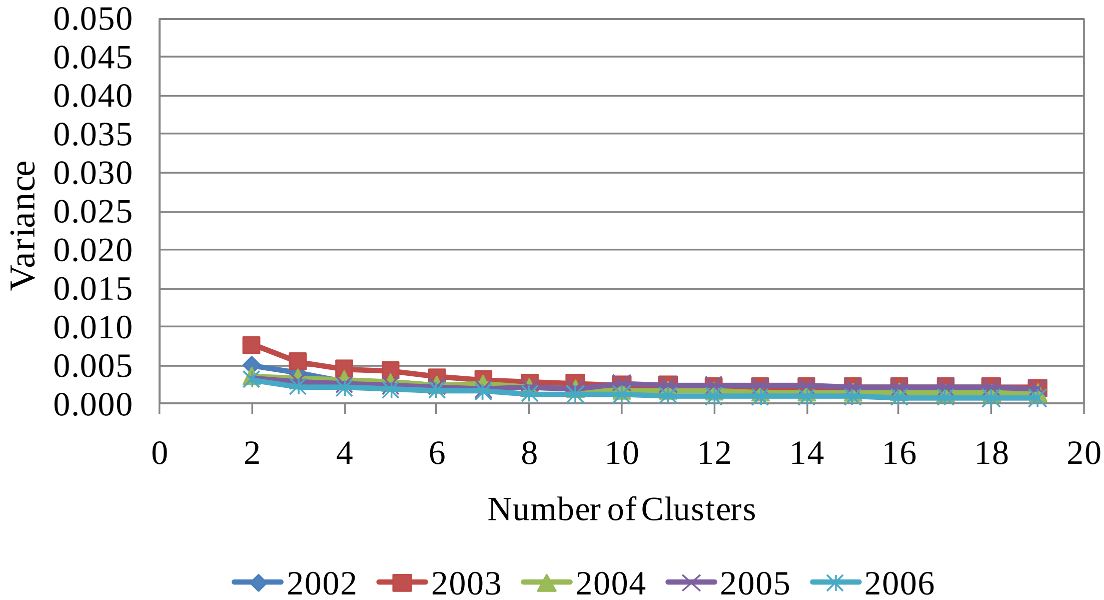

Figure 7.21. Method Seven variance 3-Card directional volume for northeast Ohio.

7.3.4 Method Eight

Method Eight, the final method, divides the stations based on both roadway location and the geographical location and then clusters each sub-data set. The one main advantage in this method is the ability to investigate one area in the state concurrently with a single roadway classification. The main disadvantage of Method Eight is the difficulty in populating the individual clusters. The results shown in Figures 7.22 through 7.24 display the same overall trends in comparison to other methods. The other findings show the limitations associated with populating all the cluster groupings.

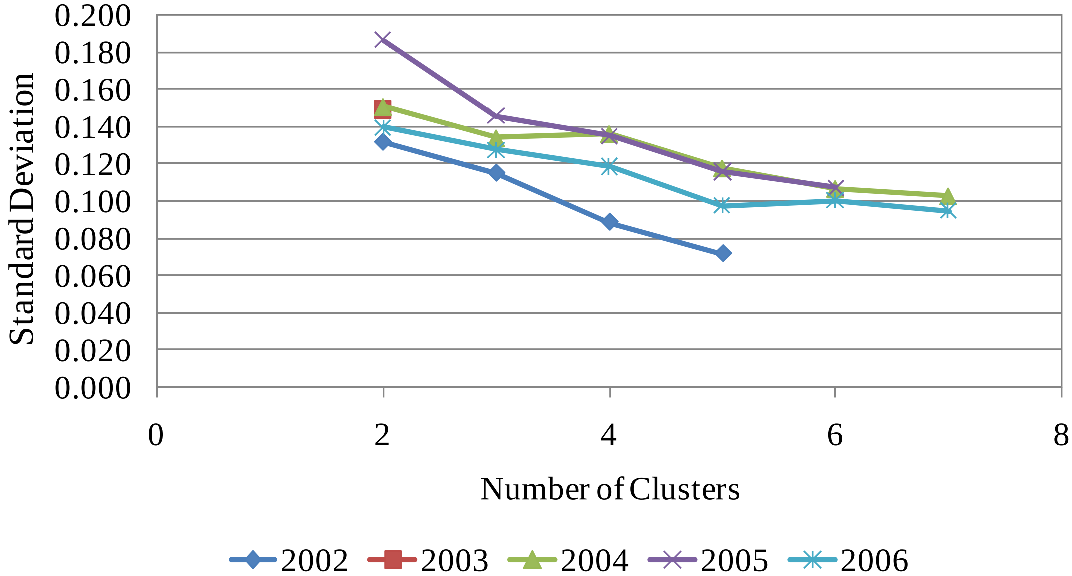

Figure 7.22. Method Eight SD 3-Card directional volume for functional class 11 of northeast Ohio.

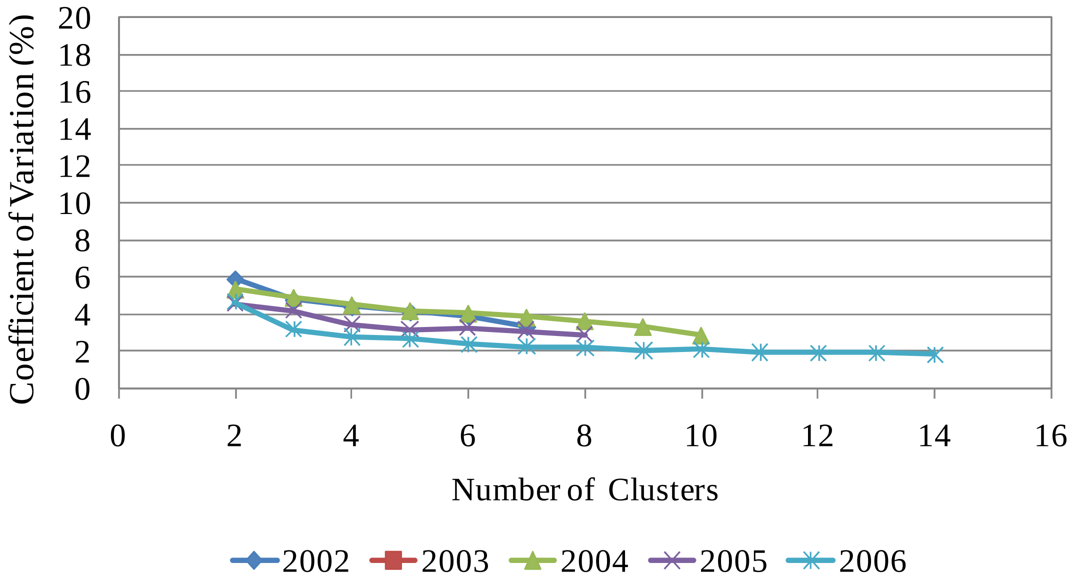

Figure 7.23 Method Eight COV 3-Card directional volume for functional class 11 of northeast Ohio.

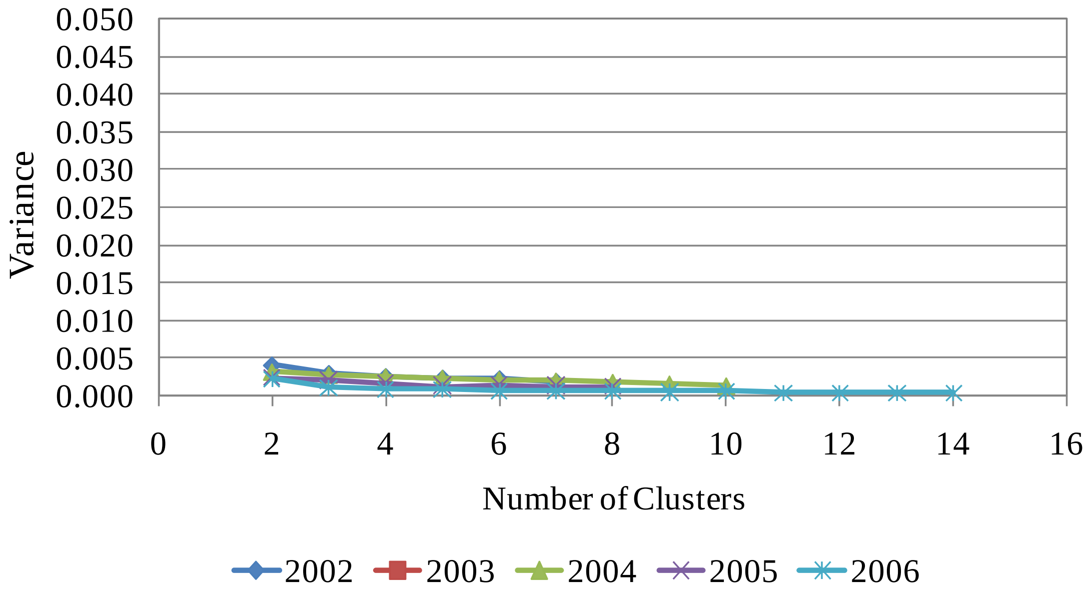

Figure 7.24. Method Eight variance 3-Card directional volume for functional class 11 of northeast Ohio.

7.3.5 Summary of Methods Five through Eight

The main findings demonstrate that Methods Five through Eight contain both advantages and disadvantages related to the selection of the optimum number of clusters per method. The next section, 7.3.6, describes the trade-offs between selecting the number of clusters per method with the overall temporal stability.

7.3.6 Stability of Clusters

The second question within the "Discussion of Cluster Analysis" section evaluates the need to add or remove permanent stations within the State of Ohio. This question is more difficult to evaluate. In order to better evaluate this question, additional criterion, separate from the statistical performance measures are required. The biggest influence on question two is how many clusters are optimal? The higher the number of clusters produces better statistical measures, however, as the number of cluster groupings increase, the ability to answer question two decreases. If two clusters are needed, no additional stations should be added. In both cases the number of current stations may be decreased. On the other hand, as the number of cluster groupings decreases the overall sensitivity on the roadway network also decreases.

The goal of this section is to provide a balance between the number of clusters and the overall stability within the network. In order to evaluate the stability on the clusters, three criteria are included to provide guidance to answer this question. The first criterion is based on the yearly number of individual stations that populate a cluster. For example, assume the same optimum number of ten clusters is required. Clusters one through five consist of 15 plus stations per cluster. In these clusters, stations may be removed from the system as long as the statistical performance measures are maintained and five to ten stations must remain per individual cluster. Continuing the example, clusters six through ten violate the statistical measures: standard deviation, coefficient of variation and variance, or they do not have sufficient stations to meet the minimum suggested number of five to ten stations, as suggested by the TMG. In these clusters, the initial recommendation is to add new stations within clusters six through ten. This criterion alone may not be sufficient to successfully answer question two because of the dynamic nature of the roadway. In most cases, the number of clusters required remains consistent from year to year, as shown previously in Figure 7.13 through Figure 7.24. Although the number of clusters remains similar from year to year, the permanent stations that populate each cluster will vary over time. For example, station one populates cluster number one for the year 2002 and then changes clusters groups in 2003, 2004 and 2005. This is a direct result of the changes within the roadway network. Depending on the individual cluster group and selecting the individual number of permanent and temporary groups based solely on criterion number one will yield ineffective results over time.

Two additional criteria should be evaluated to assist in evaluating the temporal stability within each cluster grouping. Criterion two evaluates the influence of stations in comparison to the individual cluster. For example, over the last five years station one has remained in the same cluster or does station one move between cluster groupings. One example of the challenges shown in criterion two is provided below in Figure 7.25.

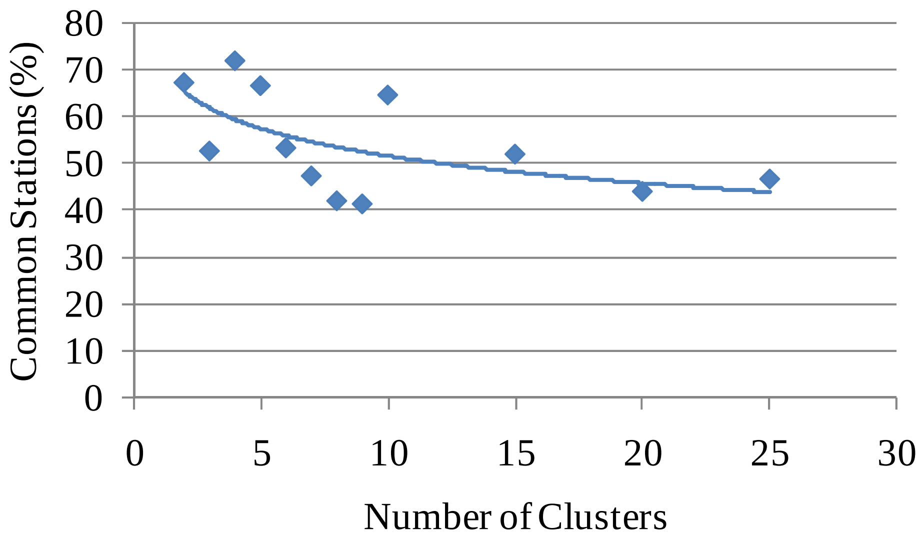

Figure 7.25. Method Five common stations (%) vs. number of clusters 3-Card directional volume.

In Figure 7.25 data from 2002 and 2003 are analyzed for the 3-Card data. The results show that as the number of clusters increases, the number of common stations defined as a percentage decreases. These results suggest the individual clusters move from year to year.

The third criterion explores the relationship and similarities between two individual stations, for example station one and two are always grouped together. If this is the case, and criterion one is not violated, there may be opportunity to remove station one or station two from the network. One of the disadvantages of the cluster analysis is the instability in the cluster especially as a result of the dynamic nature of the roadway network, in relation to criterion two and three.

7.4 Final Comparison of Results

The final comparison of the individual methods is shown in Figures 7.26 through 7.35. The comparison is based on the overall best individual results per method as described previously in Section 7.2. The format for this section includes the results for the standard deviation, the coefficient of variation, and variance for the 3-Card total volume, followed by C-Card total volume, C-Card vehicle classes one through three and C-Card vehicle classes 4 through 13 based upon data from 2002 through the end of 2005.

7.4.1 3-Card Directional Total Volume

The first set of findings is developed for the total volume for vehicles generated from the 3-Card stations based upon data from 2002 through 2006. The results shown below represent the eight methods described in the previous chapter.

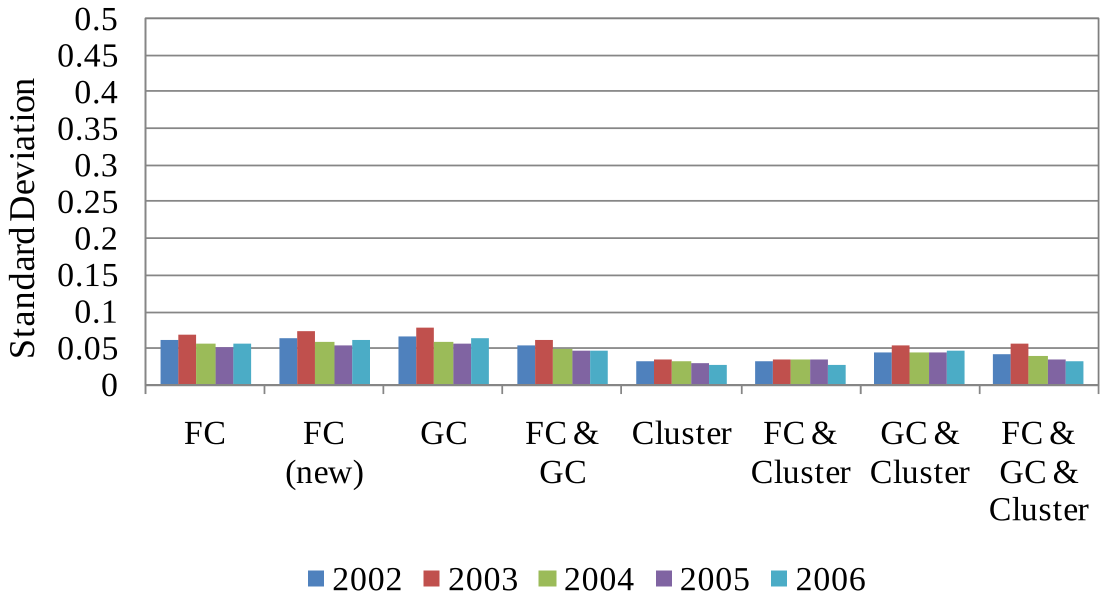

Figure 7.26. SD 3-Card directional total volume comparison for all methods.

The results show the more traditional methods for assigning groups based on the roadway functional class, geographical/spatial location or a combination of both have higher standard deviations when compared with one of the four cluster techniques, Methods Five through Eight. The lowest producing standard deviation is provided by Method Five. The main rationale behind this result is there are no boundary conditions associated with the cluster algorithm. Without these conditions the algorithm has the greatest flexibility in dividing the data into the cluster groups. Although this method has the best overall results, there may be some challenges when assigning short-term counts to each cluster group.

The second set of results compares the coefficient of variation between the eight methods. The final results remain consistent with the standard deviation. The more traditional methods have higher values while the clustering techniques produce better results. Method Five remains the overall best method statistically for grouping the data.

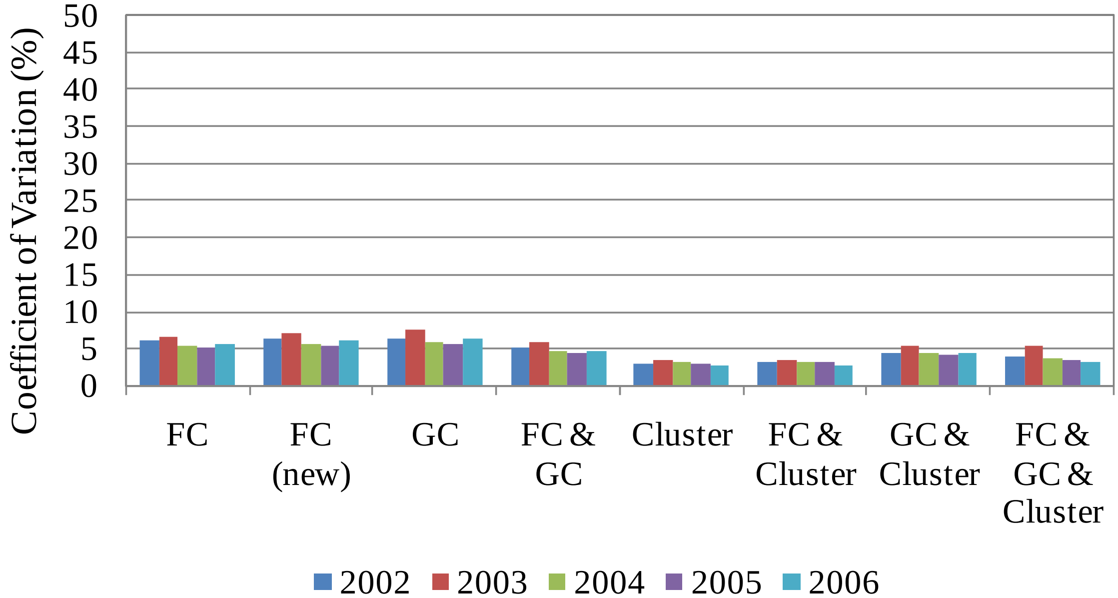

Figure 7.27. COV 3-Card directional total volume comparison for all methods.

The final results from the C-Card data set are presented in Figure 7.28 and the results remain consistent with the previous findings.

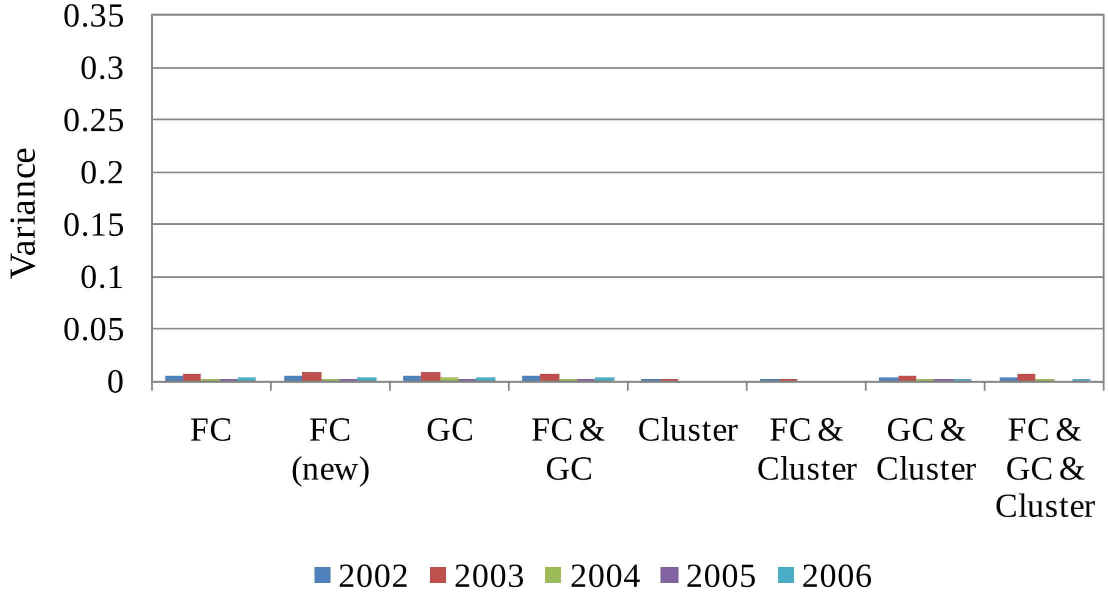

Figure 7.28. Variance 3-Card directional total volume comparison for all methods.

7.4.2 C-Card Directional Total Volume

The first set of results displayed in Figure 7.29 are based on the C-Card Total Volume from 2002 through 2007. There are two findings of interest. The first finding shows early data collection years 2002 and 2003 have higher standard deviations than more current years. The second results show that generally the non-cluster methods, Method One through Method Four, produce higher standard deviations within each group. This finding would suggest there is benefit to incorporate a cluster approach with the final selection.

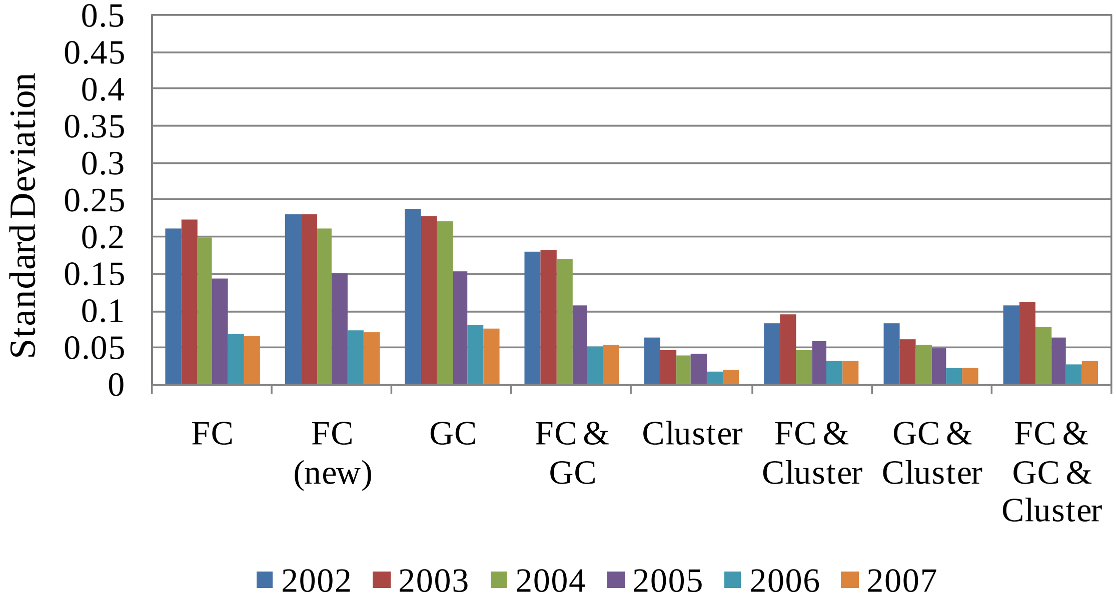

Figure 7.29. SD C-Card directional total volume comparison for all methods.

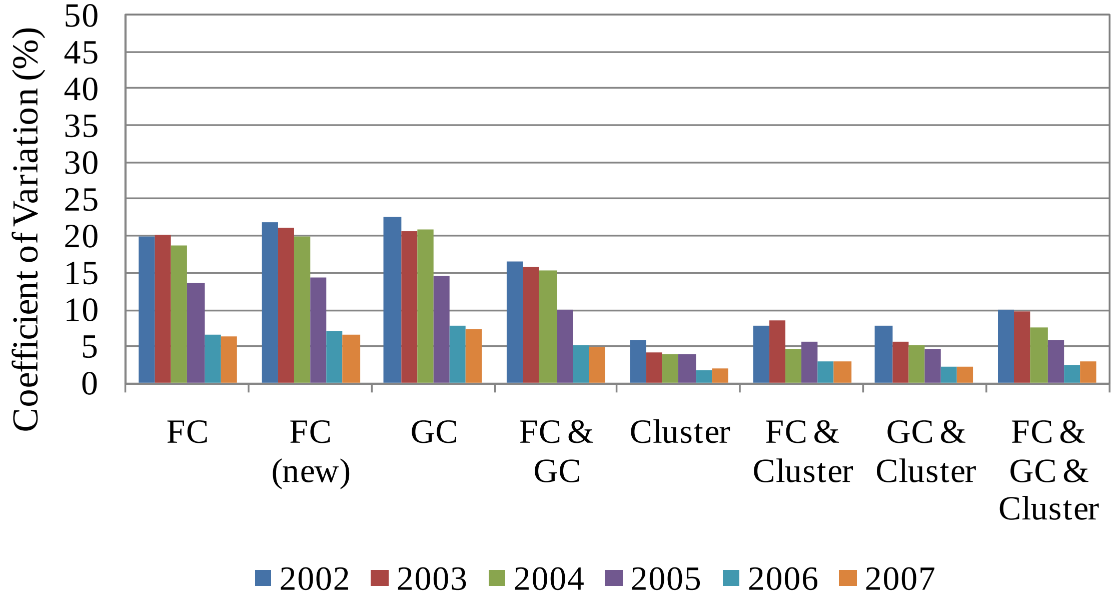

Figure 7.30. COV C-Card directional total volume comparison for all methods.

The second statistical method for the assessment of the eight methods is the coefficient of variation. The comparison of these results is shown in Figure 7.30. In this figure, similar to the standard deviation, the higher the values for the coefficient of variation represent lower performing methods. The findings within this figure show that the years of 2002 and 2003 have higher producing values, approaching 20. Additionally, the cluster techniques lower the coefficient of variation to less than 15, with Method Five producing the lowest values.

The final figure created by the C-Card directional total volumes are shown below in Figure 7.31. The results are consistent with the previous findings and suggest the implementation of one of the cluster analysis methodologies.

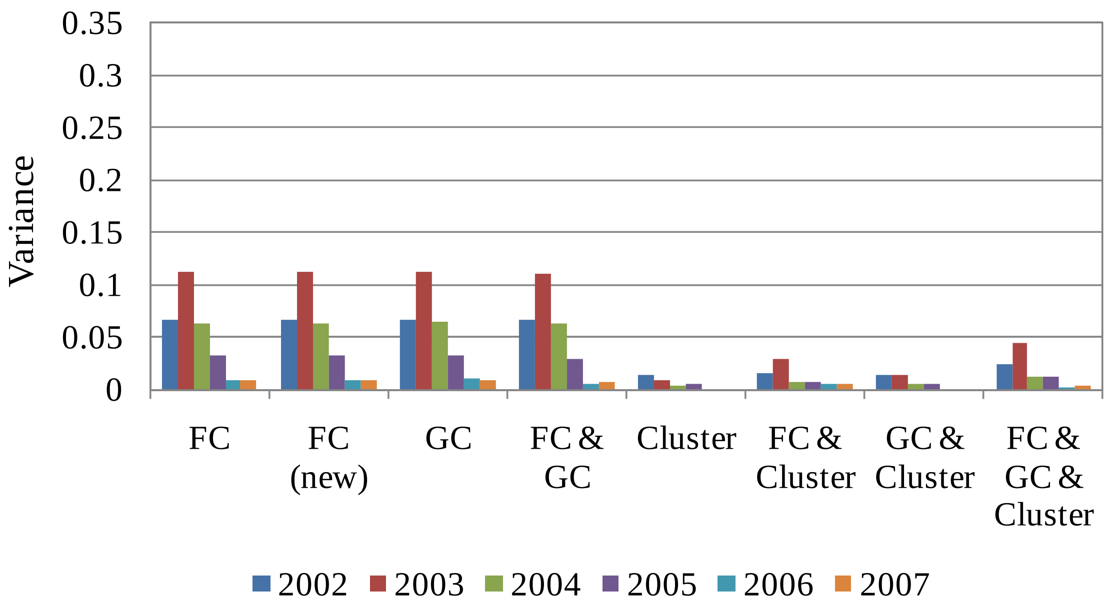

Figure 7.31. Variance C-Card directional total volume comparison for all methods.

7.4.3 C-Card Directional Vehicle Classes 1 Through 3

The results described previously in section 7.4.1 and 7.4.2 are for total vehicle groupings. In the next two sections, the vehicle groupings are derived from the C-Cards for light-duty, vehicle classes 1 through 3, and heavy-duty, vehicle classes 4 through 13. In this section the results are developed for vehicle classes 1 through 3 for Methods One through Eight. The results, Figures 7.32 through 7.34, are similar to the previous findings of the cluster techniques that produce lower standard deviations, coefficient and variation and variances. An important finding is that using the clustering method based on vehicle classes creates an additional data separation step. This step in-turn may limit both the number of clusters as was as the total number of individual results per station. The station number does not change but the number of recorded vehicles within a particular station may vary significantly.

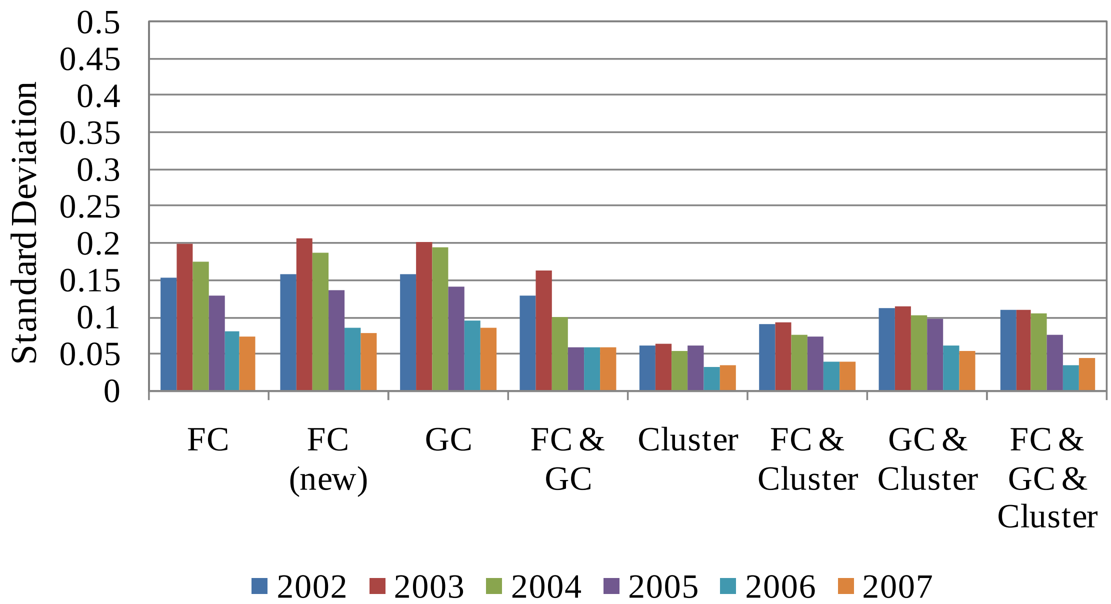

Figure 7.32. SD C-Card directional vehicle classes 1 through 3 comparison for all methods.

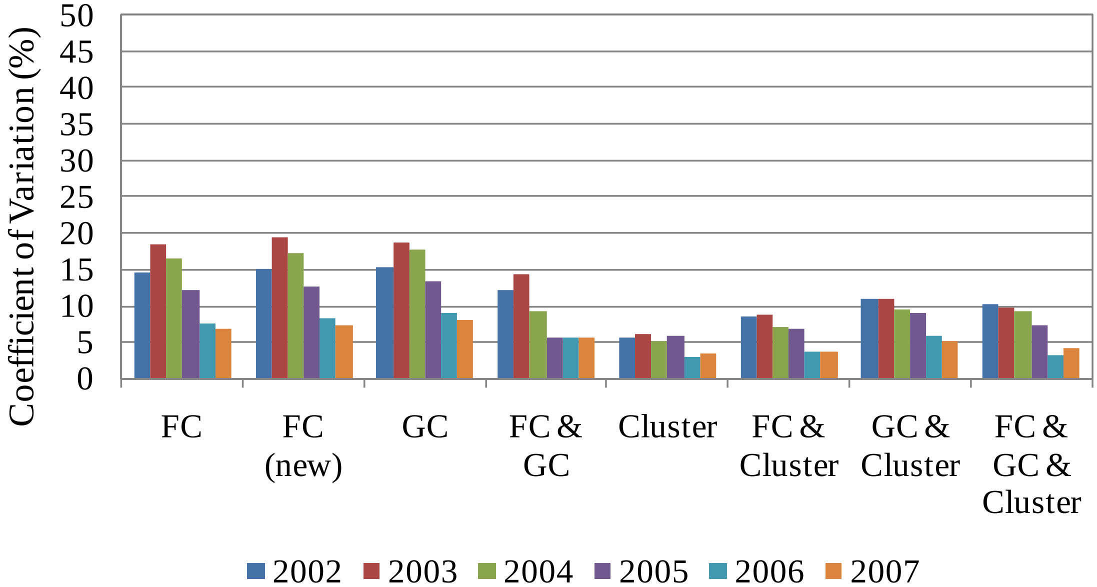

Figure 7.33. COV C-Card directional vehicle classes 1 through 3 comparison for all methods.

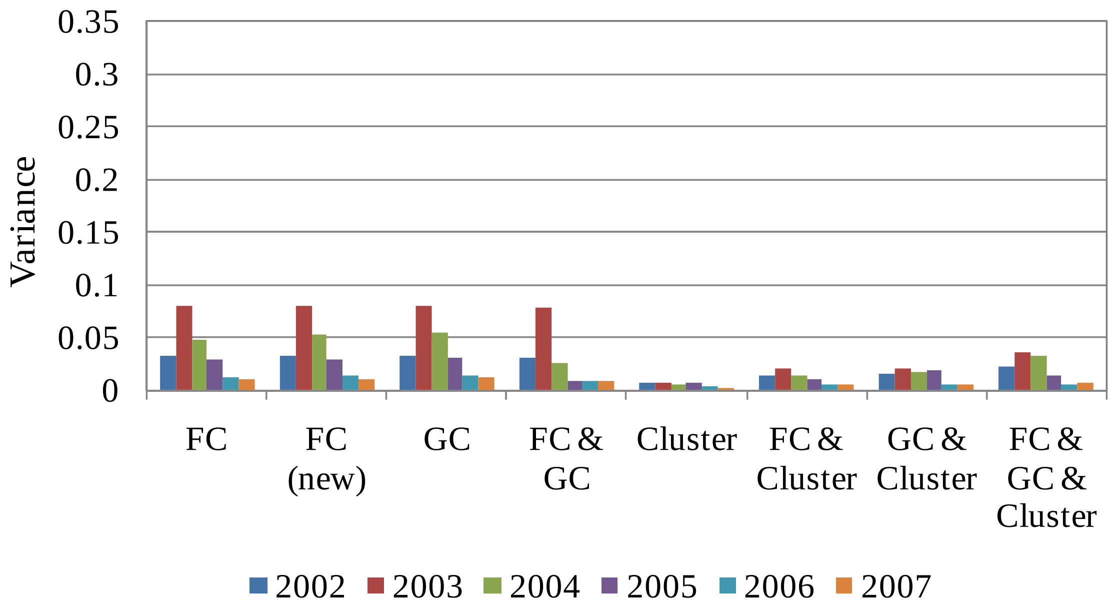

Figure 7.34. Variance C-Card directional vehicle classes 1 through 3 comparison for all methods.

7.4.4 C-Card Directional Vehicle Classes 4 Through 13

The final set of results is shown in Figures 7.35 through 7.37, developed exclusively for heavy-duty vehicles, vehicle classes 4 through 13. The summary of results remains consistent with the other findings. The cluster methods perform better than the non-cluster methods. Other results show the continued improvement between cluster values developed from data in 2002 to 2007. One additional finding, similar to the C-Card vehicle classes 1 through 3, is the impact of limited vehicle volumes per station per cluster. As a result of the vehicle volume limitation, the overall results are higher for the heavy-duty vehicle class groupings in direct comparison to both the light-duty vehicles and the total volume cluster groupings. The limitation of the data is prevalent when multiple data aggregation steps are involved, such as Methods Four and Eight. One potential recommendation is to use directional clustering in essence doubling the overall number of data points.

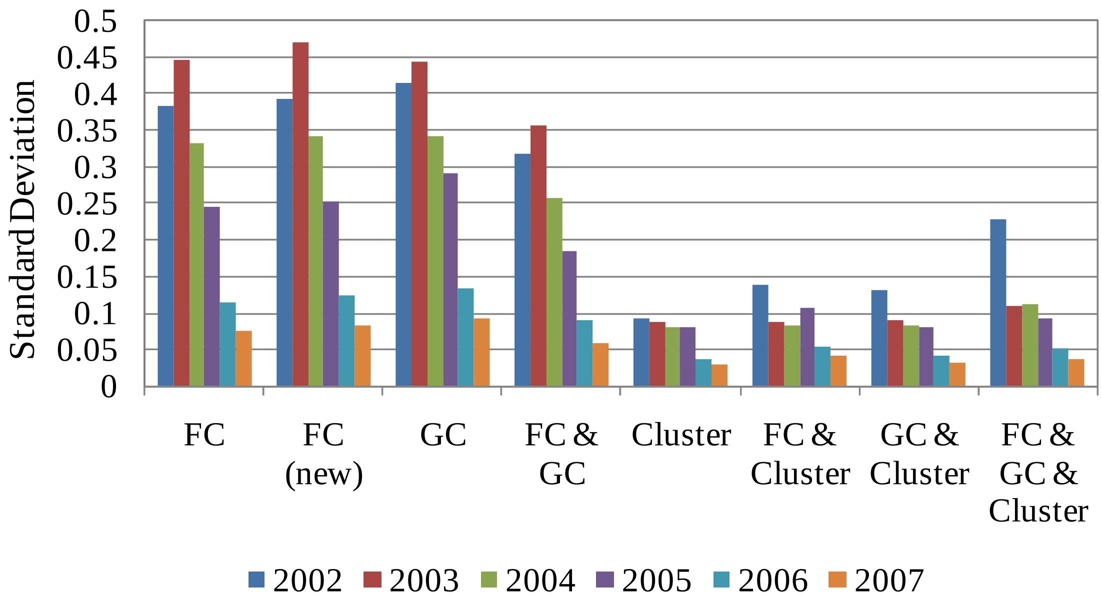

Figure 7.35. SD C-Card directional vehicle classes 4 through 13 comparison for all methods.

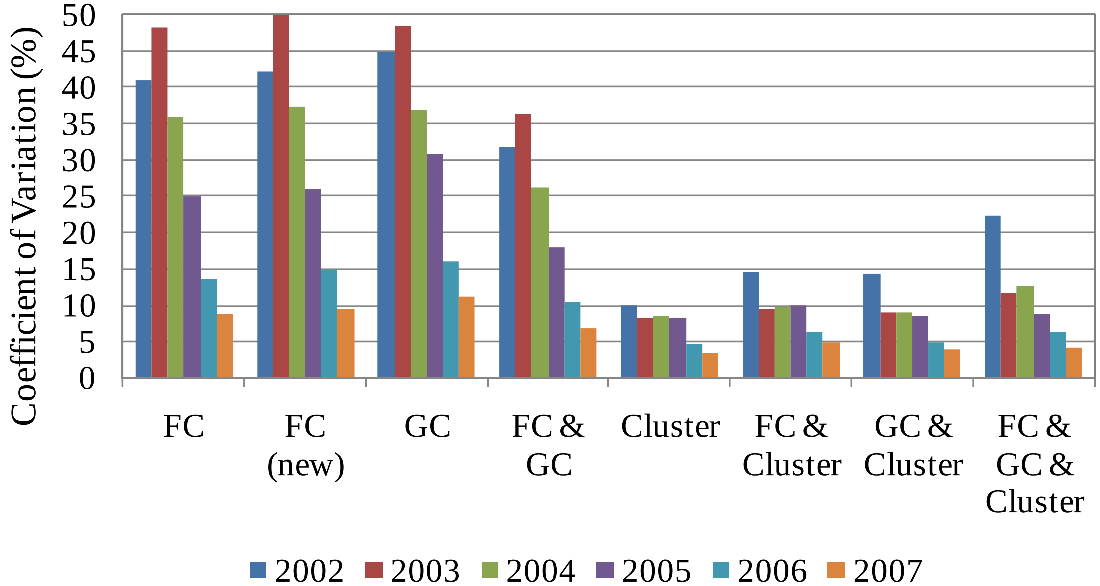

Figure 7.36. COV C-Card directional vehicle classes 4 through 13 comparison for all methods.

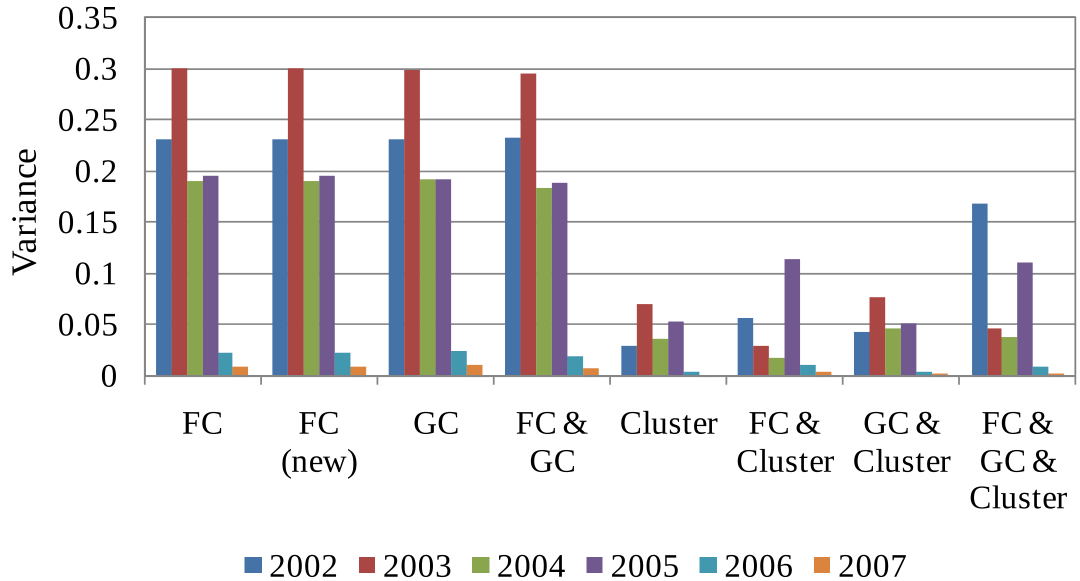

Figure 7.37. C-Card directional vehicle classes 4 through 13 variance comparison for all methods.

7.4.5 Summary of Results

In the summary of results there are three research areas of focus. The first is the comparison of the standard deviation, the coefficient of variation and variance for individual techniques utilized within each method. In some cases, such as Method One, there is one option for the division of the data. In other methods, such as Method Three, the data are divided spatially: north and south, east and west geographical locations, urban and rural, and northeast, northwest, southeast, southwest and central. The results for the individual techniques are shown and the best results are compared between all eight methods for total direction, directional, total volume, light-duty and heavy-duty vehicles.

The second set of results is developed to answer the following questions: how many cluster groupings is sufficient and where should the DOT add or remove current stations? The first question is straightforward because it is based on a series of performance criteria including the standard deviation, coefficient of variation and the variance. In most cases, the overall benefits improve as the number of clusters increases. There is, however, a point at which the addition of new cluster groupings provides little benefit. In most cases this range is between eight and twelve clusters.

There are two primary disadvantages when using higher numbers of clusters. The first is the ability to populate all the clusters with the minimum suggested number of stations; the TMG suggests at least five stations per cluster. In this research, many of the cluster groupings have less than three stations and in some cases a cluster was populated with only one station. One station per cluster violates suggestions provided within the TMG.

The second main disadvantage of clustering is the temporal instability within each cluster, explained by the overall dynamic nature of the roadway network. Two approaches may provide preliminary guidance for answering question two. These approaches are to record how many stations change clusters annually, and if the number of cluster groupings increases. Simply, the more clusters provided, the higher chance that the station may change on a per annual basis. The second suggestion for guidance is to monitor the stations that are usually grouped together. Stations with similar characteristics are then only required to have one of the stations to remain on-line.

The overall findings for both the total direction, directional and for all vehicle groupings statistically show cluster methods produce lower standard deviations, coefficient of variation and variances when compared to non-cluster methods. The following chapter describes the results obtained from the assignment of short-term counts to cluster groupings.

CHAPTER VIII

ASSIGNMENT OF SHORT-TERM COUNTS TO FACTOR GROUPINGS

8.1 Introduction

The existing practice for allocating short-term counts to ATR groups is highly dependent on engineering judgment. One potential problem with the use of engineering judgment is the sensitivity of the assignment of the short-term count (Sharma et al., 1996; Gulati, 1995). Prior research suggests the assignment procedure may influence the AADT estimates to a greater extent than the selection of the duration of the short-term counts (Sharma et al., 1996). Davis found that ineffective allocation of road segments to groups may lead to a tripling of the produced error (Davis et al., 1996). Currently there is limited guidance on how to achieve assignment accuracy necessary for obtaining reliable AADT estimates from short-term counts (Sharma et al., 1996; Aunet, 2000).

The objective of Chapter VIII is to determine the most appropriate methods to use when assigning short-term counts to factor groupings. Three techniques include:

- the traditional method,
- discriminant analysis, and
- the coefficient of variation (CoV) method

are developed and compared to determine which methodology is the most effective in assigning short-term counts with factor groupings, the fourth step in calculating AADT. The results from these methods are evaluated in Chapter IX.

8.2 Division of the Data Set

The data set developed within this study includes more than 7 million hourly records, obtained from classification continuous counters throughout the State of Ohio. The data collection time period for this study includes 2002 through 2007. The final data set is developed specifically for total volume both directions and a per direction basis. The selection of a per direction basis creates independence between the directions of flow.

Table 8.1 presents descriptive statistics of the compiled data set. All the short-term counts provided in Table 8.1 are derived from the continuous count stations where the actual AADT is known. The data are divided below annually by the number of ATRs per geographical region, average ADT, total number of factor groupings estimated from cluster analysis and the total number of sample short-term counts used to evaluate the examined methods.

Table 8.1. Characteristics of the data set.

Year	Number of ATRs per Geographical Region					Avg. AADT	Cluster Factor Groupings	Short-Term Counts
	NE	NW	SE	SW	C			
2002	57	26	7	21	15	40,734	7	31,247
2003	64	29	12	20	15	41,638	17	32,832
2004	50	37	18	19	18	34,980	18	27,863
2005	34	29	9	13	12	35,276	14	24,958
2006	45	23	10	15	12	34,154	17	25,277
2007	45	21	12	15	14	33,391	21	28,763

Based on the available data presented in Table 8.1, the monthly seasonal adjustment factors, Equation 4.16, are developed per ATR per year using the AADT, Equation 4.10**,** and the Monthly Average Weekday Traffic, Equation 4.2.

There is a need to directly quantify the ground truth performance of each assignment procedure. In order to validate the final results, Table 8.1 is divided into a series of short-term counts. These short-term counts are based on 24-hour durations, the worst case scenario; longer counts are likely to produce more accurate AADT estimates (Davis et al., 1996; Sharma et al., 2002) from the traffic counts taken from all the ATR locations. The reason for the creation of short-term counts from the ATR locations instead of the actual short-term counts is based on the AADT. In the case of the ATR created short-term counts, the final AADT is a quantifiable number, while the final AADT from the actual short-term counts are estimated, and therefore these counts are unable to directly validate the different assignment procedures. In the majority of previous studies, in order to evaluate model performance, typically only a few ATR sites are used, with a limited number of days as representative short-term counts (Sharma et al., 1994, 2001, 2002; Jin et al., 2008). In this study, each day of the year over the five year duration from all the available continuous counters are used as sample short-term counts; in total 142,177 daily counts are created. The large sample size, although it requires significant computing time, allows for a minimization of random errors and the influence of outliers in the final estimates.

8.2.1 Selection of Parameters used within the Assignment Process

The selection of parameters used in the assignment procedures vary between the methods. In the first method, the traditional assignment, the parameter of significance is the roadway functional classification. This means short-term counts taken from interstate highways are assigned to interstate specific seasonal adjustment factors groupings. The use of roadway functional class, however, is not a valid parameter for the second two methods. In the development of method two, the discriminant analysis, and method three, the coefficient of variation (CoV) approach, two other parameters are used in order to assign short-term counts to cluster groups. The first parameter is the temporal, hourly time-of day factors, and the second parameter is the ADT of that particular short-term count. The hourly time-of-day factor reflects the daily traffic variability within a 24-hour count, while the ADT represents the total volume of traffic per day on a roadway section. The combination of the two parameters capture both the variability and the magnitude of the daily volumes.

The hourly time-of-day factors include four time durations: 24 one-hour intervals, Equation 8.1, 12 two-hour intervals, Equation 8.2, 8 three-hour intervals, Equation 8.3, and 6 four-hour intervals, Equation 8.4. In Equations 8.1 through 8.4 the interval number is ordered temporally, with interval one equaling the first sampling duration. In each case the parameters are calculated for every day of the year per station over the five years of sampling. Equations 8.1 through 8.4 are presented below:

$$F_{1,i} = \frac{ADT}{HV_i} \tag{8.1}$$

$$F_{2,j} = \frac{ADT}{HV_j + HV_{j+1}} \tag{8.2}$$

$$F_{3,k} = \frac{ADT}{HV_k + HV_{k+1} + HV_{k+2}} \tag{8.3}$$

$$F_{4,l} = \frac{ADT}{HV_l + HV_{l+1} + HV_{l+2} + HV_{l+3}} \tag{8.4}$$

where:

HV = hourly volume that corresponds to the *i, j, k* or *l* hour of a day,

i = 1, 2,…, 24,

j = 1, 2,…, 12,

k = 1, 2,…, 8, and

l = 1, 2,…, 6.

The selection of four time aggregations, Equations 8.1 through 8.4, allows for the examination of each individual hourly factor in capturing changes in daily traffic patterns. A set of 24-hourly factors is expected to be more efficient when the traffic volume is high, but what happens with the low traffic volumes during off-peak periods including the night? The hourly factors based on the aggregation of consecutive traffic volumes are used in order to examine their performance on assigning low traffic counts. Furthermore, it is of great interest to quantify the accuracy of the final predictions, produced from counts with unusual daily patterns. The comparison of the four factors will show the overall impact of this aggregation on the AADT estimates. The ADT is used in order to take into account the magnitude of the total traffic within a day, which is not captured from the hourly time-of-day factors.

8.3 Traditional Assignment

The traditional method is based on the assignment of short-term counts with functional class specific roadway groupings. The SAFs are estimated for each group and the short-term counts are assigned to the groupings based on their functional/geographical class. The end result is groups of ATRs with short-term counts, each having one common attribute. Despite the simplicity and the short computational time needed, the traditional method takes into account only one variable, which cannot effectively represent all the ATRs within a factor grouping (TMG, 2001).

8.4 Discriminant Analysis

Discriminant analysis is one method which may produce lower assignment errors when compared with the traditional method. The selection of discriminant analysis over other potential statistical methods is based on three main strengths:

- The ability of DA to detect variables that allows the analyst to discriminate between different groups (Goldstein, 1978; Hand, 1981). The DA has the ability to assess the classification carried out within cluster analysis, given the resulted groups and provided that the assumptions of linearity and normality are met;
- To classify cases into groups with an accuracy based on the values of the variables to assign observations to a given group of objects (Lanchenbruch, 1975). The second application is of interest since it can be applied in the assignment step of the AADT estimation process; and
- The third strength is the ability of DA to identify the variables that contribute the most to the effective information allowing for the proper selection of the most appropriate groups (North Carolina State University, 2008).

Discriminant analysis contains two basic steps. In the first step, an F-test is used to evaluate the validity of the model. If step one is significant, then in step two the variables are assessed individually in order to determine significance in the mean by group, and then these constitute the base for the classification of the predicted variable (North Carolina State University, 2008).

The most common methods of DA are multiple DA, Fisher's linear DA (Fisher, 1936) and the K-nearest neighbors DA (ESO, 1999). The issue of predictive classification of cases is achieved by using classification functions. These functions may be used to determine to which cluster or group each case most likely belongs and the number of the classification functions is equal to the number of groups. The Direct Method of Discriminant Analysis (DMDA) is used to assign the short-term counts to SAF groups. The DMDA method compares variable testing, the short-term count data with given characteristics to a training set of variables, data obtained from the ATRs, which have already been assigned to a factor group yet possess similar assignment characteristics (SPSS for Windows, 2007).

This method is valid if the following conditions are satisfied: short-term count data are independent, data collected from ATRs have a multivariate normal distribution and factor groups have equivalent Within-Groups Covariance Matrices (WGCM). A classification score is then calculated and the short-term count is assigned to the factor group with the highest score (SPSS for Windows, 2007), assuming each short-term count is classifiable with membership in only one factor group. Equation 8.5 is used to determine classification score as:

$$S_i = c_i + w_{i1} \times x_1 + w_{i2} \times x_2 + ... + w_{im} \times x_m \tag{8.5}$$

where:

i = respective group,

m = number of variables,

c_i = constant for the group i,

w_{ij} = weight for variable j in the computation of the classification score,

x_j = observed value for the respective case for the variable j, and

S_i = classification score (Statsoft, 2008).

The DMDA method compares variables directly and calculates the classification score rather than using an extensive process of elimination to arrive at the appropriate classification like the stepwise method (SPSS for Windows, 2007). The prior probabilities of all factor groups is assumed to be equal, meaning that members of the test set are not more or less likely to be assigned to a factor group based on the probability of group membership of the training set (SPSS for Windows, 2007).

In this research, DA will be used to predict cluster membership of individual cases. The ATRGs are the clusters produced from cluster analysis and the short-term counts will represent the classified objects of the analysis. The classification score estimated for each object will determine the most proper cluster for each short-term count. The parameters used as j variables in Equation 8.6 are described in the following section.

8.4.1 Model Methodology

Eight discriminant models are developed to determine group membership of the short-term counts. The first four models, DA1 through DA4 use the hourly time-of-day factors and the ADT. This means that the first variable j of Equation 8.6 is the ADT and the 24-hourly factors $F_{1,i}$ are the remaining variables in model DA1. The variables of each model are presented in Table 8.2. The remaining four models, DA5 through DA8, only evaluate the similarities between the daily traffic pattern of the ATR data and the short-term counts, which are reflected through the hourly factors shown in Equation 8.1 to Equation 8.4. As it is shown in Table 8.2, the last four models (DA5 through DA8) do not include the ADT.

Table 8.2. Models per hourly factor type.

Model 1 (DA1):	$ADT+F_{1,1}+F_{1,2}+...+F_{1,24}$
Model 2 (DA2):	$ADT+F_{2,1}+F_{2,2}+...+F_{1,12}$
Model 3 (DA3):	$ADT+F_{3,1}+F_{3,2}+...+F_{3,8}$
Model 4 (DA4):	$ADT+F_{4,1}+F_{4,2}+...+F_{4,6}$
Model 5 (DA5):	$F_{1,1}+F_{1,2}+...+F_{1,24}$
Model 6 (DA6):	$F_{2,1}+F_{2,2}+...+F_{1,12}$
Model 7 (DA7):	$F_{3,1}+F_{3,2}+...+F_{3,8}$
Model 8 (DA8):	$F_{4,1}+F_{4,2}+...+F_{4,6}$

8.5 Coefficient of Variation Approach

A third method, called the coefficient of variation (CoV) approach, is developed to assign short-term counts to ATRGs. This method, shown in Figure 8.1, is developed from the known characteristics of a short-term count which include the duration of the count, the day of the year, the hourly volume, the ADT and the geographical location of the count. In addition to the previous variables, this method allows for the assignment of short-term counts based on directionality, total and directional.

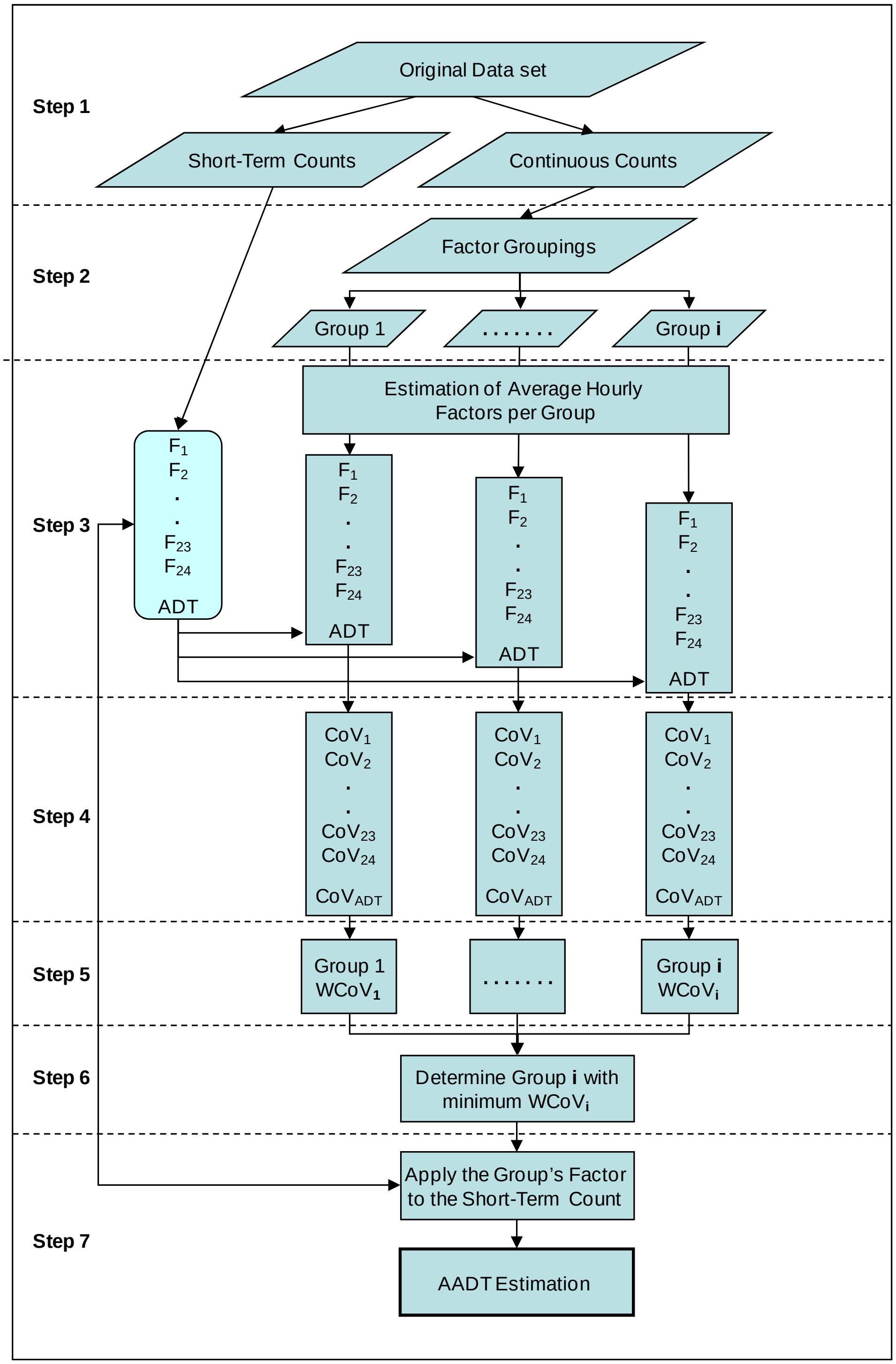

Figure 8.1. Illustration of the model development methodology.

8.5.1 Model Methodology Step One

The first step in the model methodology section divides the full data set into two sub-data sets. The first data set includes all the traffic volumes collected from the ATR sites, which are then used in the development of seasonal adjustment factors as well as the factor groupings. The second data set is the validation data set, which is comprised from all the 24-hour short-term counts included in the original full data set. These sample short-term counts are then used to assess the performance of the assignment models.

8.5.2 Model Methodology Step Two

In the second step the continuous counts are grouped together based on a traditional cluster analysis algorithm, Equation 6.1. This means the total number of cluster groups as well as the number of ATRs per cluster group will vary and there are no additional yearly constraints.

8.5.3 Model Methodology Step Three

The third step of the model process is the development of the individual hourly factors as described by Equations 8.1 through 8.4 for both the short-term and per cluster group. For example, Equation 8.1 generates 24 one-hour factors per day per short-term count. Each hourly cluster factor is calculated as a simple average of the corresponding hourly factors of the individual ATRs within a cluster.

8.5.4 Model Methodology Step Four

In the fourth step, the time of day factors generated from the individual cluster groups are directly compared with the short-term time of day factors. For example, a short-term hourly factor, factor one, developed by Equation 8.1, would correspond to a time period 12:00 AM to 1:00 AM for each day of the year. This factor would then be compared directly to the exact same factor on the same day of the year for each cluster group.

In order to compare the appropriate assignment, the hourly coefficient of variation (CoV) is calculated between the short-term count and the individual cluster groups. The lower the CoV the better the assignment is between the cluster group and the short-term count. The use of the CoV instead of the variance or the standard deviation is selected for four reasons. First, the CoV is dimensionless; therefore, the CoV estimated from different parameters may be used in the same model or may be directly compared. Second, unlike the standard deviation and the variance, the CoV is not required to be normalized. Third, the calculation of the CoV uses the average and the standard deviation of the examined parameters, which is very useful when the two means are significantly different. Lastly, the sensitivity of the CoV to very small means does not affect the estimations, since the factors and the ADT will rarely have values near zero. The lowest producing CoV between the cluster grouping and the short-term count is highly desirable.

8.5.5 Model Methodology Step Five

In step five, since the final assignment is not based on individual hour CoV, an average coefficient of variation (ACoV) based on all the hourly CoV is calculated for both the short-term and all cluster groups. A similar process of evaluation is then applied to the comparison of the ADT between the short-term and the cluster factor groupings.

After all the ACoV for the time of day factors and the CoV for the ADT are calculated, a final model is developed. The general model form is based on Equation 8.7 where the two variables are weighted differently and produce a weighted coefficient of variation (WCoV). Equation 8.6 is shown below:

$$WCoV_{\beta}^{F} = (1-\beta) \times ACoV_{F} + \beta \times CoV_{ADT} \qquad (8.6)$$

where:

β = 0, 0.1, 0.2,..., 1

F = 1, 2, 3, and 4, with each number corresponding to one hourly factor type.

Based on Equation 8.6, there are eleven models for each of the four hourly time-of-day factors. Each model produces a WCoV for each factor group. Increments of 10% are selected to provide an overall trend of the models. For a smother trend, models may be created at 5% intervals or smaller. The overall results will remain similar. Table 8.3 provides the model structure used in the results section.

Table 8.3 Models per hourly factor type.

Model 1 (M1):	$WCoV^F = 1.0 * ACoV_F$
Model 2 (M2):	$WCoV^F = 0.9 * ACoV_F + 0.1 * CoV_{ADT}$
Model 3 (M3):	$WCoV^F = 0.8 * ACoV_F + 0.2 * CoV_{ADT}$
Model 4 (M4):	$WCoV^F = 0.7 * ACoV_F + 0.3 * CoV_{ADT}$
Model 5 (M5):	$WCoV^F = 0.6 * ACoV_F + 0.4 * CoV_{ADT}$
Model 6 (M6):	$WCoV^F = 0.5 * ACoV_F + 0.5 * CoV_{ADT}$
Model 7 (M7):	$WCoV^F = 0.4 * ACoV_F + 0.6 * CoV_{ADT}$
Model 8 (M8):	$WCoV^F = 0.3 * ACoV_F + 0.7 * CoV_{ADT}$
Model 9 (M9):	$WCoV^F = 0.2 * ACoV_F + 0.8 * CoV_{ADT}$
Model 10 (M10):	$WCoV^F = 0.1 * ACoV_F + 0.9 * CoV_{ADT}$
Model 11 (M11):	$WCoV^F = 1.0 * CoV_{ADT}$

8.5.6 Model Methodology Step Six

In step six, the short-term count is assigned to the factor group cluster with the minimum WCoV. The WCoV allows for the contribution and assessment of which variable contributes more to the assignment process.

8.5.7 Model Methodology Step Seven

In the final step, step seven, the group factor is applied to the short-term count, creating an estimated AADT.

8.6 Statistical Evaluation

The statistical evaluation of the individual models and the traditional method is based on four performance criteria: absolute error (AE), of the AADT estimate Equation 8.7, the mean absolute error (MAE) Equation 8.9; the standard deviation of the absolute error (SDAE), Equation 8.9; and an analysis of variance (ANOVA) test is used to evaluate the statistical significance at the 95% confidence level of the final results. Equations 8.7 through 8.9 are shown below:

$$AE_{v,dd} = \frac{\left| AADT_{v,Actual} - AADT_{v,dd,Estimated} \right|}{AADT_{v,Actual}} \times 100 \tag{8.7}$$

$$MAE = \frac{1}{w} \sum_{s=1}^{w} \left(\frac{\left| AADT_{v,Actual} - AADT_{v,dd,Estimated} \right|}{AADT_{v,Actual}} \times 100 \right) \tag{8.8}$$

$$SDAE = \sqrt{\frac{\sum_{s=1}^{w} (AE_{v,dd} - MAE)^2}{w-1}} \tag{8.9}$$

where:

$AADT_{v,Actual}$ = actual annual average daily traffic,

$AADT_{v,dd,Estimated}$ = estimated annual average daily traffic,

w = number of short-term counts,

v = ATR index,

dd = day of year.

The ground-truth of more than 140,000 short-term counts enhances the validity of the results and minimizes the influence of outliers. The performance of the three methods presented above is evaluated against each other. The purpose of this comparison is to answer the question of which assignment method perform the best, given the current state of the data collection. The findings from the previous methods are documented in Chapter IX. Guidance suitable for use by an engineer or designer in the decision of developing AADT volumes throughout the state can be developed using the findings from the empirical models.

CHAPTER IX

RESULTS AND SELECTION OF THE MOST APPROPRIATE ASSIGNMENT PROCEDURE

9.1 Introduction

The results obtained from the three assignment methods described in Chapter VIII are presented in the following sections. The traditional method to allocate short-period counts to ATRGs is based on total volume factors. The results from the DA and the CoV method are shown for both total and directional volume factors. The final results presented within this chapter are divided into two sections. These sections include the comparison of the hourly factor groupings, as well as the individual comparison of the models, and the second section compares the results from the total, directional groupings as well as traditional methods for assigning short-term counts. The final comparison of the three methods at the end of this chapter answers the question, “What is the most effective way to assign short-period counts to ATRGs?”

9.2 Discriminant Analysis

The selection of the most efficient model includes the comparison of the four hourly factors, Equations 8.1 to 8.4. Based on these factors, there are two sets of discriminant models. The first set, DA1 through DA4, Table 8.2, uses both the hourly time-of-day factors and the average daily traffic. The second set of models, DA5 through DA8, does not include the ADT. There are two sets of results within the DA method. The first result is the comparison between the four methods for developing hourly factors. The set of results is the comparison between the eight DA models for the total volume and the eight DA models developed with the directional data. In each case, the X-axis is the name of the model which is defined previously in Table 8.2. The y-axis is the mean absolute error, Figures 9.1 and 9.3, and the standard deviation of the mean absolute error, Figures 9.2 and 9.4.

The first analysis is the comparison of the hourly time-of-day factors. Models DA1 and DA5 are 24 one-hour time of day factors and each model increase sequentially up to Models DA4 and DA8, which are 6 four-hour time-of day factors. In all cases the 24 one-hour time-of-day factors produce lower MAE and standard deviation of the mean absolute error. For total direction with ADT, the MAE decreases on average from 14.8% to 13.4% and directionally from 12.2% to 11.4%. When ADT is not included in the model the MAE decreases on average from 14.8% to 13.4% and directionally from 14.2% to 13.1%. In addition to the MAE, the standard deviation of the mean absolute error also decreases as the number of hourly time-of-day factors increases. For both the total direction and directional based DA models, model DA5 has the lowest mean absolute error and standard deviation of the mean absolute error.

The second set of results from the DA is the comparison between the mean absolute errors and the standard deviation of the mean absolute errors between the total and the directional based assignments. When comparing the impact of total versus directional based assignment using the overall most efficient model, DA5, the mean absolute error decreases from 13.1% to 11.0% and the standard deviation of the mean absolute error decreases from 14.5% to 12.5%. These results show the directional based assignment lowers both statistical performance measures.

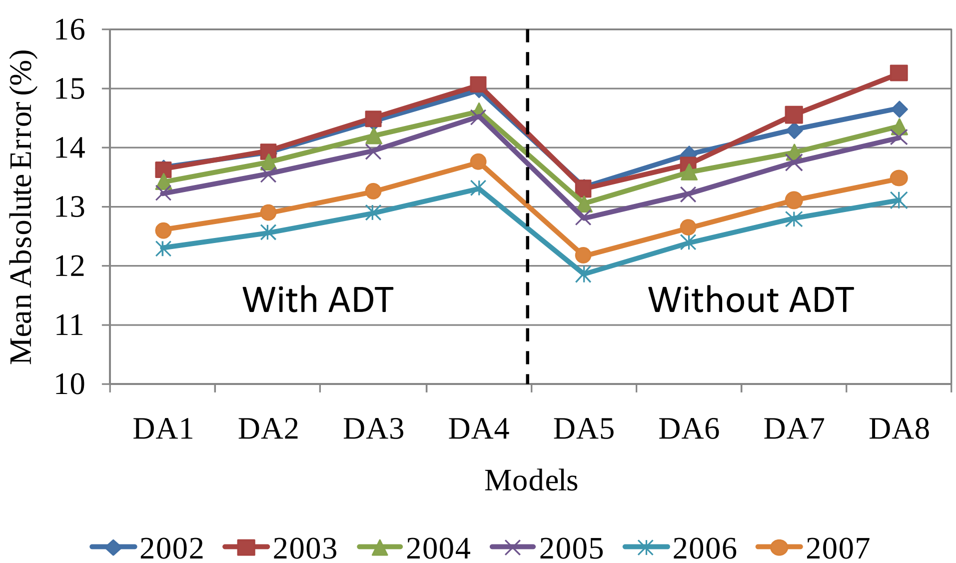

Figure 9.1. MAE per year and model for total volume based SAFs.

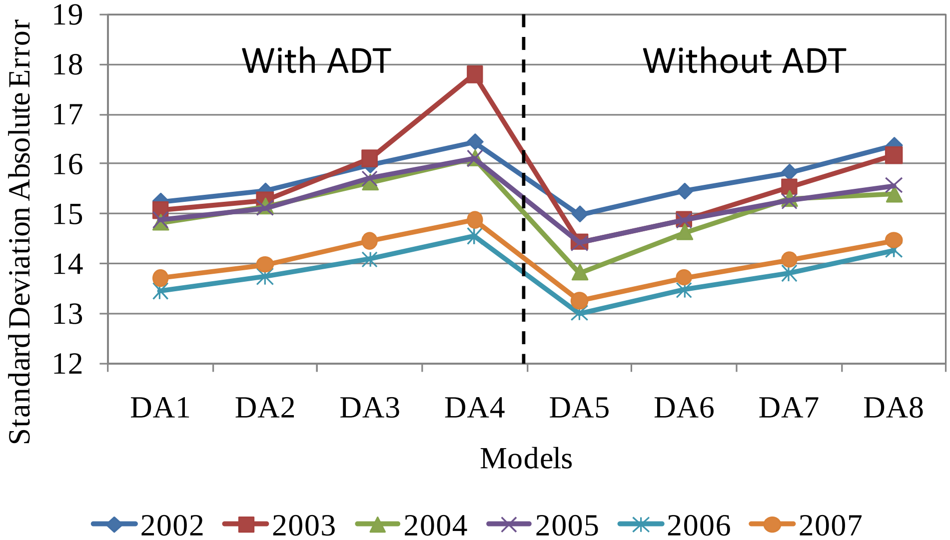

Figure 9.2. Standard deviation per year and model for total volume based SAFs.

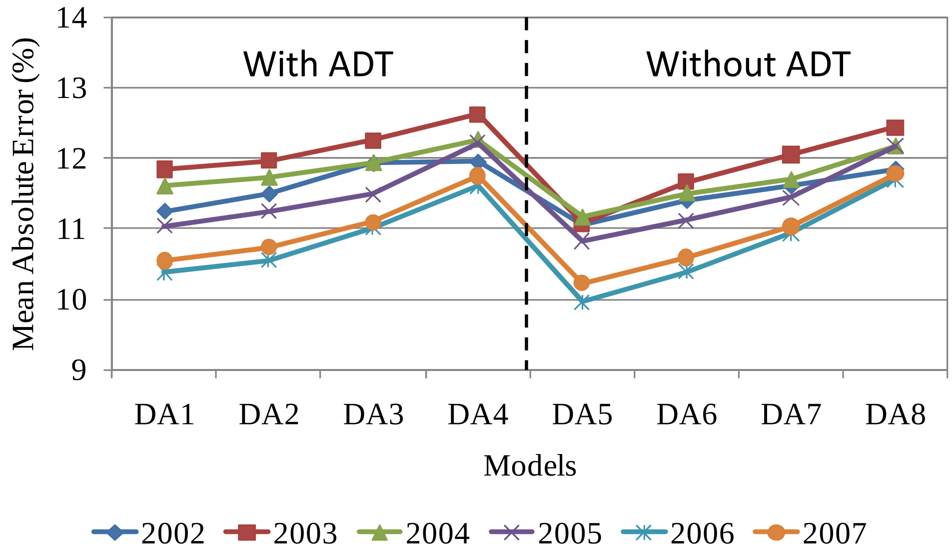

Figure 9.3. MAE per year and model for directional volume based SAFs.

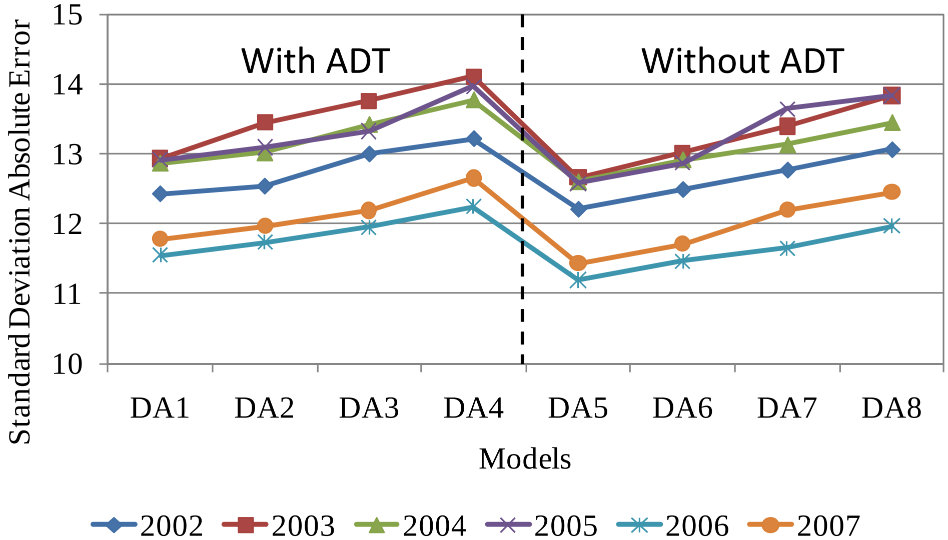

Figure 9.4. Standard deviation per year and model for directional volume based SAFs.

9.3 CoV Method

The initial results are based on the comparison between dividing the day into 24 one-hour factors, 12 two-hour, 8 three-hour and 6 four-hour factors. Since there is consistency in the results across the years, the average results instead of the yearly trends are shown. In general, the results found in Figure 9.5 are consistent across the four methods with lower errors associated with the models with less weight on the ACoV of the ADT. In some cases, Models 1 through 4, there is a statistical difference at the 95% confidence level between the best case one-hour time-of-day factors versus the worst case four-hour factors. In comparison, between the total direction and the directional based analysis, the directional based analysis across all models produces lower mean absolute assignment errors.

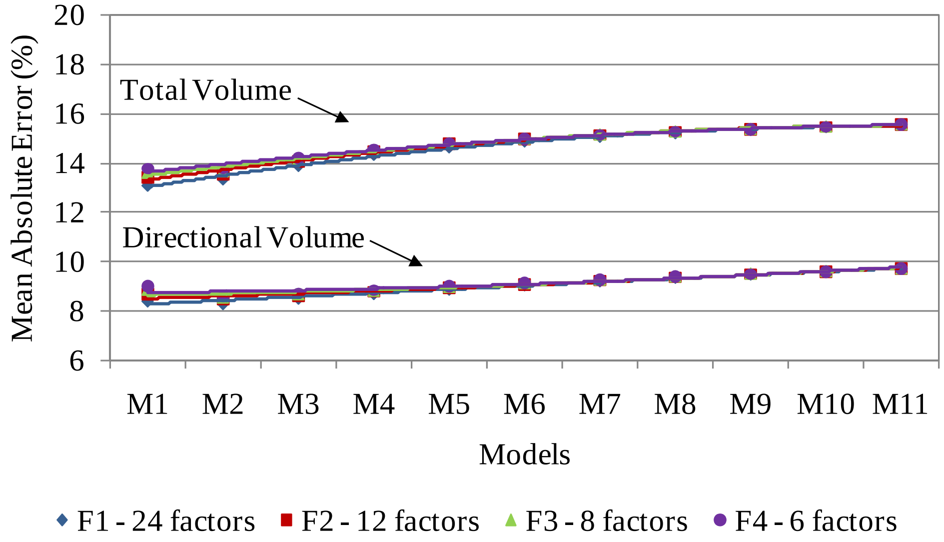

Figure 9.5. Mean absolute errors for the four hourly time-of-day factors.

There is a slight statistical benefit, in the performance of models M1 through M4, with the 24 one-hour factors in comparison to the other factors. As a result of this benefit, the remaining results are based on the 24 one-hour time-of-day factors, which are slightly more effective than the other three sets of factors.

The comparison of the model performance using the 24 one-hour factors is shown below in Figures 9.6 and 9.7. There is statistical significance between the total volume and the directional mean absolute errors. There is also statistical significance between the individual model's performance. No statistical tests are preformed to directly test the difference within total or directional specific on a yearly basis. The general assignment errors tend to increase in all cases as the weight of the CoV of the ADT increases. Furthermore, they are significantly improved over other studies that produce average errors of 20% (Davis et al., 1996).

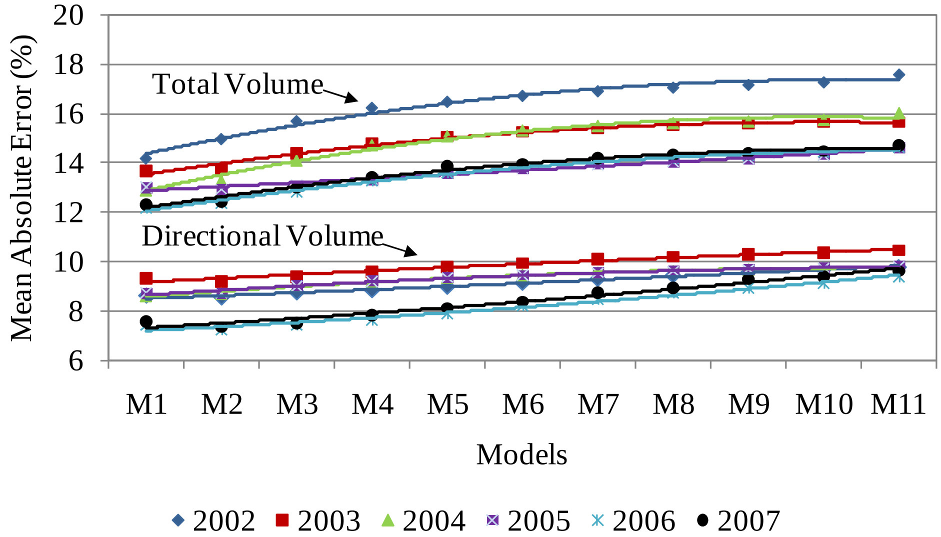

Figure 9.6. Mean absolute errors for all models based on hourly factors.

Similar conclusions to the MAE are drawn for the SDAE, Figure 9.7. M1 and M2 are the most accurate models while M11 is the least accurate. Similar to the results shown in Figure 9.6, the directional volumes produce lower standard deviations of the absolute errors when compared with the total volumes.

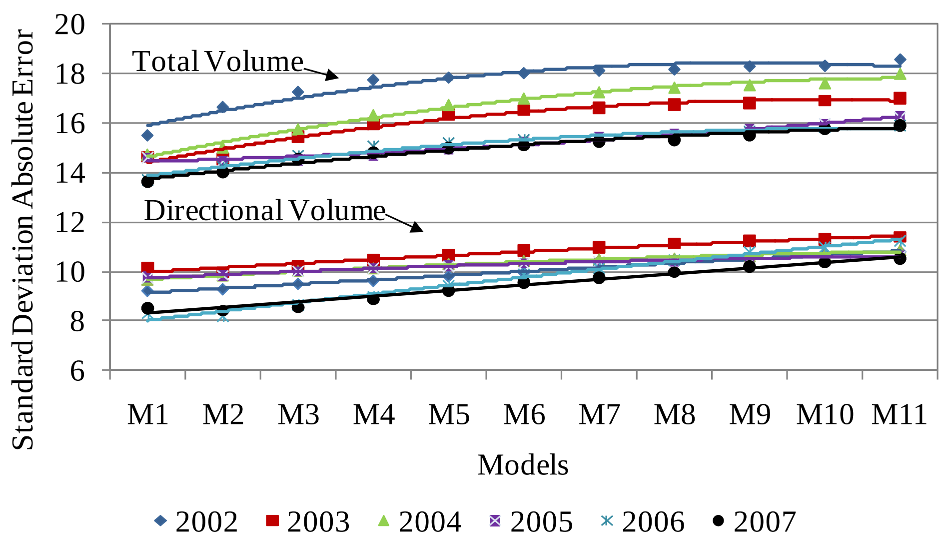

Figure 9.7. Standard deviation of the absolute error for all models based on hourly factors.

There are two outcomes from Figures 9.6 and 9.7. First, the models with less weight on the CoV from the ADT produce lower mean absolute errors with a tighter distribution about the mean. Second, the directional volumes produce statistically significant lower MAE and SDAE when compared to the total volumes.

9.4 The Comparison of Model Results

9.4.1 The Comparison Between Traditional and DA Results

Section 9.4.1 compares the results between the traditional allocation of short-term counts and the DA. Prior to the evaluation of the results, tests of statistical significance are performed for the three populations per year. The results show that 91% of the compared methods are significantly different at a 95% confidence interval. Figures 9.8 and 9.9 compare the results of the traditional method with those of the total volume-based model, as well as the directional volume-based model, DA5, which produces the lowest errors. In both figures, DA5 clearly generates the most accurate AADT for every year.

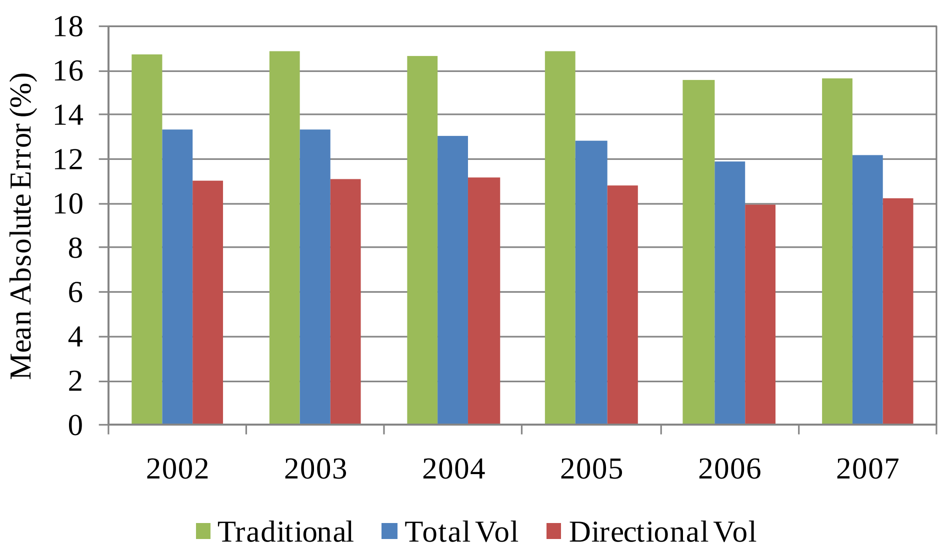

Figure 9.8. MAE for the traditional method and the fifth discriminant model, DA5.

The directional volume based DA yields a 5.7 average decrease in the MAE, corresponding to a 30.7% improvement in the accuracy of the final estimates. The corresponding improvement to the SDAE is 58.0%. The average percent improvement in the MAE and the SDAE when total volume-based DA is used instead of the traditional method is 21.3% and 51.0% respectively. The directional factors perform better than the total volume based SAFs. The corresponding average MAE and SDAE decrease is 15.8% and 13.2%.

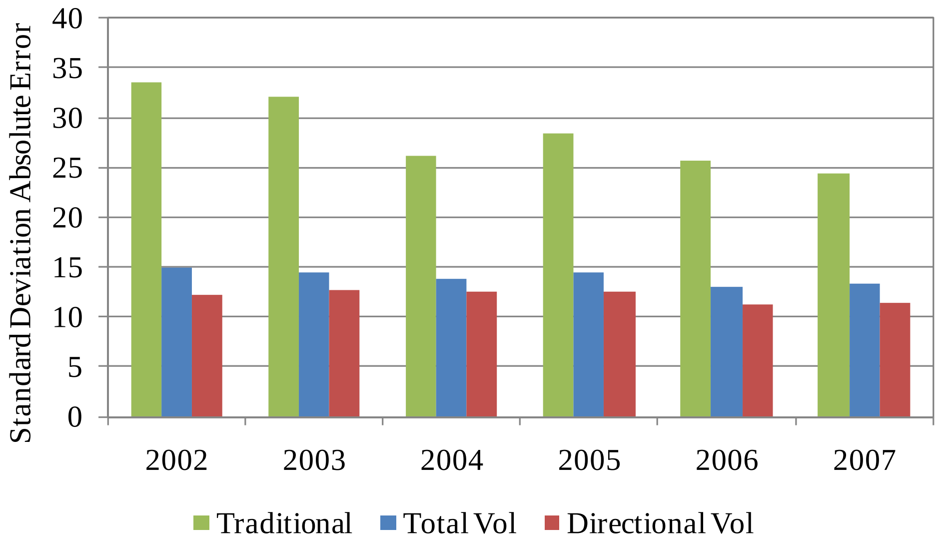

Figure 9.9. SDAE for the traditional method and the fifth discriminant model, DA5.

9.4.2 The Comparison Between Traditional and CoV Results

The temporal comparisons between the traditional method, total volume and directional volume analysis are shown in Figures 9.10 and 9.11. The overall results show the traditional method for assigning short-term counts produces the highest mean absolute errors as well as the greatest distribution of the standard deviation of the mean absolute errors for each of the five years. The traditional method produces mean absolute errors of 16 to 16.5%. The second method using the weighted coefficient of variation for the total volumes improves the absolute errors of 12 to 14% and lowers the standard deviation of the mean absolute errors of 13 to 15%.

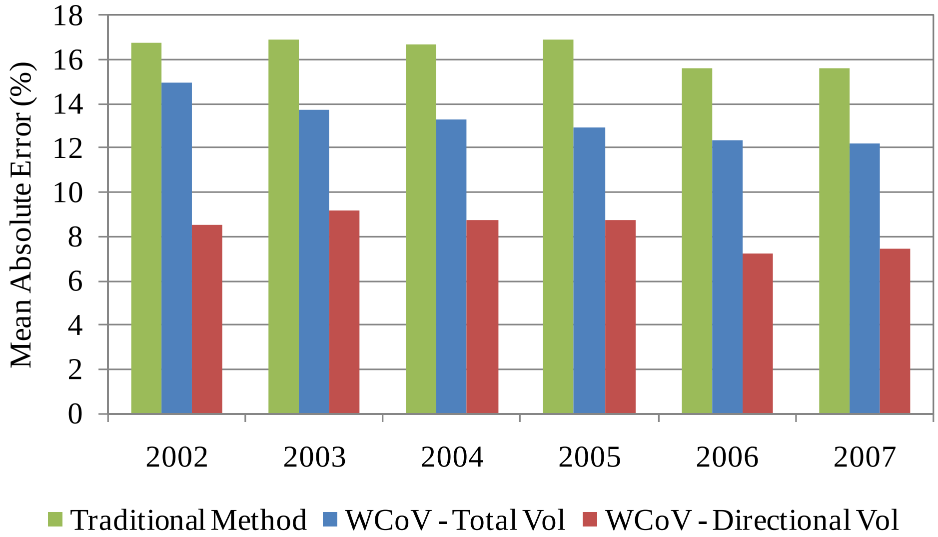

Figure 9.10. MAE over time for total and directional volume-based factors.

The most efficient method is the development of directional specific assignments. The directional specific assignments improve the mean absolute error to 6-8%, which is approximately half the error of the traditional method. The standard deviation of the mean absolute error also improves to 6-10%. This is one third the standard deviation of the traditional method. Two potential explanations for this finding are the statistical difference between the two populations are the directional sample size is almost double, which in turn yields more factor groupings and as the number of groups increase, the greater the possibility to assign a short-term count to a group with similar traffic pattern and ADT.

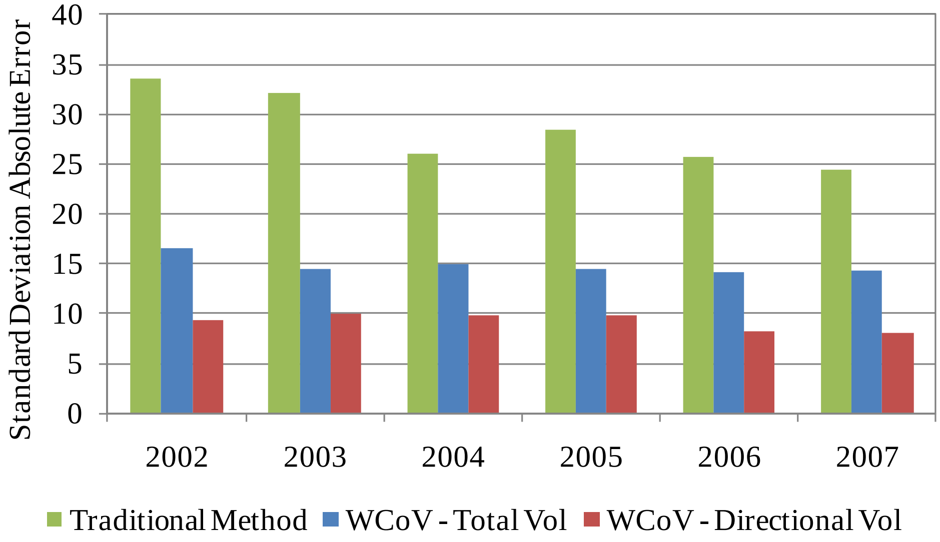

Figure 9.11. SDAE over time for total and directional volume-based factors.

9.5 Final Comparison of the Three Methods

The final comparison includes the traditional method, the best performing discriminant model, DA5,based on directional volume factors, and the second CoV model, M2. Figures 9.12 and 9.13 illustrate the MAE and the SDAE respectively of each method over time. It is apparent from both Figures 9.12 and 9.13 as well as statistical tests that the CoV method performs better than the other two techniques for all years.

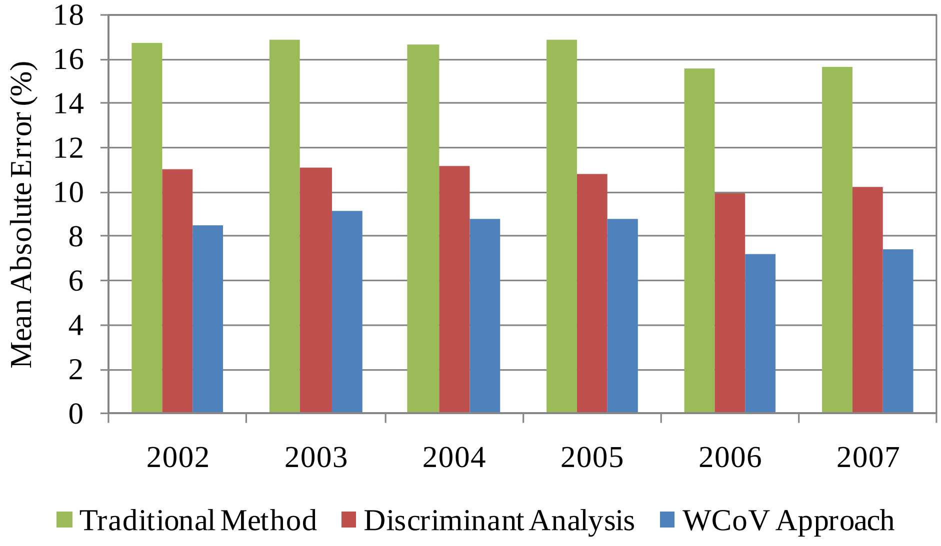

Figure 9.12. MAE over time for DA, COV and traditional method.

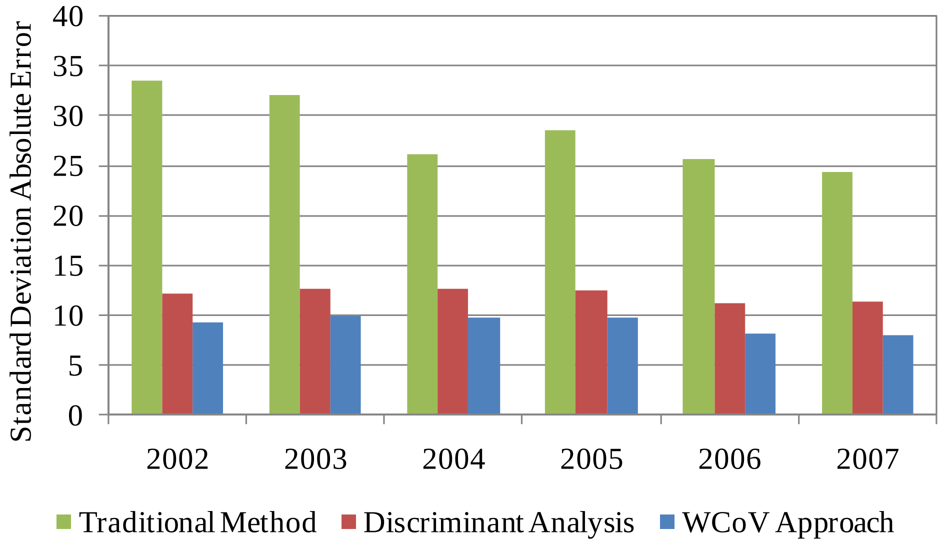

Figure 9.13. SDAE over time for DA, COV and traditional method.

When the CoV model is used instead of the traditional method, the MAE decreases on average by 8.01% and the SDAE by 14.21%. The equivalent MAE and SDAE percentage improvement is approximately 52% and 66%. The discriminant model DA5 improves the MAE by 31% and the SDAE by 58% over the traditional method.

9.6 Summary of Results

There are three methods developed for the assignment of short-term counts to ATRGs. These methods include the traditional, discrimant analysis and the CoV approach. In this study the discriminate analysis and the CoV approach perform better than the traditional method. The CoV approach based on the lowest mean absolute error and standard deviation of the absolute error is considered the most effective of all three methods. The last finding shows the directional assignment is more accurate than the total direction assignment.

CHAPTER X

CONCLUSIONS AND RECOMMENDATIONS

10.1 Introduction

Chapter X provides the conclusions and recommendations from this research study. Conclusions are presented with regards to the following subject matters:

- improving the estimation of seasonal adjustment factors;
- the development of factor groupings;
- the assignment of short-term counts to factor groupings; and
- the overall significance of the findings.

Brief descriptions of each task along with recommendations derived from the assessment of the results are provided in the following sections.

10.2 Estimation of Seasonal Adjustment Factors

The development and analysis of the most effective individual seasonal adjustment factors are based on five individual methodologies. These methodologies include:

- estimation of AADT using five approaches;
- developing different vehicle groupings;
- comparison between multiple SAFs and individual SAFs;
- determination of the best months to collect truck data; and
- the impact on AADT of the length and the timing of a short-term count.

The remaining portion of Section 10.2 provides some recommendations on these methodologies.

10.2.1 Five AADTs

Five methods are used for the calculation of the AADTs. According to the findings of this research, all five methods produce similar results across each of the seven SAFs for both the ATR and WIM data sets. The first method, simple average (AADTa), produces slightly better results for both ATR and WIM data sets. These results are consistent with past research (Wright, 1997), the simple average approach produces slightly more accurate estimates than the other methods when the data set includes very little missing data. On the other hand, if a large amount of missing data exists in a data set, the AASHTO method is recommended (TMG, 2001).

10.2.2 Vehicle Class Groupings per Roadway Functional Classifications

Seasonal adjustment factors are applied to thirteen individual vehicle classes separately as well as to groups of vehicle classes. The objective of the analysis is to examine the impact of this aggregation on the AADT. The individual vehicle classes in comparison to aggregated vehicle classes have higher mean absolute errors. The most accurate single class AADT are obtained for vehicle class 2, passenger cars, and vehicle class 9, standard semi-trucks. The first vehicle class, motorcycles, results in the largest mean absolute errors, while the new recommended method by TMG (TMG, 2008) does not improve the predictions. Other vehicles classes that did not perform well are vehicle classes 7, 10, 11, 13, 14 and 15. The small sample size results in an increased mean absolute error, especially when compared with more common vehicle types which have higher sample sizes. Vehicle groupings with higher volumes should be considered in order to produce lower mean absolute errors. The results from the analysis show that one vehicle grouping for trucks produces the lowest heavy-duty mean absolute error. In general, the more groups of vehicle classes examined, the higher the predicted errors.

10.2.3 Multiple Factors

The analysis includes two scenarios. Analysis one is the application of one seasonal adjustment factor to all functional classes and analysis two is the use of multiple factors. In the first scenario the three best performing factors are F_{WADT}, F_{MAWDT} and F_{MADT}. According to the results, the use of multiple factors yields slightly lower errors than using one individual factor. The mean absolute error increases when the number of the examined groups increases. Furthermore, the total volume factors produce better AADT estimates than the directional factors when four vehicle groups are used. The application of the multiple factors method is limited only to the traffic monitoring programs that use functional classification to group their continuous counts. The comparison between the total volume and the directional volume analysis reveals that the latter produces more accurate results when one, two or three groups of vehicles classes are used.

10.2.4 Temporal Analysis for Monthly Short-Term Data Collection

The main objective of this analysis is the determination of the best months to collect truck data. The comparisons show that the worst months are November and December, while spring and summer months produce lower mean absolute errors. August and September are the best months to collect truck data. The results show that there are no consistencies with the overall best individual roadway functional classification. This may be attributed to the number of permanent stations or a possible underlying trend within the data set. It may be drawn in the final comparison that the ATR data set generally produces less error than the corresponding WIM data set.

10.2.5 Day of the Week and Sampling Duration for the Short-Term Data Collection

There are two objectives examined within this part of the study. The first objective evaluates the impact of short-term counts on AADT. The second objective evaluates the influence of the day of week when the short-term count is sampled with respect to AADT. The results from the day of the week and duration of the short-term data collection analysis show 24-hour durations produce the highest mean absolute errors, followed by 48-hour and then 72-hour sampling durations. In general, the largest decrease in the mean absolute error occurs between the 24 and the 48-hour counts. There is little improvement in the mean absolute errors when comparing the 48-hour counts to the longer durations.

The day of the week also influences the increase or decrease of the mean absolute error, in addition to the sampling duration. The findings show Mondays produce the highest mean absolute errors, followed by Tuesdays and Thursdays. Wednesdays have the lowest errors of the week.

10.3 Development of Factor Groupings

There is a significant debate between researchers and practitioners on what is the most effective method to group continuous recorders. This study examines four traditional and four cluster-based grouping methods in order to identify advantages and disadvantages within each approach. The non-cluster methods include geographical and/or functional classifications of ATRs. The remaining four techniques combine cluster analysis with traditional approaches. The overall findings, for both total and directional factors, show cluster methods produce lower errors when compared to non-cluster methods. The lowest errors are generated when clustering is used alone. As more classifications of a data set are combined with cluster analysis, Method Six through Eight, the variation within each cluster and the required computational time increases. The advantage of the combined grouping techniques is an easier to interpret grouping used in assigning short-term counts to cluster groups. Although clustering exclusively provides the overall best result, the assignment of short-term counts in some cases is hard to justify. As a result of the assignment of short-term counts, it is recommended to use Method Seven which includes clustering with the geographical location.

The second set of results is developed to evaluate how many cluster groupings are sufficient for accurate results and where current stations should be added or removed. In general, the overall accuracy improves as the number of clusters increases. There is however, a point in which the addition of new cluster groupings provides little benefit. This range is between eight and twelve clusters. There are two main disadvantages with higher cluster numbers. The first disadvantage is the inability to populate all the clusters with the minimum suggested number of stations. The TMG suggests at least five per cluster. The second main disadvantage of clustering is the temporal instability within each cluster. Stations have different cluster memberships from year to year. The reason for this is the overall dynamic nature of the roadway network.

The more clusters provided, the higher the likelihood that the station will change on a per annual basis. A practical solution may be to monitor the stations typically grouped together. In these cases, stations with similar characteristics would only require one of the two stations to be online at one particular time. New factor groupings are recommended to be created every year.

10.4 Assignment of Short-Term Counts to Factor Groupings

The assignment of short-term counts to factor groupings is the final step of the AADT estimation process. There are two new techniques that are developed in this study to assign short-term counts to factor groupings. The first technique is called the discriminate analysis and the second technique is called the CoV approach. In each case the two techniques are compared with the traditional method for assigning short-term counts.

10.4.1 Discriminant Analysis

The discriminant analysis is the first method examined to assign short-term counts to factor groups. Eight models are developed using two parameters: hourly time-of-day factors and the average daily traffic volume. The results from the four sets of factors show that a set of 24 one-hour factors produces better results than a set of twelve, eight or six factors. The evaluation of the two parameters shows the hourly factors reduce the variation and improves the accuracy of the results. The lowest errors are produced by Model Five, DA5, which includes the 24 one-hour time-of-day factors. The comparison between total two-way and the directional volume-based factors reveals that the latter produces more accurate estimates. The standard deviation of the estimated AADTs is also improved at the same extent. It may also be concluded from the results that the discriminant analysis produces lower mean absolute error when compared with the traditional assignment.

10.4.2 CoV Approach

The CoV approach is a statistically-based method, consisting of seven steps, used with assigning short-term counts to factor groupings. Forty-four models are developed that take into account two parameters: hourly time-of-day factors and average daily volumes. From this research four factor methodologies are developed, which include 24 one-hour, 12 two-hour, 8 three-hour and 6 four-hour time-of-day factors. The results show that 24 hourly time-of-day factors are more effective than a set of twelve, eight or six aggregate factors. The second finding is based on the model development. The most effective models place more weight on the average coefficient of variation of the time-of-day factors than the coefficient of variation of the ADT. This finding is plausible because the time of day factors provide a better measure of the variability within the traffic stream than the single ADT value.

The comparison between the total and the directional factor analyses show the directional-based models are 40% more accurate than those of the total volume analysis when assigning short-term counts to factor groupings. There are two possible explanations for this finding. The first explanation is the statistical difference between the two directions, and the second explanation is the doubling sample size, which in turn yields more factor groupings. This creates a higher possibility to assign a short-term count to a group that has similar traffic patterns.

The final comparison between the traditional method, the DA and the CoV approach shows the CoV approach is the most efficient method for estimating AADT. The overall best model is developed directionally using 24 one-hour time-of-day factors. This model form improves the accuracy over the traditional method by 52% and 66% for the MAE and the SDAE.

10.5 Overall Significance of the Findings

Figure 10.1 shows the range and the percentage of the absolute difference of the AADT estimates obtained from the CoV approach and the traditional method. For 65% of the short-term counts the predictions between the two methods differ by less than 250 vehicles. 15% of the predictions fall within a range of 250-500 vehicles, whereas the remaining 20% of the short-term counts have a difference greater than 500 vehicles per day. These results express the real absolute difference of the outcomes produced from the traditional and the proposed method.

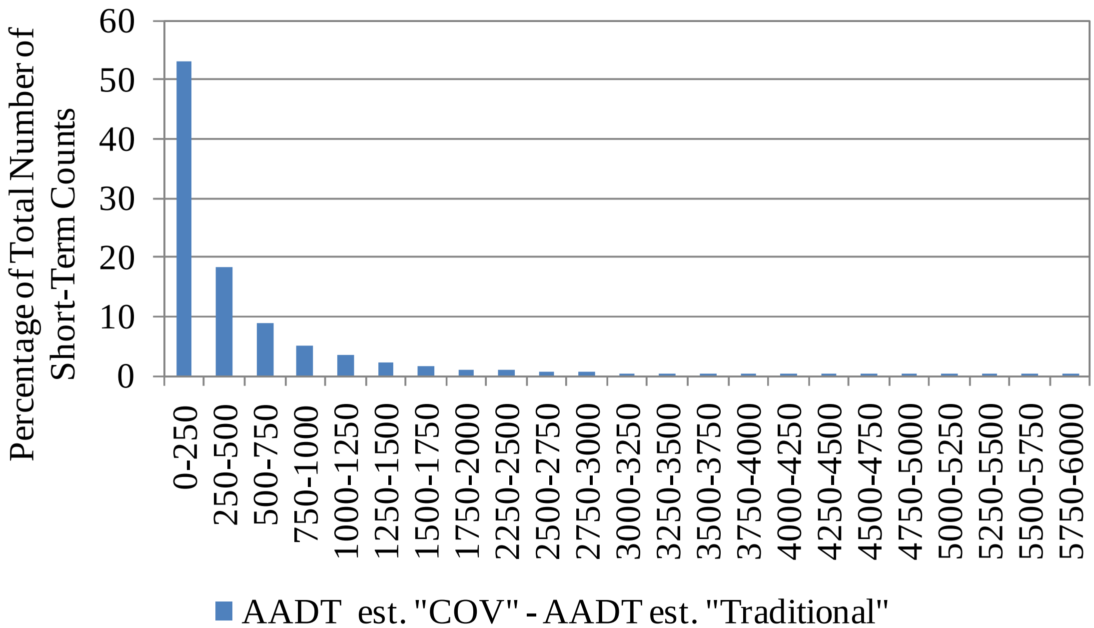

Figure 10.1. Range and percentage of the absolute AADT difference between the CoV approach and the traditional method for total volume using directional factors.

In Figure 10.2, the Y-axis represents the percentage of the total number of short-term counts, whereas the x-axis shows the AADT difference between the two methods. It is obvious from the curve that the two methods produce estimates that are normally distributed.

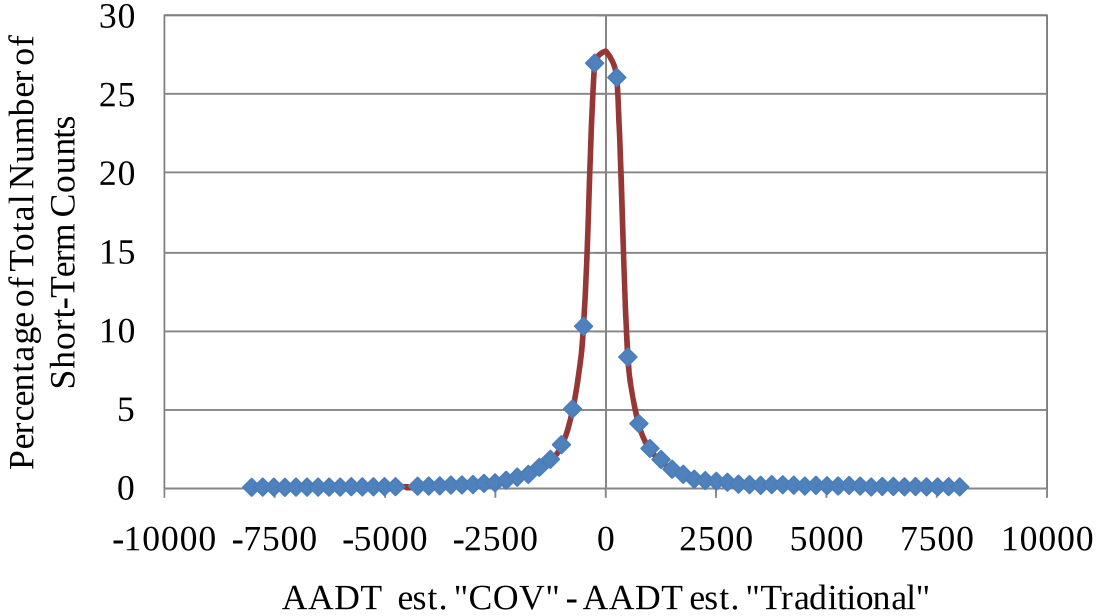

Figure 10.2. Percentage of the AADT difference between the CoV approach and the traditional method for total volume using directional factors.

It may be concluded from Figures 10.1 and Figure 10.2 that a small amount of the final estimates differ substantially between the two methods. A careful examination of these counts reveals that they do not share any similar functional or geographical characteristic, except for the high ADT; the average ADT of these counts is greater than 20,000. The more accurate AADTs improve current practice and may impact transportation agencies that use it in their programs. The better predictions may also positively affect positively other scientific areas, since the AADT is being used diversely by practitioners, researchers, consultants, companies and many non-transportation related industries.

10.6 Proposed Method

In conclusion, the main purpose of the process recommended in this study is to estimate a more accurate AADT from a short-term count, conducted at a specific location within one of the five geographical regions of the state of Ohio. The proposed process includes the following steps:

- the cleaning and organization of the data obtained from the continuous recorders located within this particular geographical part;
- the estimation of seasonal adjustment factors for each station;
- the application of cluster analysis along with the new method of determining the optimum number of clusters in order to develop the final factor groupings;
- the application of the CoV approach to assign the short-term count with one of the groups defined in the previous step; and
- the estimation of the final AADT by applying the group factor, which corresponds to the weekday and the month of the short-term count, to the average daily volume of the count.

The above recommendations developed from this research are expected to assist in the improvement of traffic monitoring programs and in the accuracy of AADT estimates. DOTs may benefit from this research by taking into account the assumptions and the criteria established in this study and adjusting them to their needs. Transportation agencies will be able to implement the new methodologies presented in the report. Guidelines and new specifications may also be defined based on the previous results.

CHAPTER XI

IMPLEMENTATION PLAN

The implementation plan developed for this research study is divided into eight sections. These sections are described in more detail in the remaining portion of this chapter.

11.1 Recommendations for Implementation

The recommendations for the implementation of this research project are based on the results and the procedural recommendations provided in Chapter X, Section Six. The implementation for previous years of data is already developed and the AADT for the short-term counts have been estimated. This implementation plan is designed for ODOT to use the methodology developed in this project for future AADT estimation. In terms of "Raw Data" ODOT is not required to modify their current methodology for collecting traffic counts along roadway segments.

11.2 Steps needed to Implement Findings

The steps that are required for the implementation of these findings are based on moving data between software packages. In order to implement these findings at the present time, ODOT will need a database platform, Microsoft Excel and SPSS. There are six recommended steps required to implement these findings.

11.2.1 Step One

The first step of this implementation plan is to download the data from TKO and import the data into a database platform. This step is required in the development of the initial calculation of the seasonal adjustment factors for light-duty, heavy-duty and total volume vehicles. The rationale behind the use of a database platform is based on the volume of traffic counts that are currently collected. Microsoft Excel may be used instead if fewer factors need to be calculated. The output from the database platform is the finalized seasonal adjustment factors. Additional information is provided in Chapter IV of this report.

11.2.2 Step Two

The second step of this implementation plan is to export the seasonal adjustment factors from the database and import these factors into Microsoft Excel. In step two, the user will be able to visually validate the findings and compare the current and previous seasonal adjustment factors. Once the user is satisfied with the results the data provided within Microsoft Excel has two options. In the first option the ATRs are grouped based on traditional methods and may be calculated within Microsoft Excel. If, however, the more effective cluster based groupings are desired, the user will then import the data in SPSS a statistical software package. A complete description on the traditional and non-traditional methods for grouping the data are provided in Chapter V of this report.

11.2.3 Step Thee

The third step of this implementation plan is to group the ATR data based on the cluster algorithm. This step is required only for the non-traditional methods, Methods Five through Eight, for grouping data. The key in clustering the data is based on the number of individual stations that are required to populate a cluster group. The TMG recommends five stations per group. This study, however, did not notice a significant difference in performance between the TMG recommendations and lower the number of stations per group to two or three. The research shows in general there should be between eight and twelve total cluster groupings for the State of Ohio. The clustering and assignment of stations to cluster groups is an iterative procedure described in detail in Chapter VI. When the user is satisfied with the number of clusters they may proceed to step four.

11.2.4 Step Four

The fourth step in the implementation plan is the exporting of the results from SPSS to Microsoft Excel. Microsoft Excel is used to visually validate the ATR groupings, especially the cluster based groupings which are derived statistically. Once all the ATR groupings are considered satisfactory, there is no additional requirement for the continuous count data.

11.2.5 Step Five

The fifth step in the implementation plan is the assignment of the short-term counts to the ATR groupings. The assignment procedure may be done on two different software platforms. For the traditional method, the assignment is completed within the Microsoft Excel platform. If, however, the coefficient of variation method is required, the groupings should be re-imported to the database platform.

11.2.6 Step Six

The last step in the implementation plan is the calculation of the AADT for the short-term counts. This may be done in either the database platform or Microsoft Excel. In general, steps one through four are required to be calculated once per year. Steps five and six are calculated on an as needed basis.

11.3 Suggested Time Frame for Implementation

The suggested timeframe to implement the new methodology is between six months and one year. The main rationale for this duration is the need to update the current software, learn the computer code and analyze the final data, especially the assignment of the short-term counts with the ATR groups.

11.4 Expected Benefits from Implementation

The expected benefits will include a more accurate methodology for estimating the AADT from short-term counts. Chapter X, Section 5 provides additional quantification of the estimates based on the current method and the recommended method. In this analysis all the short-term counts from 2002 through 2007 were used and AADTs were estimated.

11.5 Potential Risks and Obstacles to Implementation

The primary obstacle associated with the implementation of these results is the use of multiple computer software packages. As a result of the voluminous amount of data and the statistical requirements associated with analyzing this data there are limited software options. When possible, common software such as SPSS and Microsoft Excel was purchased. The database software is Microsoft Sequel Server 2005 edition. Although not as common as the other two software platforms, Microsoft Sequel Server 2005 edition is highly compatible with the other two packages.

11.6 Strategies to Overcome Potential Risks and Obstacles

At the present time the research team is working with the ODOT technical liaisons on developing a graphical interface that will streamline the different software packages.

11.7 Potential Users and Other Organizations that may be Affected

The potential users of this information will include the ODOT Office of Innovation, Partnerships and Energy, ODOT planners, local consultants and metropolitan planning organizations, as well as other parties interested in the estimation of AADT.

11.8 Estimated Costs of Implementation

There are three main cost categories associated with the implementation of this methodology. The first cost is associated with training appropriate ODOT personnel. The second cost is the purchase of software required to analyze the volume counts. The final cost is associated with the development of a front end interface that will link the database, the statistical software and the Excel files together. The cost of the third category will provide the most benefit and ease in transition from the previous methodology to the new methodology.

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Review of Traffic Monitoring Factor Groupings and the Determination of Seasonal Adjustment Factors for Cars and Trucks

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for the
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16. Abstract

One of the most common traffic volume parameters reported by statewide traffic monitoring programs is annual average daily traffic (AADT). Departments of Transportation (DOT) and other state agencies use a series of continuous vehicle detection devices in association with smaller more mobile short-term counts. Once the short-term counts are recorded a series of adjustment factors (time of day, day of week, month of year, or seasonal) are applied to the short-term counts. The end result is an estimated AADT for a particular segment of roadway. Traditionally, as defined in section two of the Traffic Monitoring Guide (TMG), there are three methodologies, geographic/functional assignment of roads to groups, cluster analysis and the same road application factor. In each case, there are advantages and disadvantages and currently there is not a final peer reviewed nationally suggested method. The benefits associated with this research include an improved method for estimating AADT throughout Ohio.

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DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official view or policies of the Ohio Department of Transportation (ODOT) or the Federal Highway Administration (FHWA). This report does not constitute a standard, specification, or regulation.

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Length			Length		
inches	millimeters	25.4	millimeters	inches	0.039
inches	centimeters	2.54	centimeters	inches	0.394
feet	meters	0.305	meters	feet	3.281
yards	meters	0.914	meters	yards	1.094
miles	kilometers	1.61	kilometers	miles	0.621
Area			Area		
square inches	square millimeters	645.1	square millimeters	square inches	0.00155
square feet	square meters	0.093	square meters	square feet	10.764
square yards	square meters	0.836	square meters	square yards	1.196
acres	hectares	0.405	hectares	acres	2.471
square miles	square kilometers	2.59	square kilometers	square miles	0.386
Volume			Volume		
gallons	liters	3.785	liters	gallons	0.264
cubic feet	cubic meters	0.028	cubic meters	cubic feet	35.314
cubic yards	cubic meters	0.765	cubic meters	cubic yards	1.308
Mass			\Mass		
ounces	grams	28.35	grams	ounces	0.035
pounds	kilograms	0.454	kilograms	pounds	2.205
short tons	megagrams	0.907	megagrams	short tons	1.102

APPENDIX A

DATA CLEANING AND MINING

Table A.1. 60-minute 3-Card sample of the format provided by the TKO.

Item	Columns	Width	Alpha/Numeric	Description
1	1 - 1	1	A	3
2	2 - 3	2	N	39
3	4 - 5	2	N	FC
4	6 - 11	6	A	Sta. no.
5	12 - 12	1	N	Direction
6	13 - 13	1	N	Lane
7	14 - 15	2	N	Year
8	16 - 17	2	N	Month
9	18 - 19	2	N	Day
10	20 - 20	1	N	Day of Week
11	21 - 25	5	N	Volume counted between 00.01 - 01.00
12	26 - 30	5	N	Volume counted between 01.01 - 02.00
13	31 - 35	5	N	Volume counted between 02.01 - 03.00
14	36 - 40	5	N	Volume counted between 03.01 - 04.00
15	41 - 45	5	N	Volume counted between 04.01 - 05.00
16	46 - 50	5	N	Volume counted between 05.01 - 06.00
17	51 - 55	5	N	Volume counted between 06.01 - 07.00
18	56 - 60	5	N	Volume counted between 07.01 - 08.00
19	61 - 65	5	N	Volume counted between 08.01 - 09.00
20	66 - 70	5	N	Volume counted between 09.01 - 10.00
21	71 - 75	5	N	Volume counted between 10.01 - 11.00
22	76 - 80	5	N	Volume counted between 11.01 - 12.00
23	81 - 85	5	N	Volume counted between 12.01 - 13.00

Table A.1. 60-minute 3-Card sample of the format provided by the TKO (continued).

Item	Columns	Width	Alpha/Numeric	Description
24	86 - 90	5	N	Volume counted between 13.01 - 14.00
25	91 - 95	5	N	Volume counted between 14.01 - 15.00
26	96 - 100	5	N	Volume counted between 15.01 - 16.00
27	101 - 105	5	N	Volume counted between 16.01 - 17.00
28	106 - 110	5	N	Volume counted between 17.01 - 18.00
29	111 - 115	5	N	Volume counted between 18.01 - 19.00
30	116 - 120	5	N	Volume counted between 19.01 - 20.00
31	121 - 125	5	N	Volume counted between 20.01 - 21.00
32	126 - 130	5	N	Volume counted between 21.01 - 22.00
33	131 - 135	5	N	Volume counted between 22.01 - 23.00
34	136 - 140	5	N	Volume counted between 23.01 - 24.00
35	141 - 141	1	A	Footnotes 0= no restrictions
36	142 - 143	2	N	Time interval (60 min)
37	144 - 145	2	N	Record Number
38	146 - 149	4	N	Start time for record (hhmm)
39	150 - 153	4	N	End time for record (hhmm)

Table A.2. 15-minute 3-Card sample of the format provided by the TKO.

Item	Columns	Width	Alpha/Numeric	Description
1	1 - 1	1	A	3
2	2 - 3	2	N	39
3	4 - 5	2	N	FC
4	6 - 11	6	A	Sta. no.
5	12 - 12	1	N	Direction
6	13 - 13	1	N	Lane
7	14 - 15	2	N	Year
8	16 - 17	2	N	Month
9	18 - 19	2	N	Day
10	20 - 20	1	N	Day of Week
11	21 - 25	5	N	Volume counted between 00.01 – 00.15
12	26 - 30	5	N	Volume counted between 00.16 – 00.30
13	31 - 35	5	N	Volume counted between 00.31 – 00.45
14	36 - 40	5	N	Volume counted between 00.45-01.00
15	41 - 45	5	N	Volume counted between 01.01 – 01.15
16	46 - 50	5	N	Volume counted between 01.16 – 01.30
17	51 - 55	5	N	Volume counted between 01.31 – 01.45
18	56 - 60	5	N	Volume counted between 01.45-02.00
19	61 - 65	5	N	Volume counted between 02.01 – 02.15
20	66 - 70	5	N	Volume counted between 02.16 – 02.30
21	71 - 75	5	N	Volume counted between 02.31 – 02.45
22	76 - 80	5	N	Volume counted between 02.45-03.00

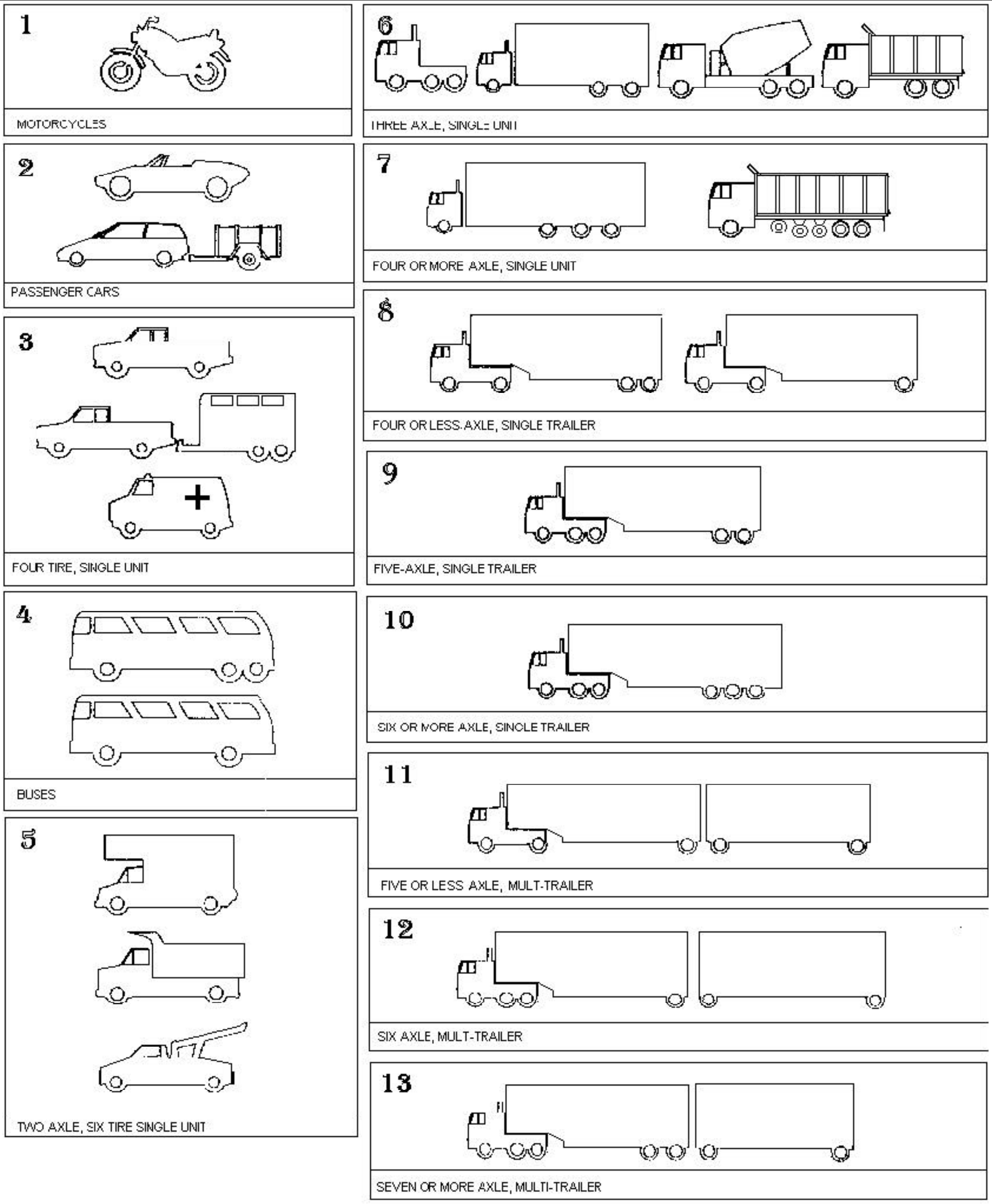
Table A.3. 60-minute C-Card sample of the format provided by the TKO.

Item	Columns	Width	Alpha/Numeric	Description
1	1 – 1	1	A	C
2	2 – 3	2	N	39
3	4 – 9	6	A	Station Number
4	10 – 10	1	N	Dir.
5	11 – 11	1	N	Lane
6	12 – 13	2	N	YY
7	14 – 15	2	N	MM
8	16 – 17	2	N	DD
9	18 – 19	2	N	HH
10	20 – 24	5	N	Total vol.
11	25 – 29	5	N	Class 1
12	30 – 34	5	N	Class 2
13	35 – 39	5	N	Class 3
14	40 – 44	5	N	Class 4
15	45 – 49	5	N	Class 5
16	50 – 54	5	N	Class 6
17	55 – 59	5	N	Class 7
18	60 – 64	5	N	Class 8
19	65 – 69	5	N	Class 9
20	70 – 74	5	N	Class 10
21	75 – 79	5	N	Class 11
22	80 – 84	5	N	Class 12
23	85 – 89	5	N	Class 13
24	90 – 94	5	N	Class 14
25	95 – 99	5	N	Class 15
26	100 – 100	1	N	Footnotes
27	101 – 102	2	N	Time Interval (60 min)
28	103 – 104	2	N	Record number
29	105 – 108	4	N	Start time (hhmm)
30	109 – 112	4	N	End time (hhmm)

Table A.4. 15-minute C-Card sample of the format provided by the TKO.

Item	Columns	Width	Alpha/Numeric	Description
1	1 – 1	1	A	C
2	2 – 3	2	N	39
3	4 – 9	6	A	Station Number
4	10 – 10	1	N	Dir.
5	11 – 11	1	N	Lane
6	12 – 13	2	N	YY
7	14 – 15	2	N	MM
8	16 – 17	2	N	DD
9	18 – 19	2	N	HH
10	20 – 24	5	N	Total vol.
11	25 – 29	5	N	Class 1
12	30 – 34	5	N	Class 2
13	35 – 39	5	N	Class 3
14	40 – 44	5	N	Class 4
15	45 – 49	5	N	Class 5
16	50 – 54	5	N	Class 6
17	55 – 59	5	N	Class 7
18	60 – 64	5	N	Class 8
19	65 – 69	5	N	Class 9
20	70 – 74	5	N	Class 10
21	75 – 79	5	N	Class 11
22	80 – 84	5	N	Class 12
23	85 – 89	5	N	Class 13
24	90 – 94	5	N	Class 14
25	95 – 99	5	N	Class 15
26	100 – 100	1	N	Footnotes
27	101 – 102	2	N	Time Interval (15 min)
28	103 – 104	2	N	Record number
29	105 – 108	4	N	Start time (hhmm)
30	109 – 112	4	N	End time (hhmm)

Table A.5. FHWA vehicle classification scheme.



Class One	Motorcycles. all two-wheeled 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 Two	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.

Table A.5. FHWA vehicle classification scheme (continued).

Class Three	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 Four	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.
Class Five	Trucks. all vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., having three axles.
Class Six	Three Axle Single Unit Trucks. all trucks on a single frame with three axles.
Class Seven	Four or More Axle Single Unit Trucks. all trucks on a single frame with four or more axles.
Class Eight	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 Nine	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 Ten	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 Eleven	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 Twelve	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 Thirteen	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.
Class Fourteen	Class fourteen is defined by ODOT personnel for special studies.
Class Fifteen	Class fifteen will, by default, identify any vehicle which does not conform to the classification criteria for Class 1 through Class 14.
Note. The data provided in this table is based on the FHWA vehicle classification descriptions Source. (FHWA, 2001, TMG Section 4).	

Table A.6. 60-minute 4-card sample of the format provided by the TKO.

Item	Columns	Width	Alpha/Numeric	Description
1	1 – 1	1	A	4
2	2 – 3	2	N	39
3	4 – 5	2	N	FC
4	6 – 8	3	N	Station Number
5	9 – 9	1	N	Dir.
6	10 – 11	2	N	YY
7	12 – 13	2	N	MM
8	14 – 15	2	N	DD
9	16 – 17	2	N	HH
10	18 – 19	2	N	Class 1
11	20 – 23	4	N	Class 2
12	24 – 26	3	N	Class 3
13	27 – 28	2	N	Class 4
14	29 – 31	3	N	Class 5
15	32 – 33	2	N	Class 6
16	34 – 35	2	N	Class 7
17	36 – 37	2	N	Class 8
18	38 – 40	3	N	Class 9
19	41 – 42	2	N	Class 10
20	43 – 44	2	N	Class 11
21	45 – 46	2	N	Class 12
22	47 – 48	2	N	Class 13
23	49 – 49	1	N	Motorcycle indicator
24	50 – 50	1	N	V-class combo
25	51 – 51	1	N	Lane
26	52 – 80	31	A	Optional State data

Table A.7. C-card “Raw data” file example in Microsoft SQL.

C390001531105042212013110000000089700212000040002800016000010001500124000100000200000000002	0600112011300	6
C390001531205042212011020000000811001760000100020000040000200010000720000200002000010000 1	0600112011300	6
C39000153130504221200511000000042400084000000000000000100000000000000100000000000000000001	0600112011300	6
C39000153540504221200774000000063800130000000000200001000000000100001000000000100000000000	0600112011300	6
C39000153550504221201111000000077300172000000000130001300000000080012800003000010000000000	0600112011300	6
C39000153560504221201279000000094100163000000000320002100001000060010700006000010000100000	0600112011300	6
C39000153110504221301393000000099600209000010004000016000010002100103000040000100001000000	0600113011400	6
C39000153120504221301166000000089600172000000000800005000000000600069000010000700002000000	0600113011400	6
C39000153130504221300606000000050200101000000000100002000000000000000000000000000000000000	0600113011400	6
C39000153540504221300823000000066100143000010000400001000000000200009000000000100001000000	0600113011400	6
C39000153550504221301170000000077300196000020002400011000010001000144000040000400001000000	0600113011400	6
C39000153560504221301319000000097700170000300025000170000500006001050000700004000000000000	0600113011400	6
C39000153110504221401444000000104900241000000002400014000010000800091000040001000000000002	0600114011500	6
C39000153120504221401351000010103400225000010001200005000000000700059000000000700000000000	0600114011500	6
C39000153130504221400695000030057100112000000000200002000000000300001000000000000000000001	0600114011500	6
C39000153540504221401088000000091000169000010000000001000000000300003000000000000000000001	0600114011500	6
C39000153550504221401257000000085200207000010002500007000010000900134000060001100001000003	0600114011500	6
C39000153560504221401256000000091800163000000000270002000003000120010600005000020000000000	0600114011500	6
C39000153110504221501528000000120900196000010001900008000020001000079000000000200001000001	0600115011600	6
C39000153120504221501397000000114000178000000000700007000010000600053000020000300000000000	0600115011600	6
C39000153130504221500892000020076300124000000000000000000000000000000000000000000000000003	0600115011600	6
C39000153540504221501511000010123900268000000000000000000000000300000000000000000000000000	0600115011600	6
C39000153550504221501458000010106100204000000000220000800000000140013800005000040000000001	0600115011600	6
C390001531105042212013110000000089700212000040002800016000010001500124000100000200000000002	0600112011300	6
C39000153120504221201102000000081100176000010002000004000020001000072000020000200001000001	0600112011300	6
C39000153130504221200511000000042400084000000000000000100000000000000100000000000000000001	0600112011300	6
C39000153540504221200774000000063800130000000000200001000000000100001000000000100000000000	0600112011300	6
C39000153550504221201111000000077300172000000000130001300000000080012800003000010000000000	0600112011300	6
C39000153560504221201279000000094100163000000000320002100001000060010700006000010000100000	0600112011300	6
C39000153110504221301393000000099600209000010004000016000010002100103000040000100001000000	0600113011400	6
C39000153120504221301166000000089600172000000000800005000000000600069000010000700002000000	0600113011400	6
C39000153130504221300606000000050200101000000000100002000000000000000000000000000000000000	0600113011400	6
C39000153540504221300823000000066100143000010000400001000000000200009000000000100001000000	0600113011400	6
C39000153550504221301170000000077300196000020002400011000010001000144000040000400001000000	0600113011400	6

Table A.8. C-Card “Clean data” file example in Microsoft SQL.

C	39	153	5	6	5	4	22	18	1383	0	1171	90	0	11	2	1	13	86	4	4	0	1
C	39	153	1	1	5	4	22	19	1082	1	887	110	2	3	3	0	4	67	0	4	0	1
C	39	153	1	2	5	4	22	19	1029	0	864	123	1	3	0	0	4	30	1	3	0	0
C	39	153	1	3	5	4	22	19	393	2	333	57	0	0	0	0	1	0	0	0	0	0
C	39	153	5	4	5	4	22	19	606	0	549	56	1	0	0	0	0	0	0	0	0	0
C	39	153	5	5	5	4	22	19	1010	0	790	123	1	5	1	0	9	77	1	2	1	0
C	39	153	5	6	5	4	22	19	1135	0	954	67	2	3	3	0	10	91	2	3	0	0
C	39	153	1	1	5	4	22	20	958	0	799	79	1	3	6	0	7	55	0	8	0	0
C	39	153	1	2	5	4	22	20	838	0	707	86	0	8	3	0	1	24	0	8	0	1
C	39	153	1	3	5	4	22	20	293	0	258	30	0	2	0	0	0	1	0	0	0	2
C	39	153	5	4	5	4	22	20	470	0	418	51	0	0	0	0	0	1	0	0	0	0
C	39	153	5	5	5	4	22	20	870	1	682	113	2	3	2	0	3	64	0	0	0	0
C	39	153	5	6	5	4	22	20	873	0	726	57	1	5	2	0	2	79	0	1	0	0
C	39	153	1	1	5	4	22	21	793	0	649	60	2	3	0	0	4	53	0	21	1	0
C	39	153	1	2	5	4	22	21	727	0	603	75	0	2	2	0	2	29	0	13	1	0
C	39	153	1	3	5	4	22	21	195	0	176	17	0	0	0	0	1	0	0	0	1	0
C	39	153	5	4	5	4	22	21	387	0	346	39	0	0	0	0	0	2	0	0	0	0
C	39	153	5	5	5	4	22	21	752	1	598	77	3	7	0	0	3	58	0	5	0	0
C	39	153	5	6	5	4	22	21	798	0	653	56	0	8	2	0	3	70	0	6	0	0
C	39	153	1	1	5	4	22	22	589	1	455	46	0	3	5	0	2	61	2	11	2	1
C	39	153	1	2	5	4	22	22	550	0	458	54	0	1	4	0	2	23	0	7	1	0
C	39	153	1	3	5	4	22	22	154	0	144	10	0	0	0	0	0	0	0	0	0	0
C	39	153	5	4	5	4	22	22	272	0	246	22	0	0	0	0	0	3	0	1	0	0
C	39	153	5	5	5	4	22	22	566	0	449	49	2	2	1	0	4	50	0	8	1	0
C	39	153	5	6	5	4	22	22	550	0	446	26	1	7	4	0	2	52	1	11	0	0
C	39	153	1	1	5	4	22	23	409	0	308	42	0	1	4	0	3	43	0	8	0	0
C	39	153	1	2	5	4	22	23	393	0	334	39	0	1	0	1	0	15	0	3	0	0
C	39	153	1	3	5	4	22	23	101	0	88	11	1	0	0	0	0	1	0	0	0	0
C	39	153	5	4	5	4	22	23	176	0	159	16	0	0	0	0	0	1	0	0	0	0
C	39	153	5	5	5	4	22	23	395	0	293	37	0	3	2	0	1	44	0	11	4	0

APPENDIX B

SAF PER YEAR

ATRs

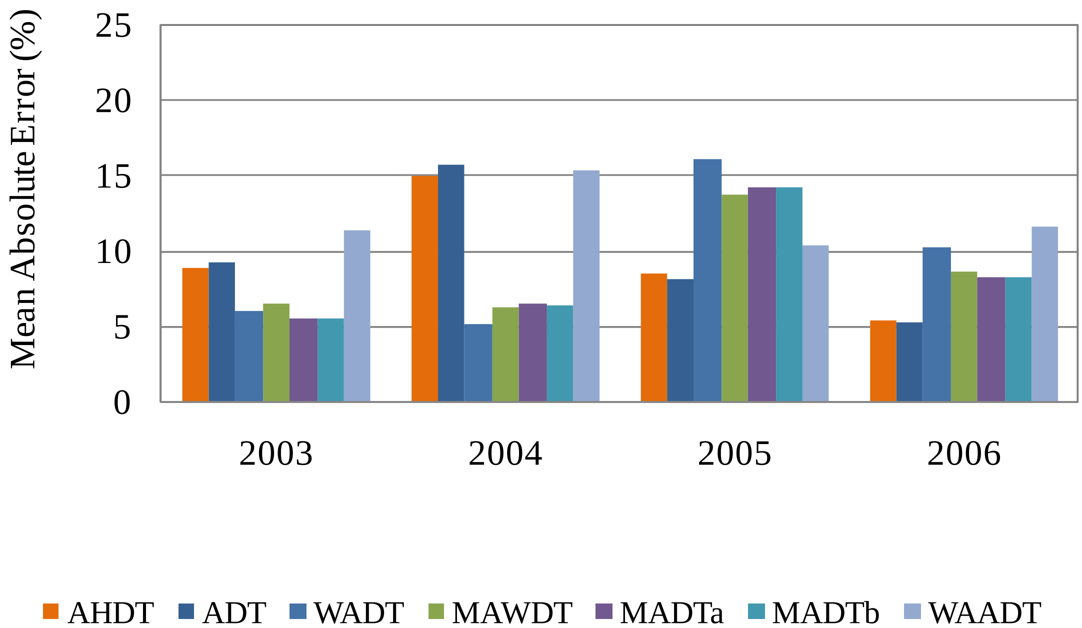


Figure B.1. January ATRs SAFs from 2002-2006.

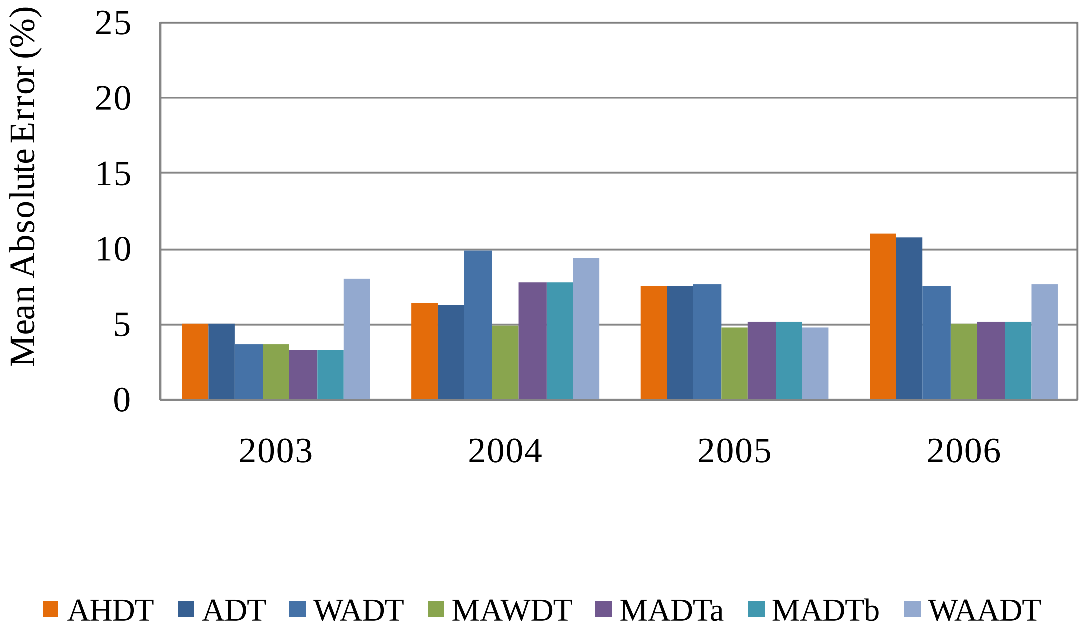


Figure B.2. February ATRs SAFs from 2002-2006.

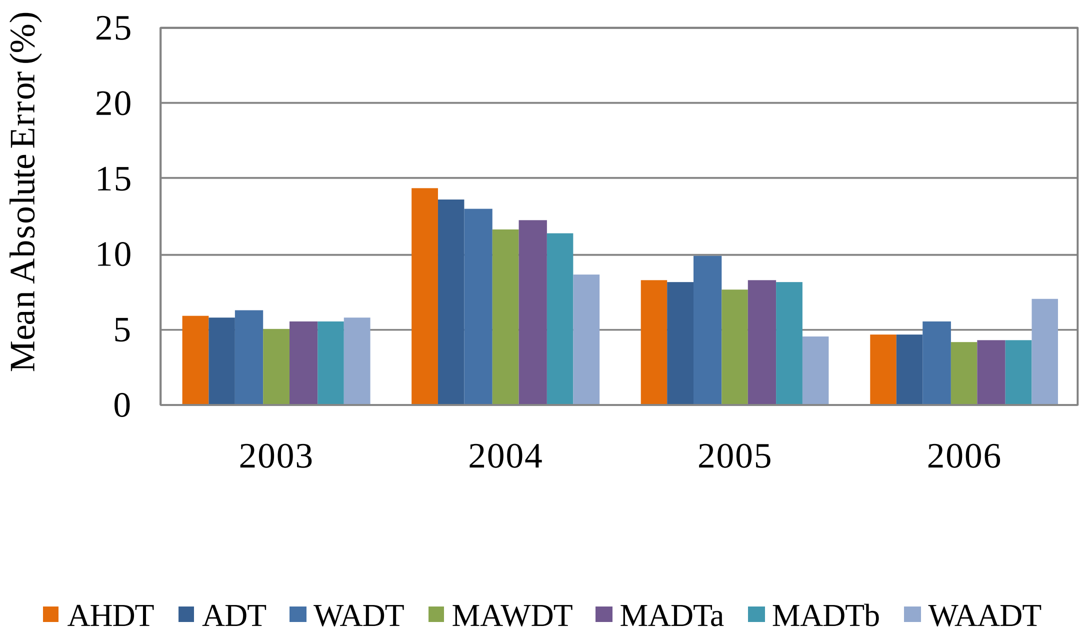


Figure B.3. March ATRs SAFs from 2002-2006.

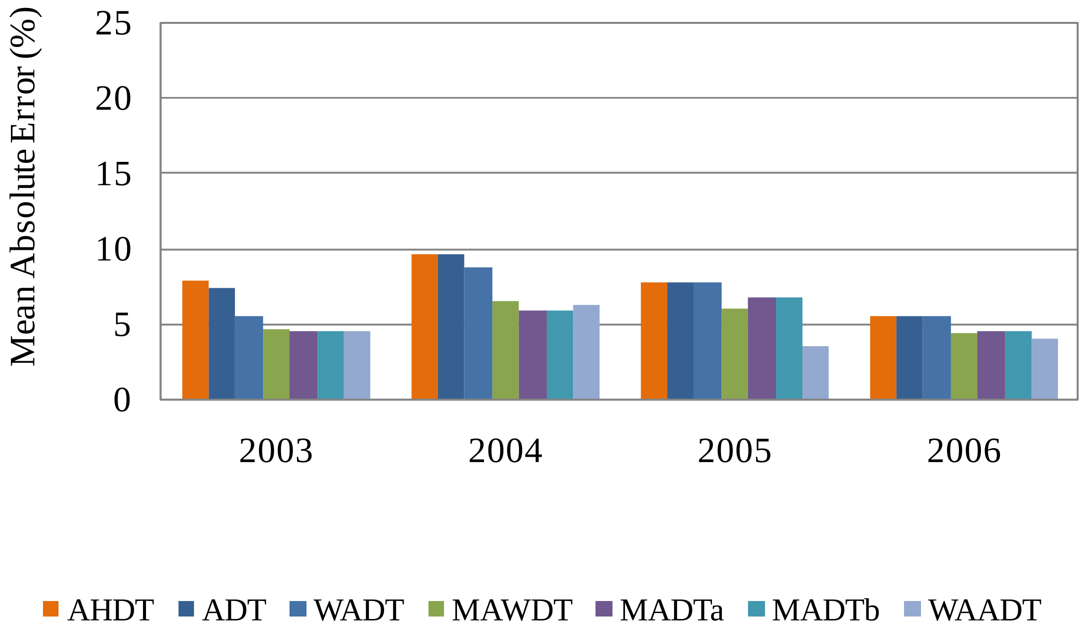


Figure B.4. April ATRs SAFs from 2002-2006.

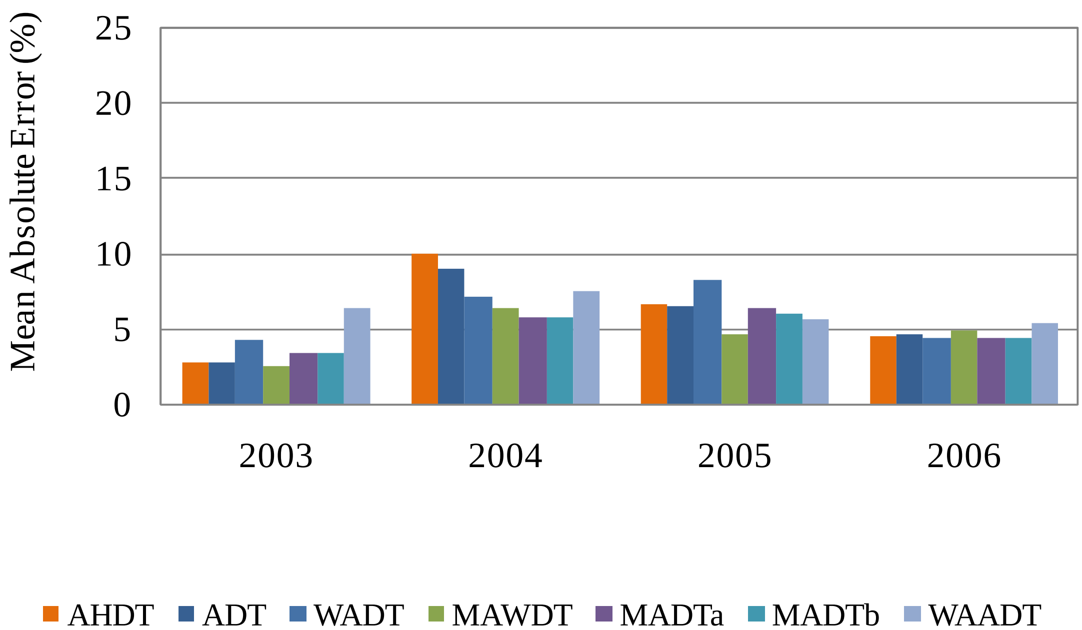


Figure B.5. May ATRs SAFs from 2002-2006.

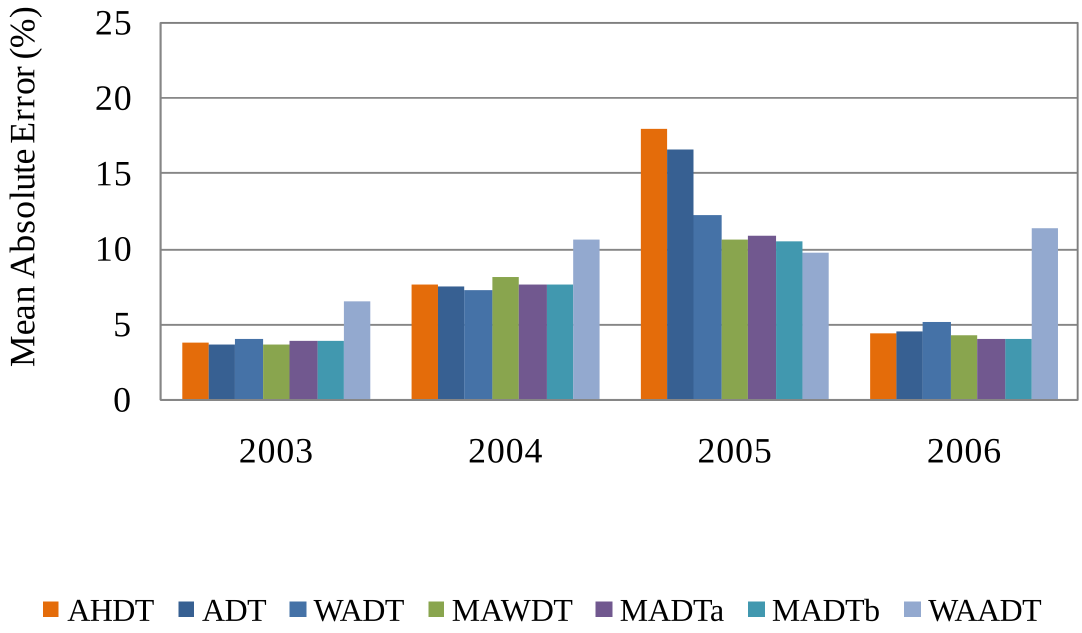


Figure B.6. June ATRs SAFs from 2002-2006.

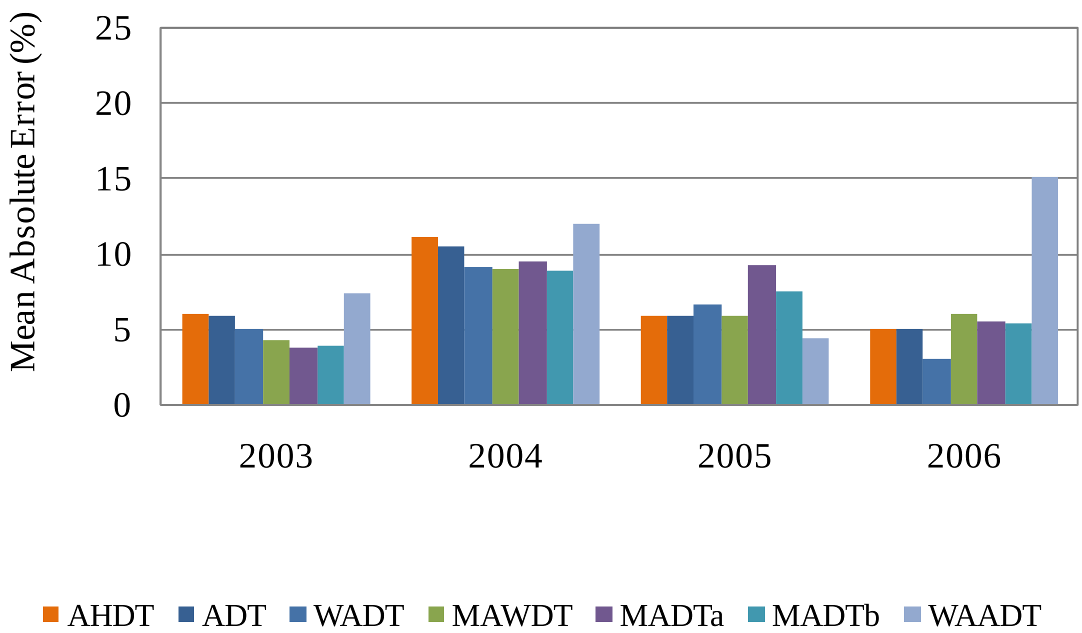


Figure B.7. July ATRs SAFs from 2002-2006.

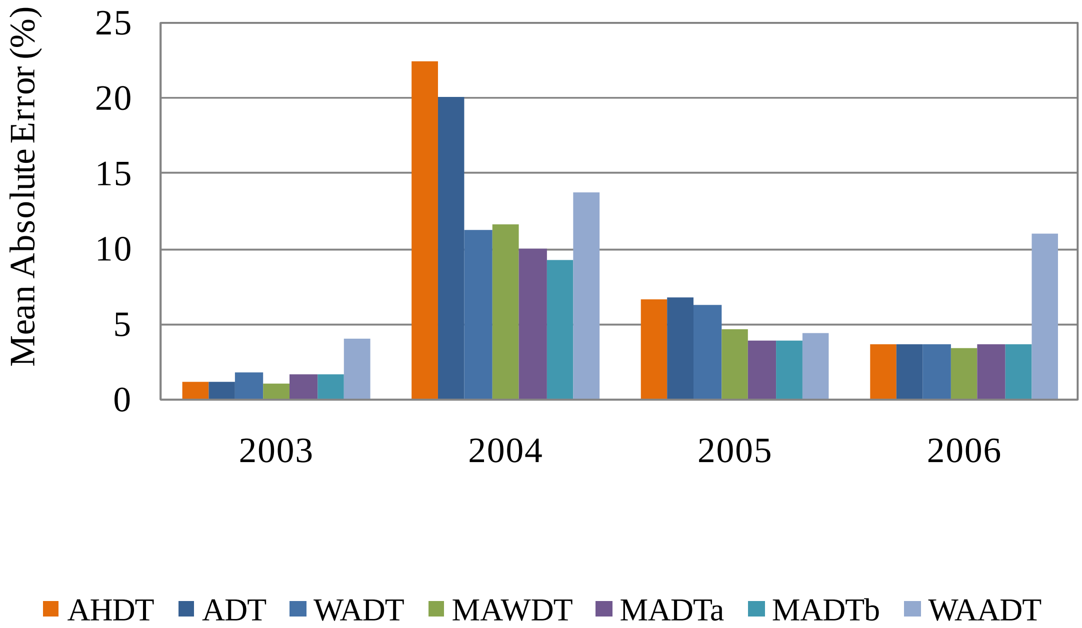


Figure B.8. August ATRs SAFs from 2002-2006.

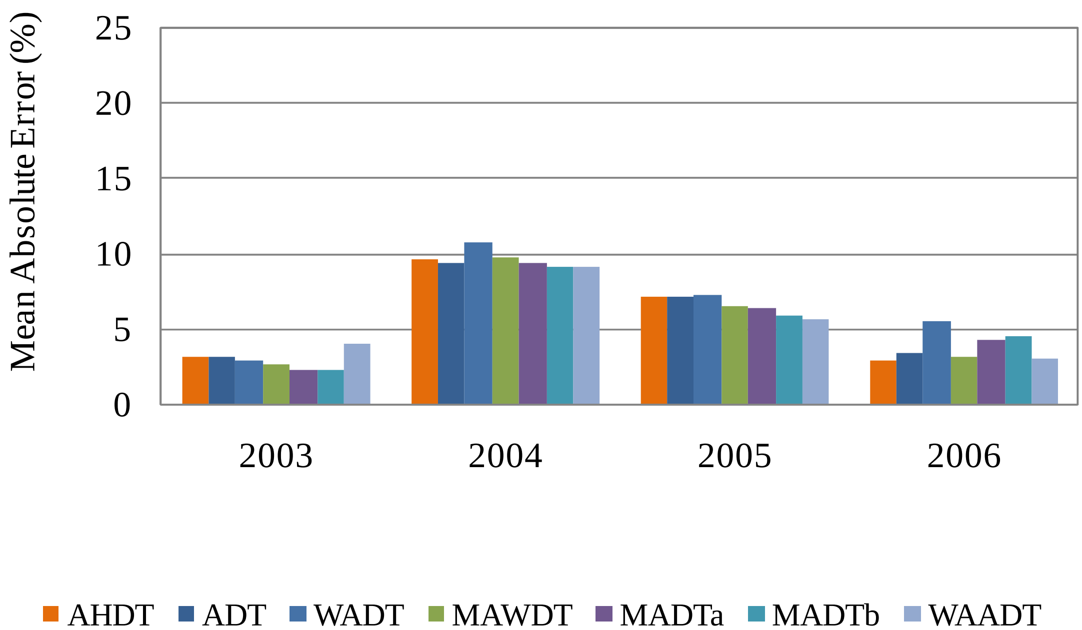


Figure B.9. September ATRs SAFs from 2002-2006.

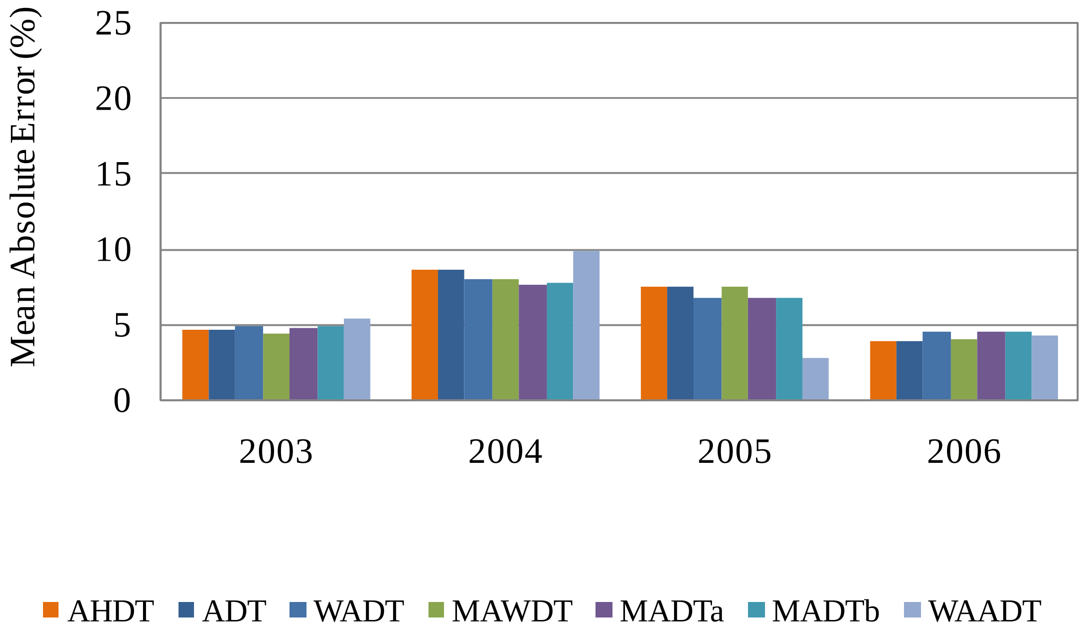


Figure B.10. October ATRs SAFs from 2002-2006.

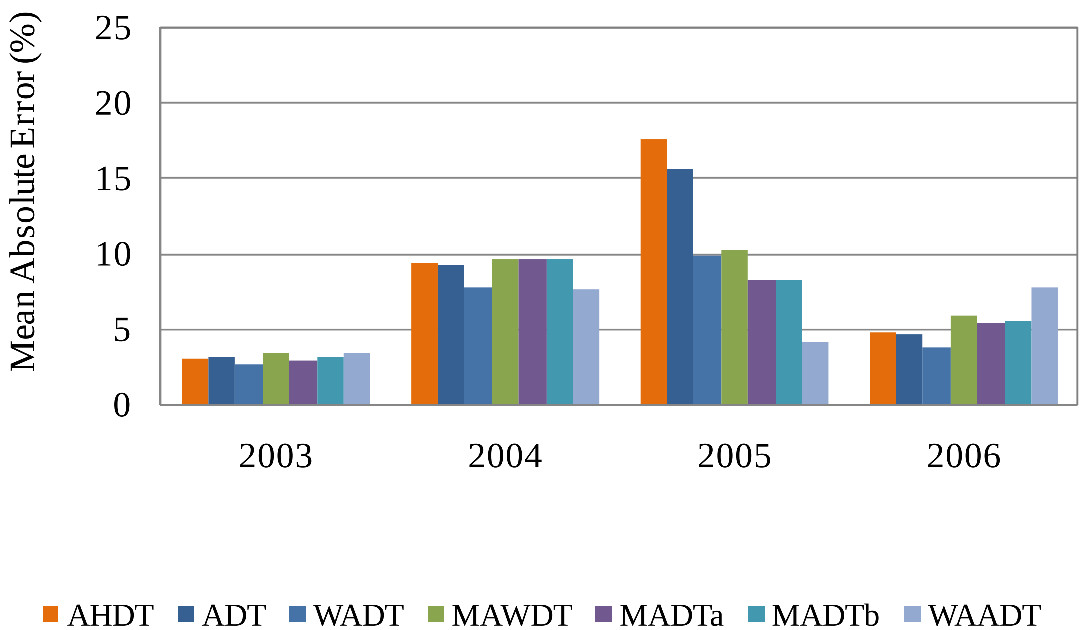


Figure B.11. November ATRs SAFs from 2002-2006.

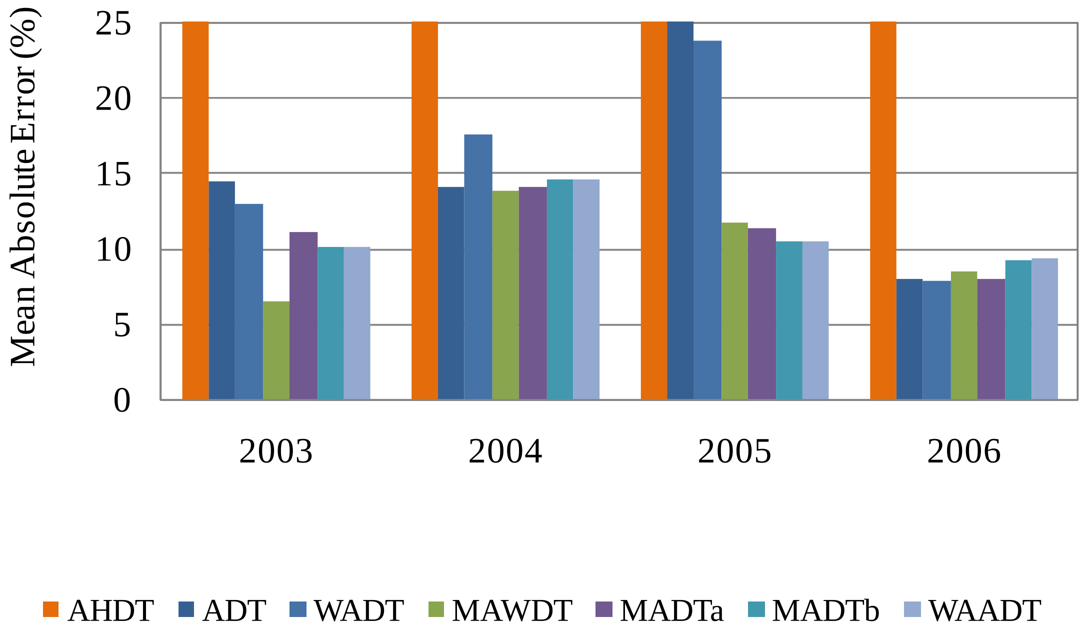


Figure B.12. December ATRs SAFs from 2002-2006.

WIMs

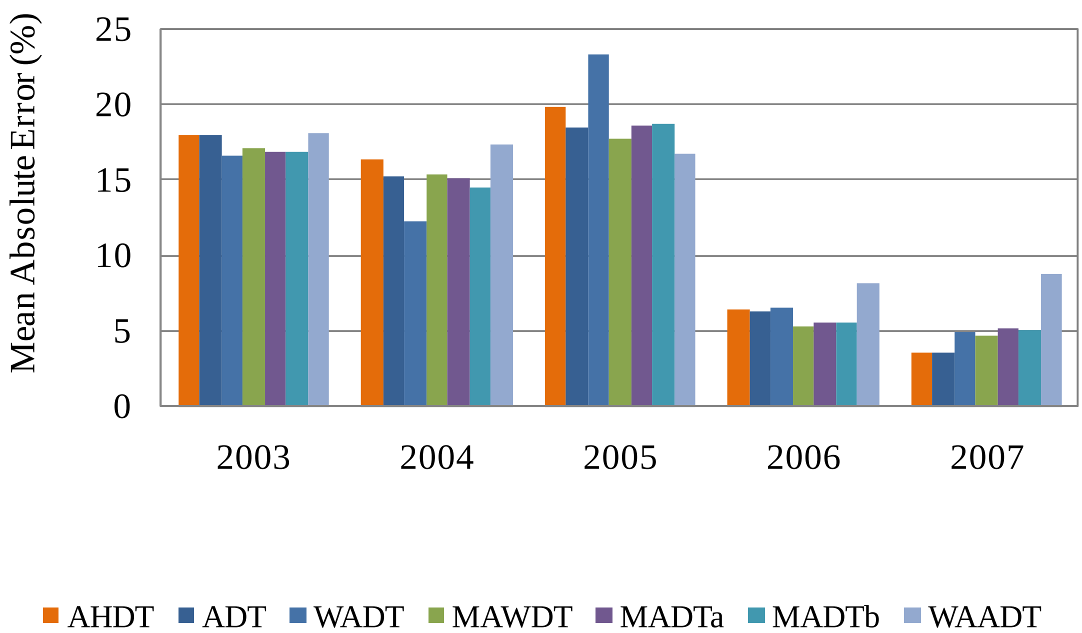


Figure B.13. January WIMs SAFs from 2002-2007.

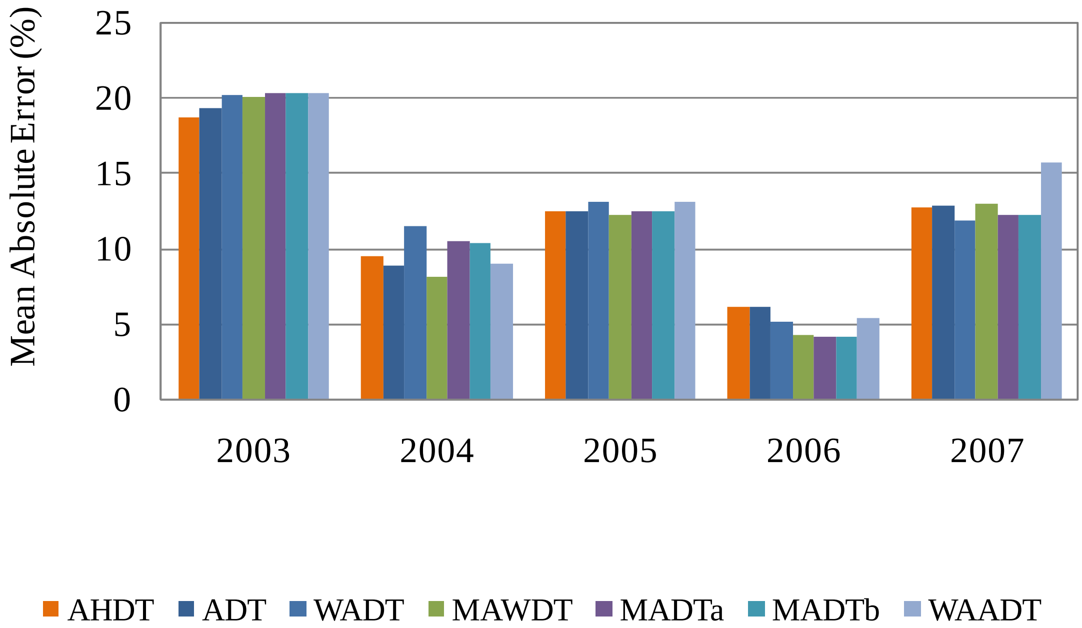


Figure B.14. February WIMs SAFs from 2002-2007.

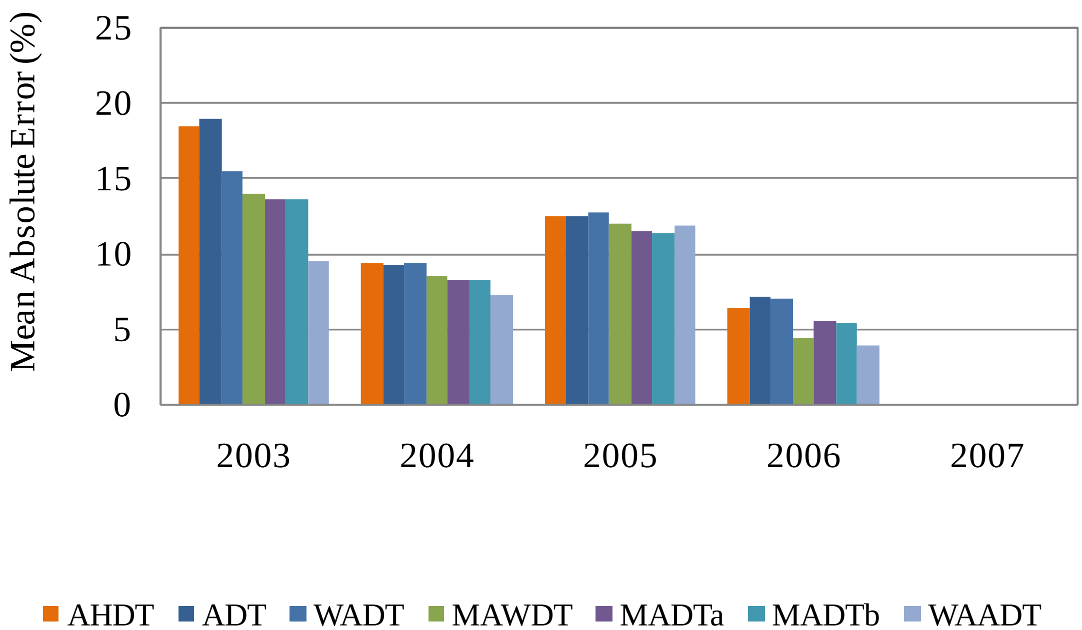


Figure B.15. March WIMs SAFs from 2002-2006.

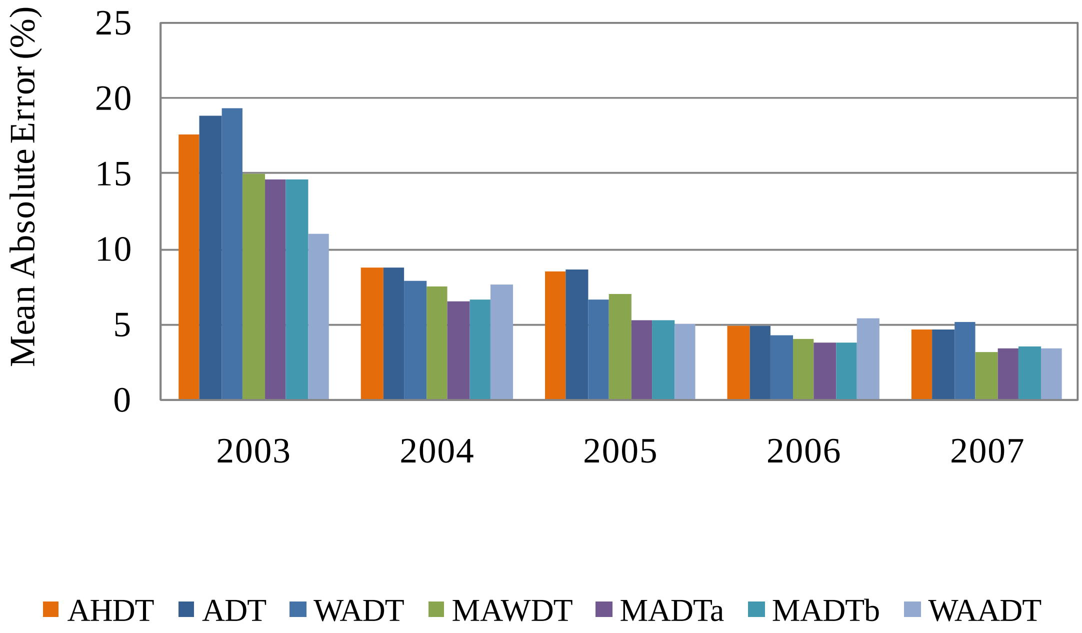


Figure B.16. April WIMs SAFs from 2002-2007.

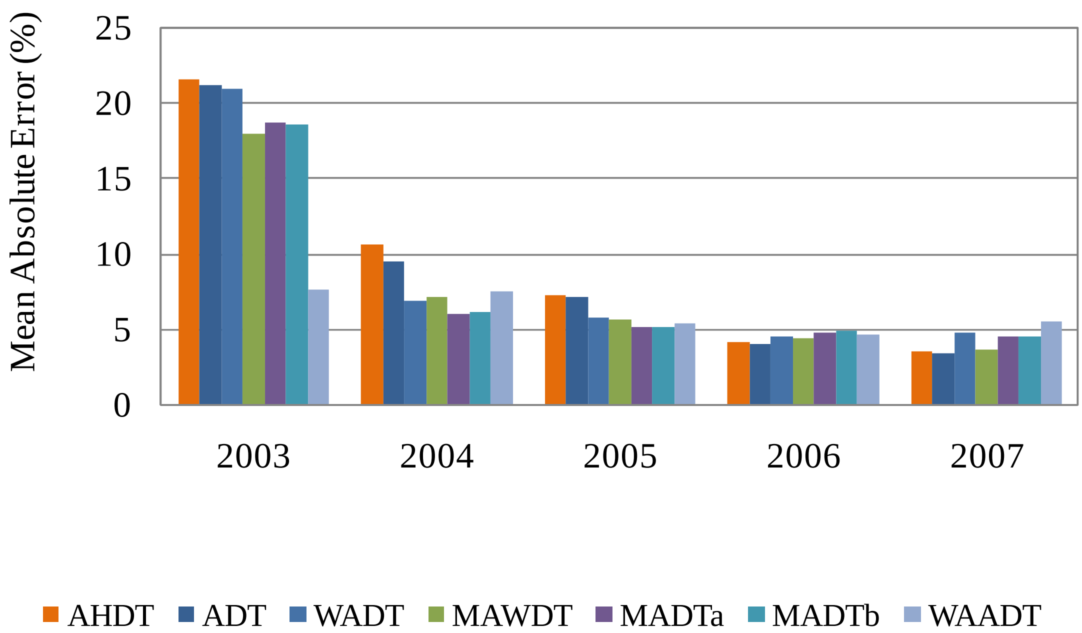


Figure B.17. May WIMs SAFs from 2002-2007.

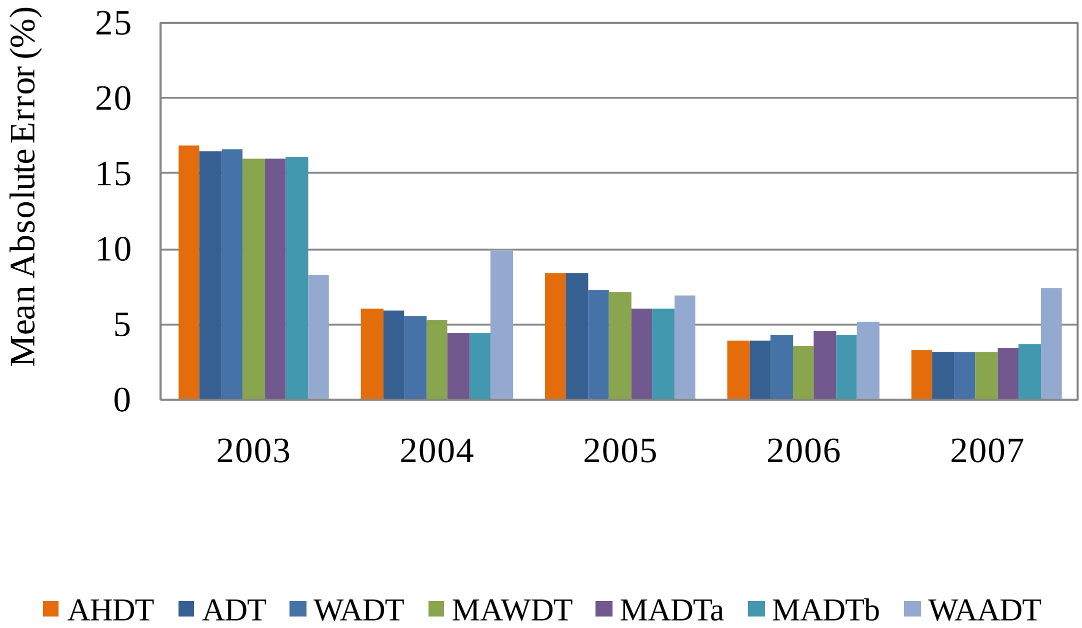


Figure B.18. June WIMs SAFs from 2002-2007.

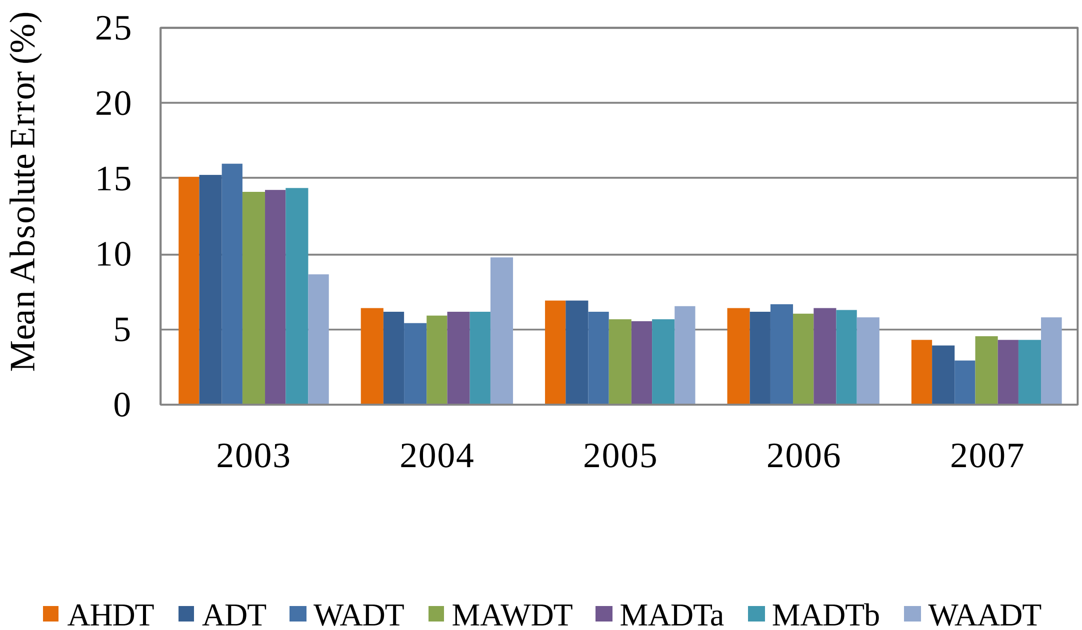


Figure B.19. July WIMs SAFs from 2002-2007.

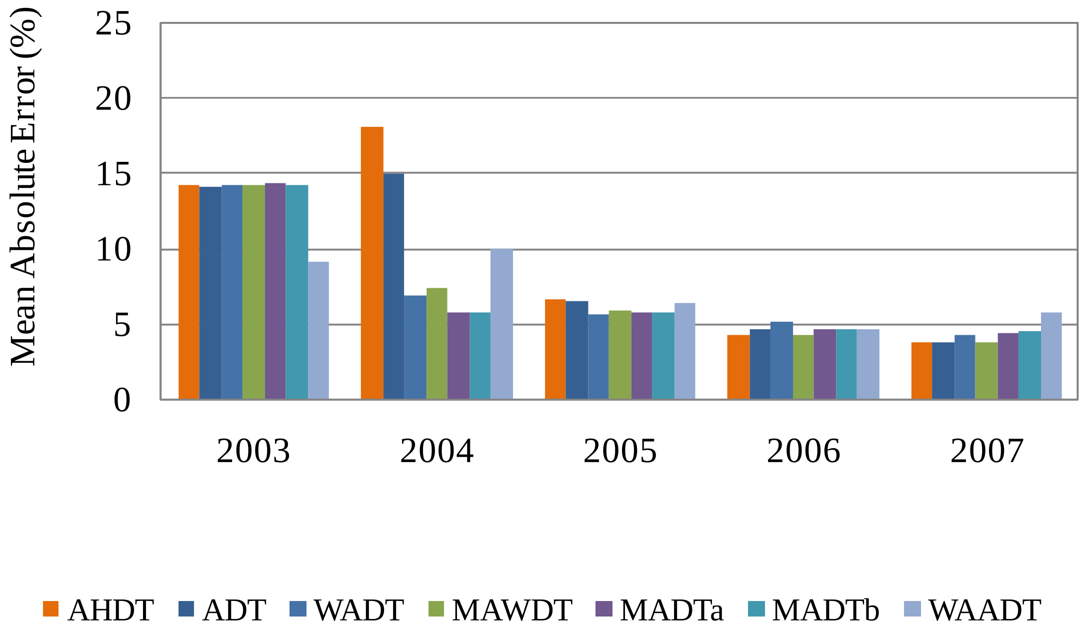


Figure B.20. August WIMs SAFs from 2002-2007.

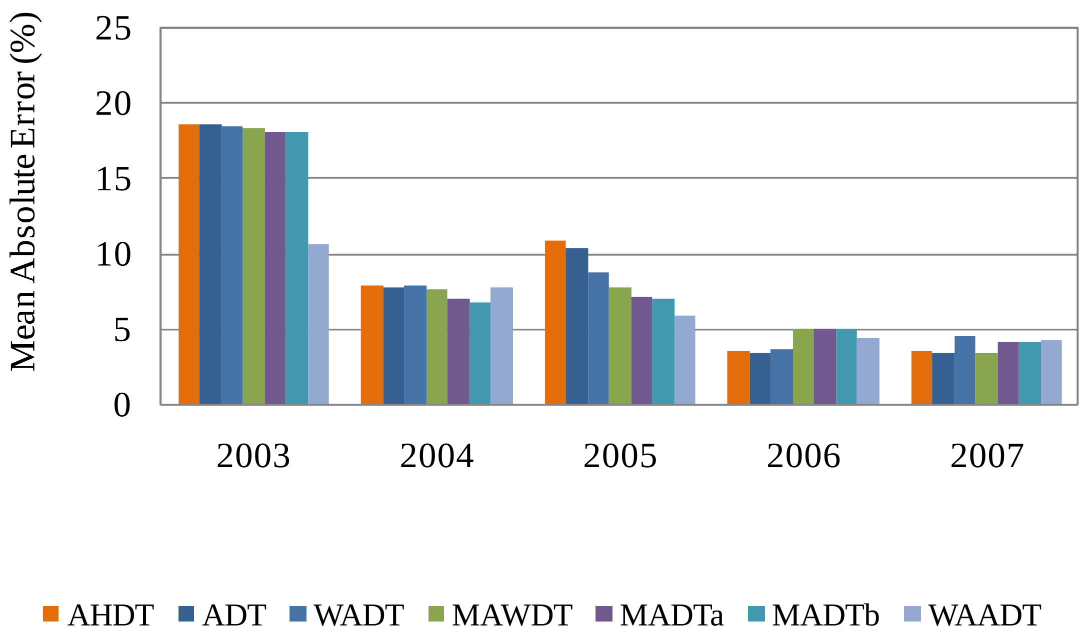


Figure B.21. September WIMs SAFs from 2002-2007.

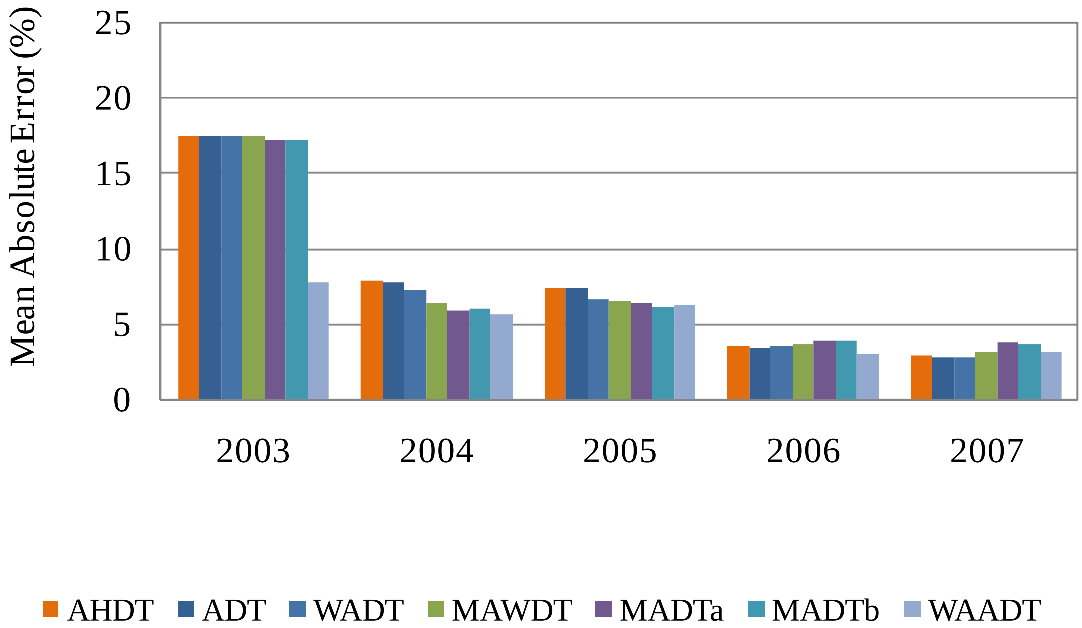


Figure B.22. October WIMs SAFs from 2002-2007.

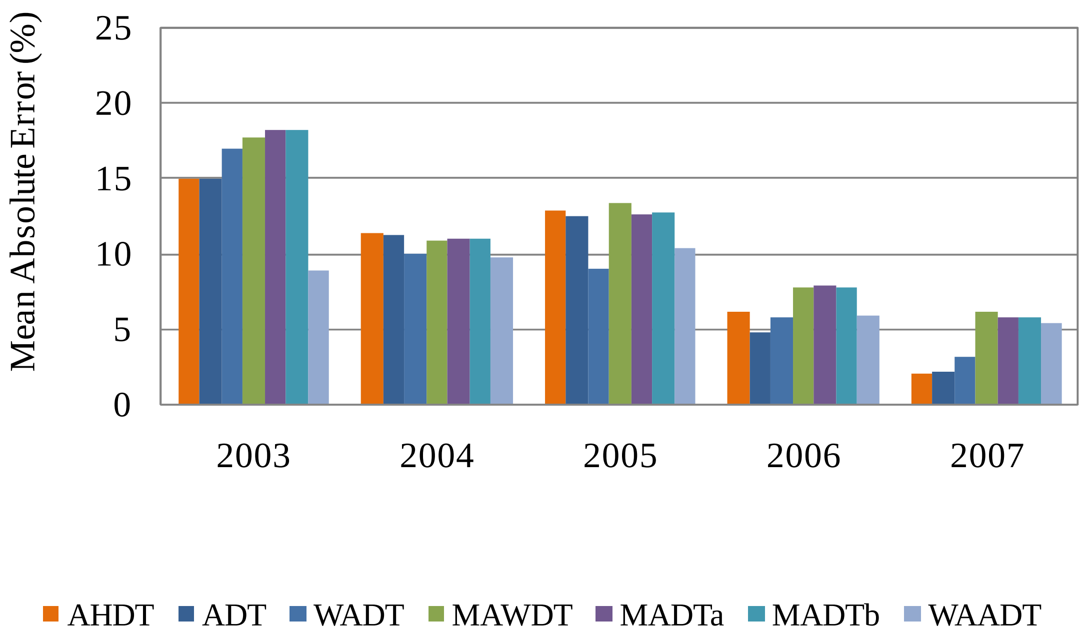


Figure B.23. November WIMs SAFs from 2002-2007.

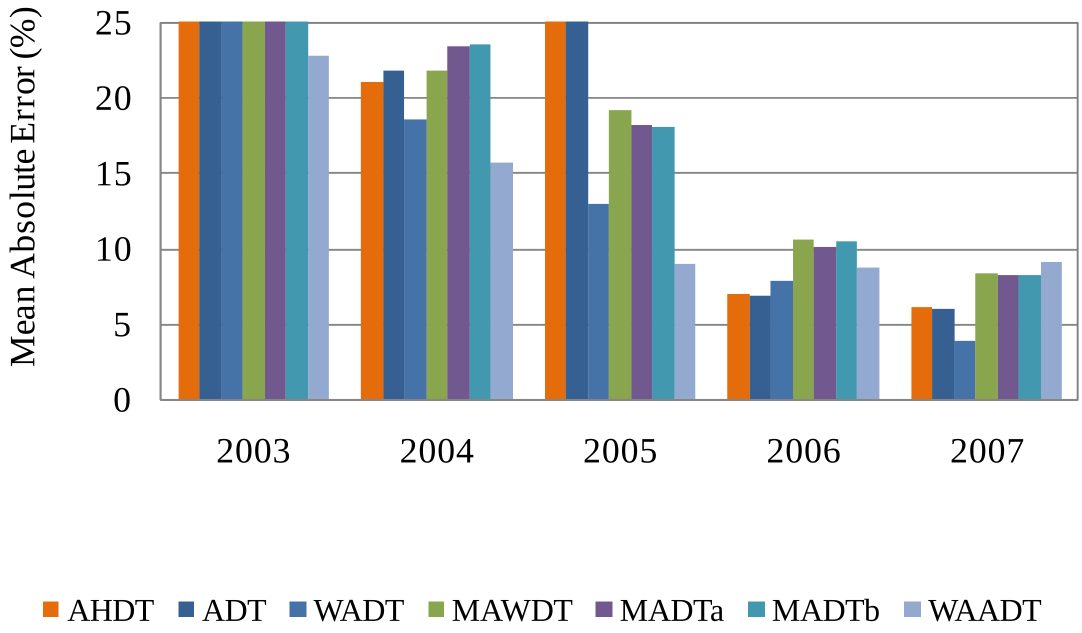


Figure B.24. December WIMs SAFs from 2002-2007.

APPENDIX C

TOTAL VS. DIRECTIONAL SAF

ATRs

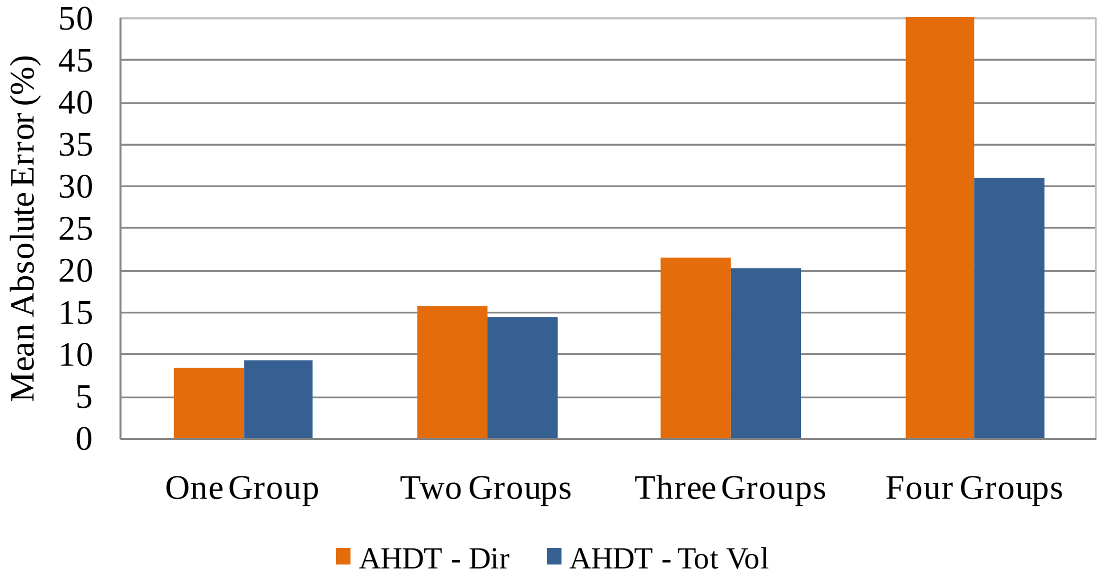


Figure C.1. ATRs AHDT (Directional vs. Total Volume).

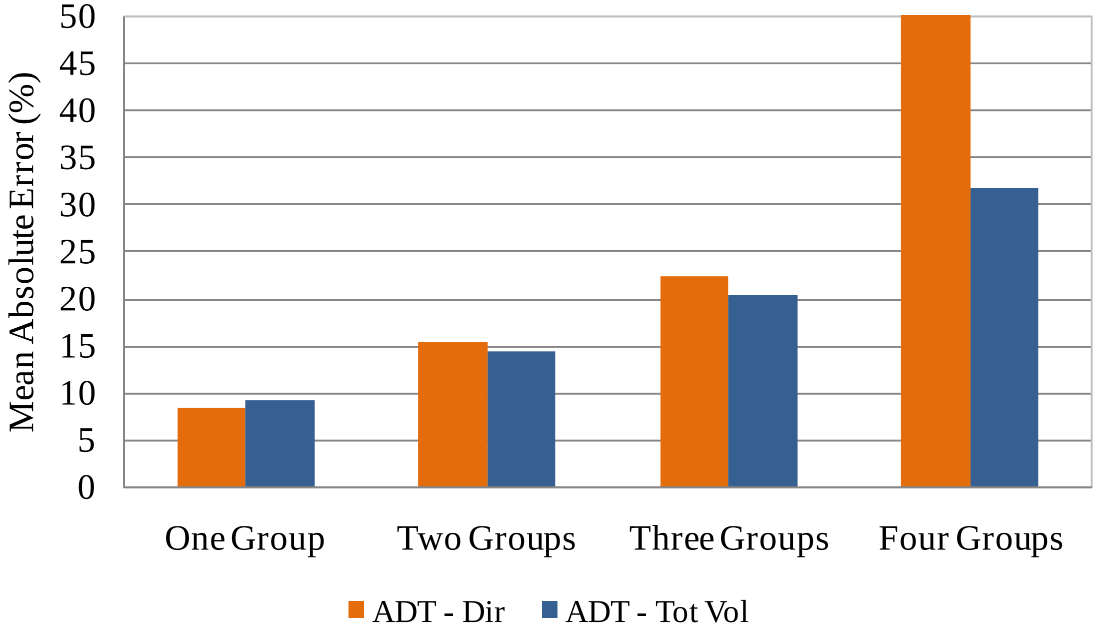


Figure C.2. ATRs ADT (Directional vs. Total Volume).

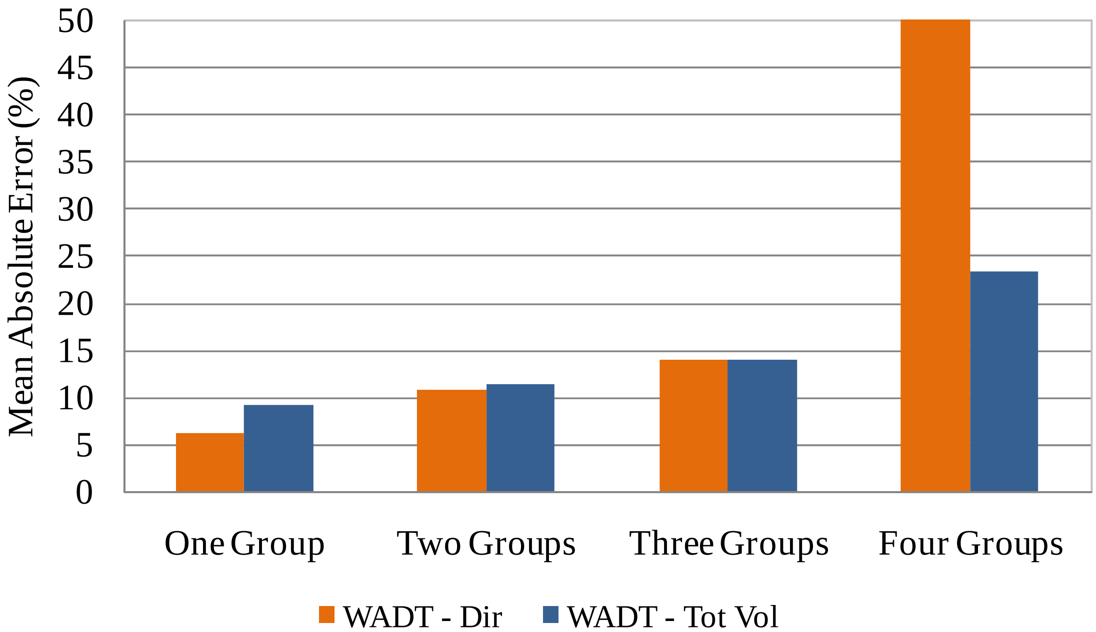


Figure C.3. ATRs WADT (Directional vs. Total Volume).

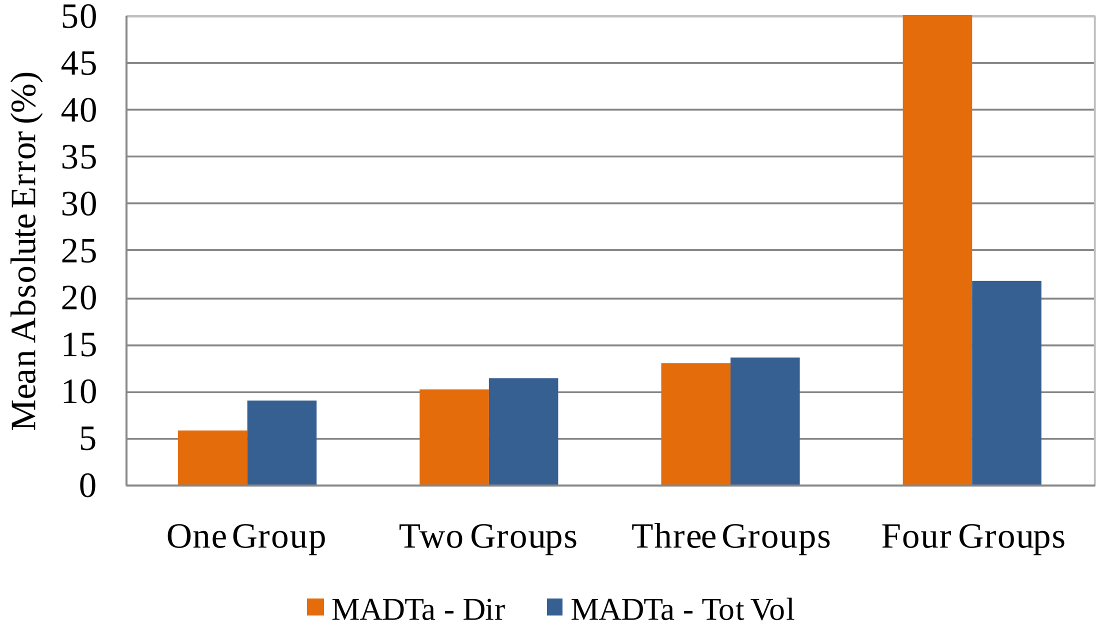


Figure C.4. ATRs MADTa (Directional vs. Total Volume).

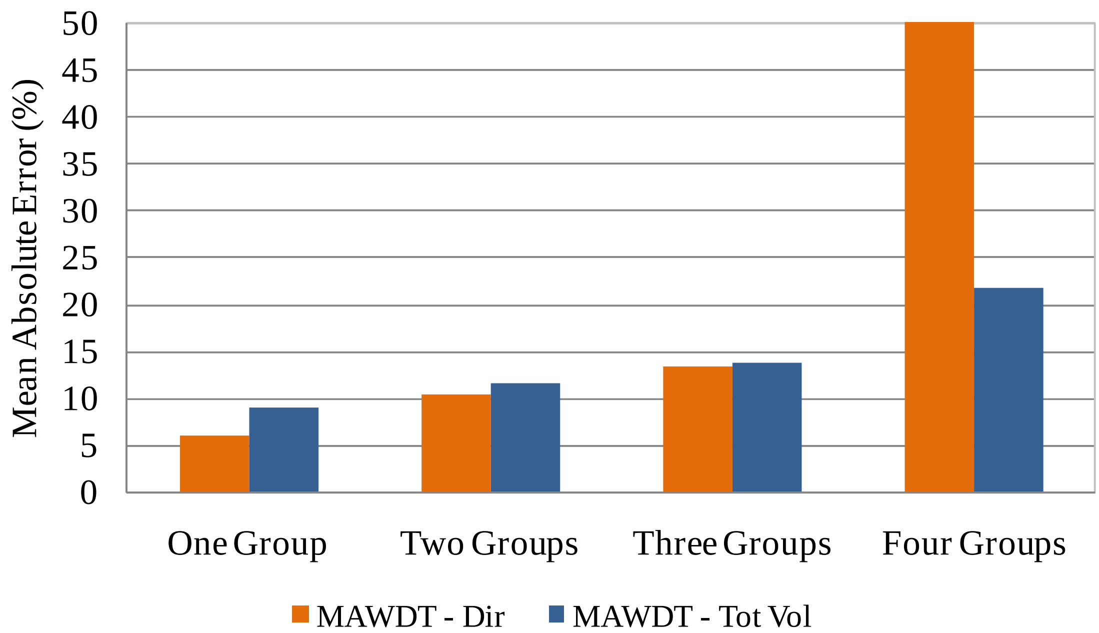


Figure C.5. ATRs MAWDT (Directional vs. Total Volume).

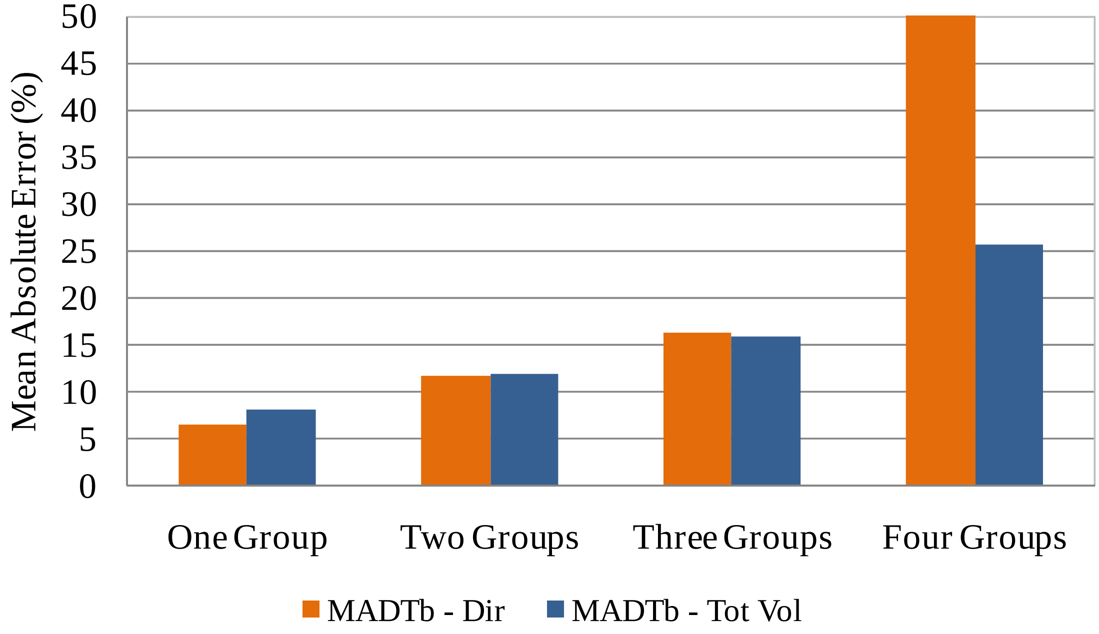


Figure C.6. ATRs MADTb (Directional vs. Total Volume).

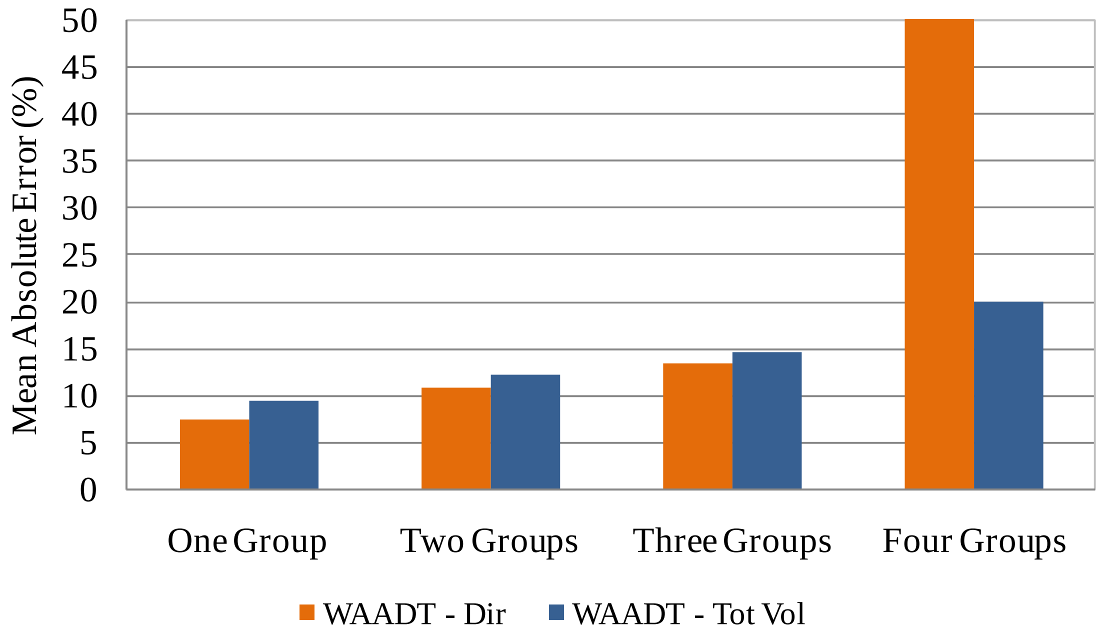


Figure C.7. ATRs WAADT (Directional vs. Total Volume).

WIMs

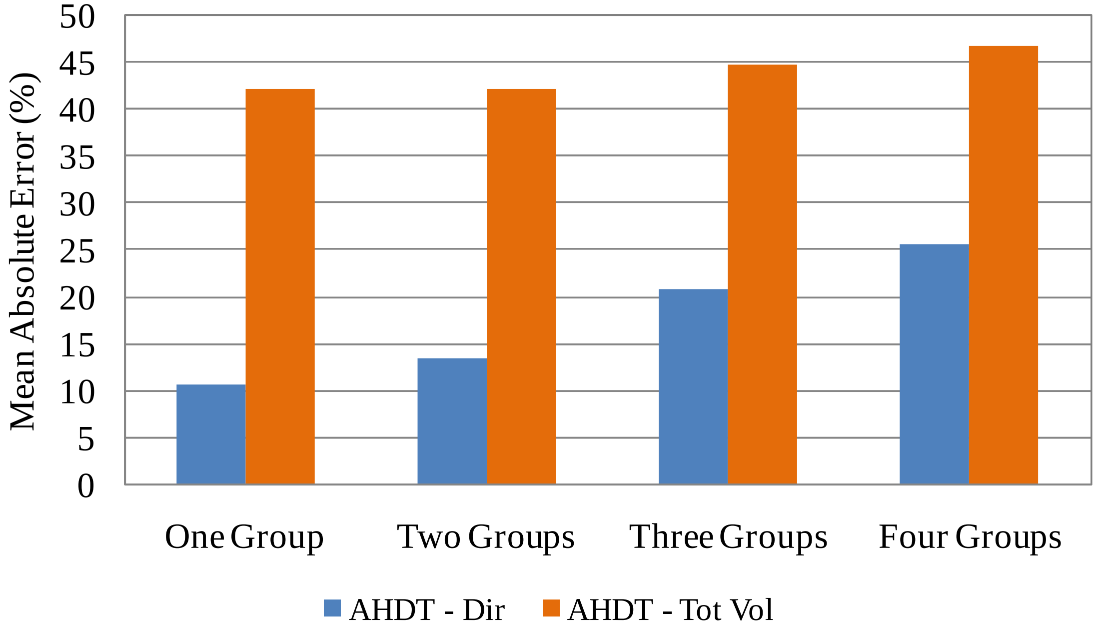


Figure C.8. WIMs AHDT (Directional vs. Total Volume).

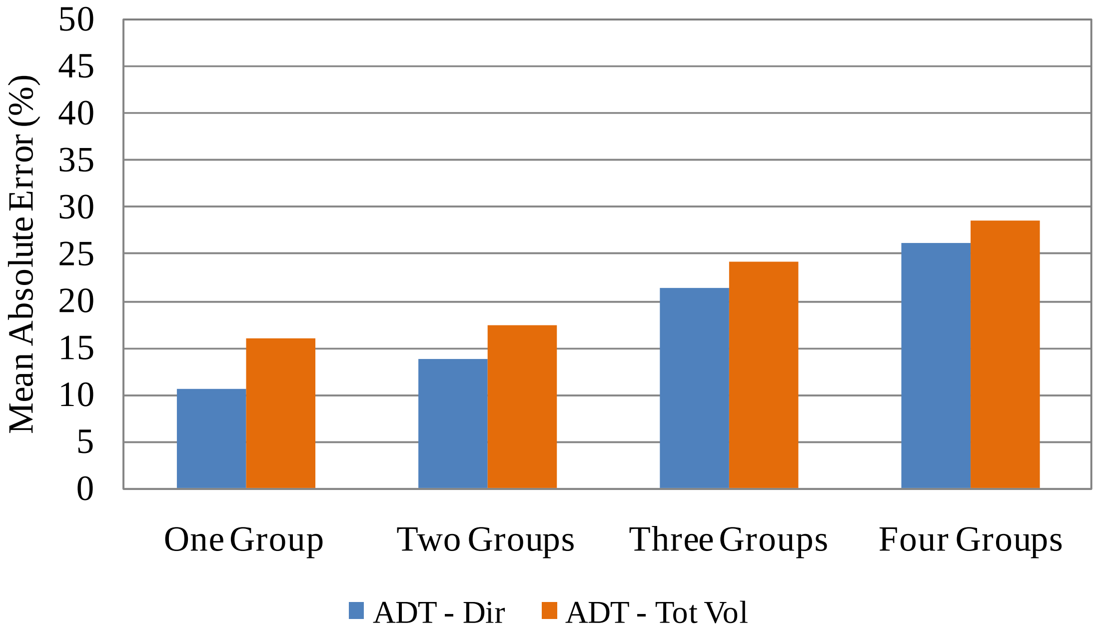


Figure C.9. WIMs ADT (Directional vs. Total Volume).

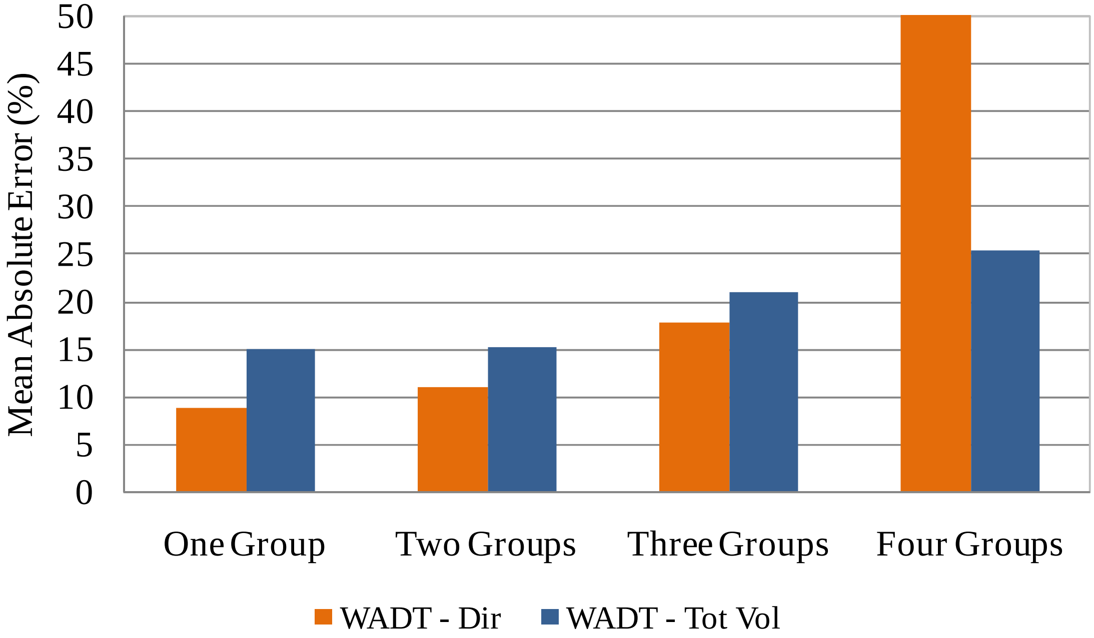


Figure C.10. WIMs WADT (Directional vs. Total Volume).

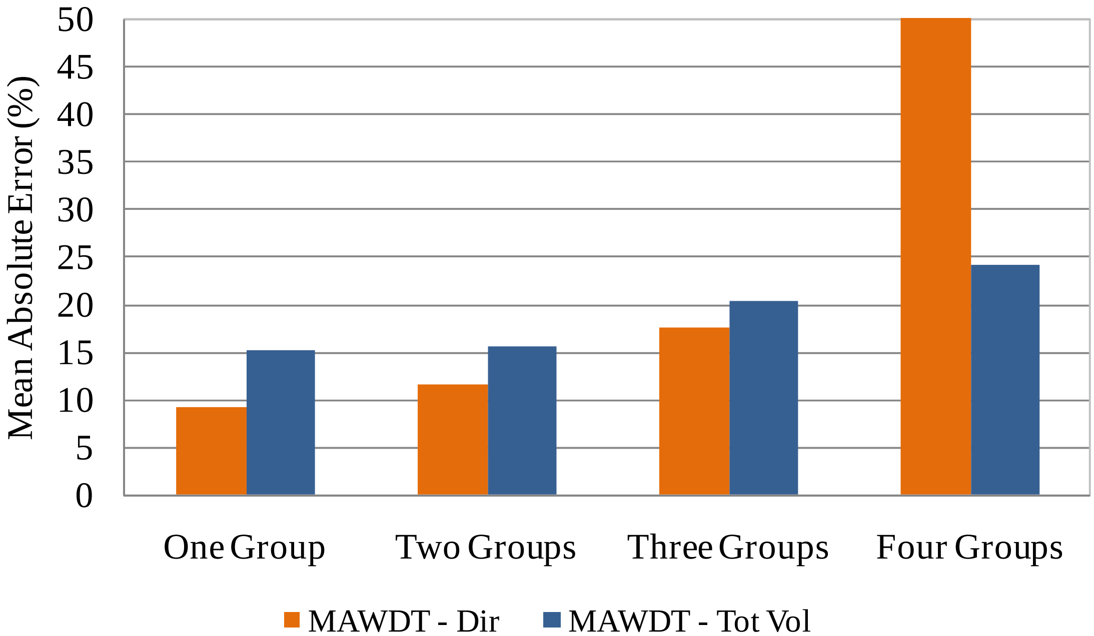


Figure C.11. WIMs MAWDT (Directional vs. Total Volume).

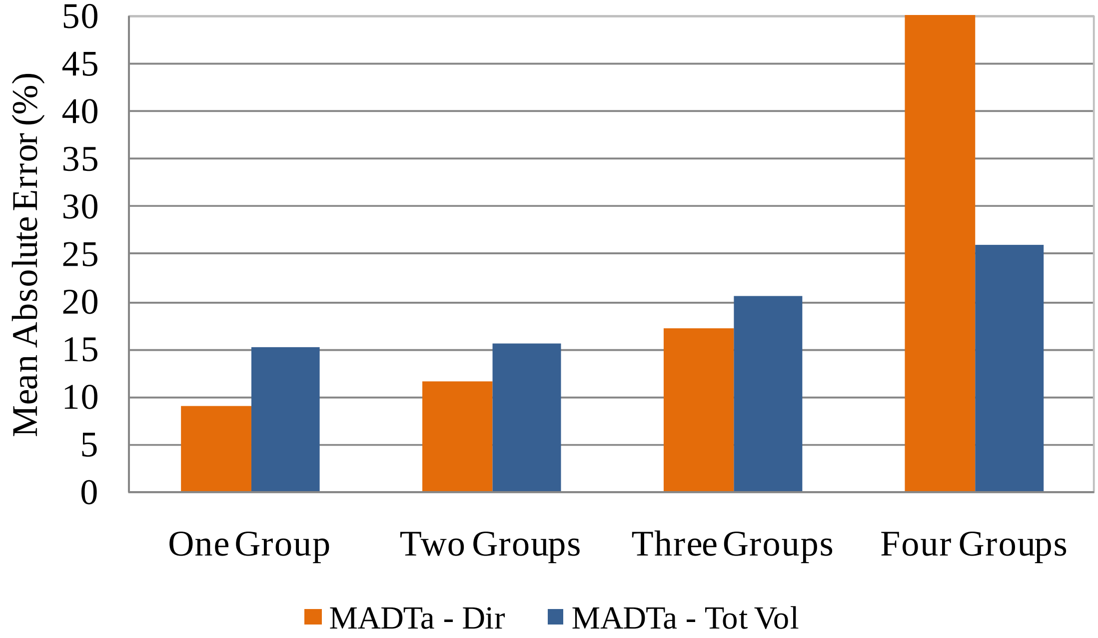


Figure C.12. WIMs MADTa (Directional vs. Total Volume).

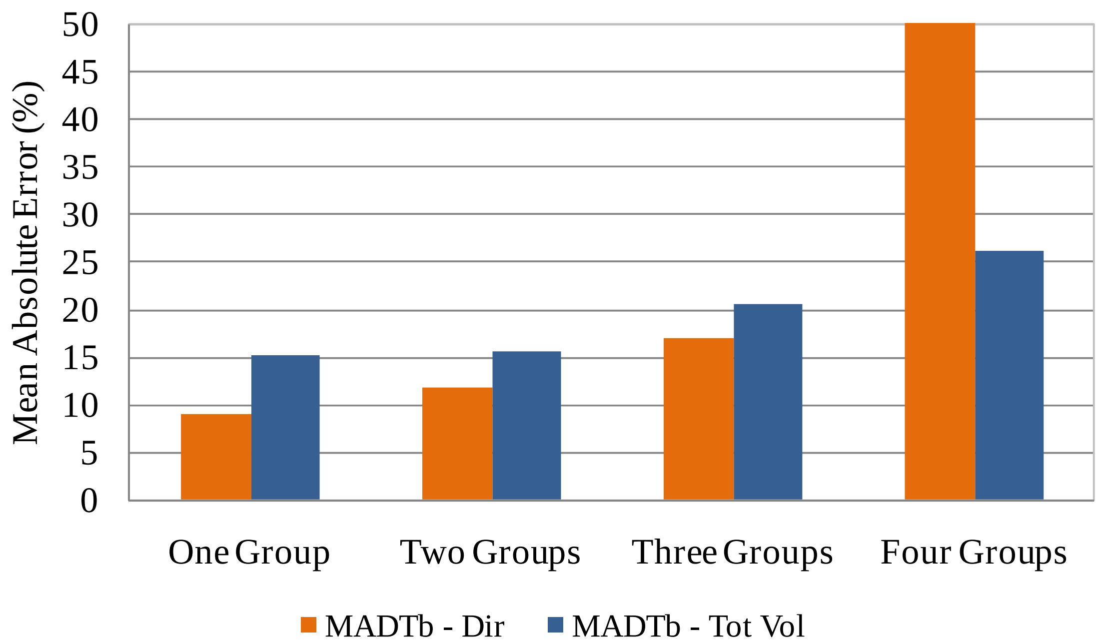


Figure C.13. WIMs MADTb (Directional vs. Total Volume).

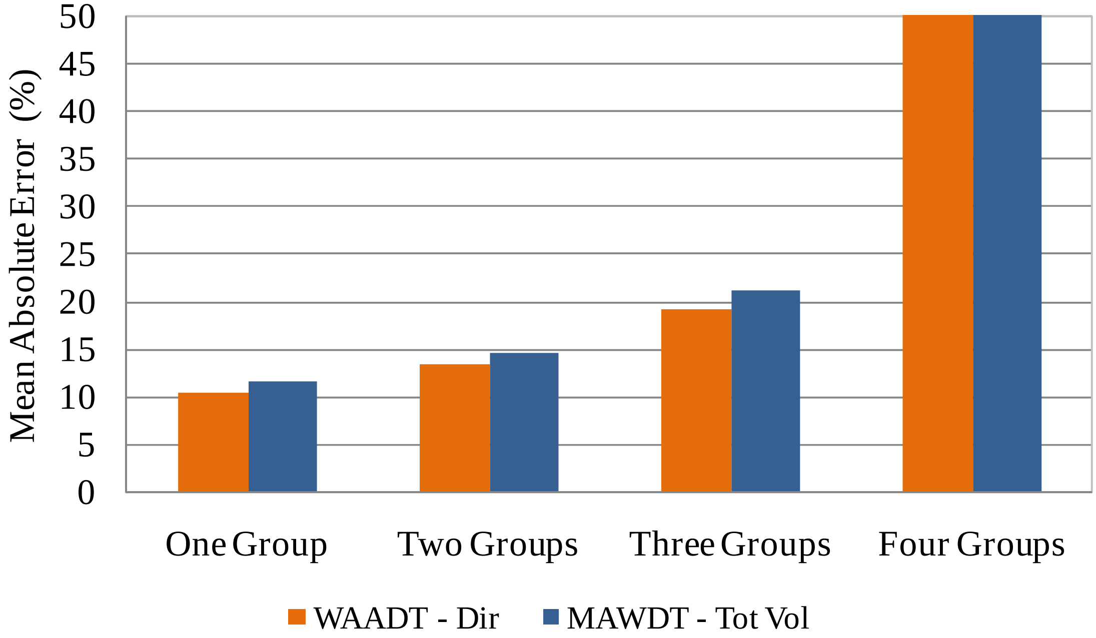


Figure C.14. WIMs WAADT (Directional vs. Total Volume).

APPENDIX D

SAF PER VEHICLE AND FUNCTIONAL CLASS

ATRs

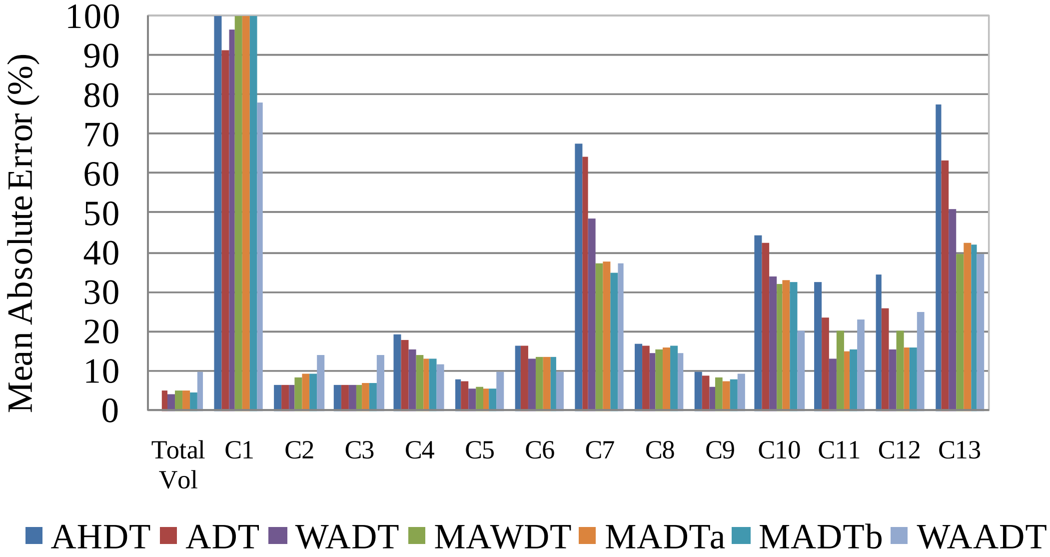


Figure D.1. ATRs Functional Class 1.

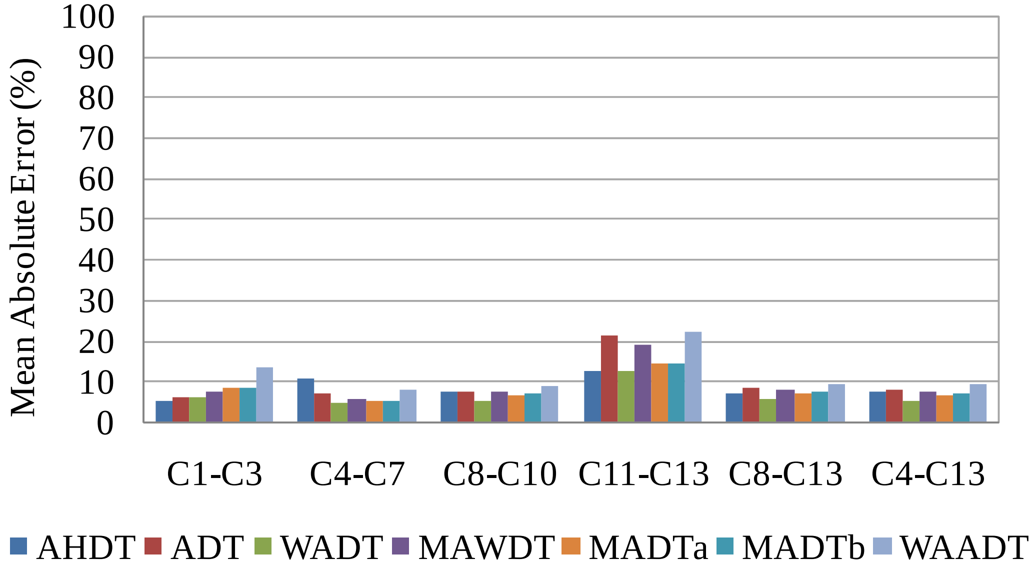


Figure D.2. ATRs Aggregate Classes - Functional Class 1.

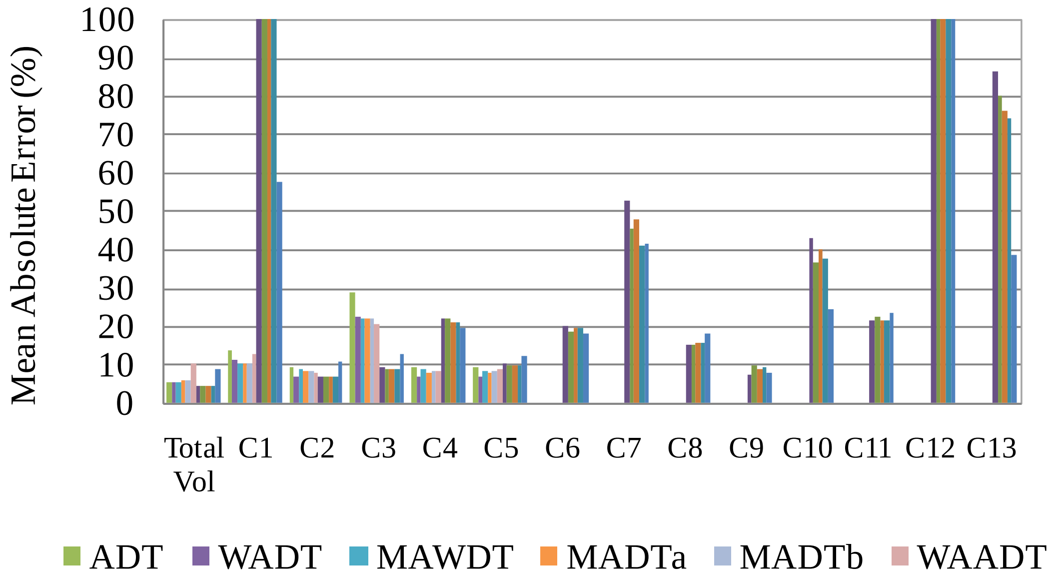


Figure D.3. ATRs Functional Class 2.

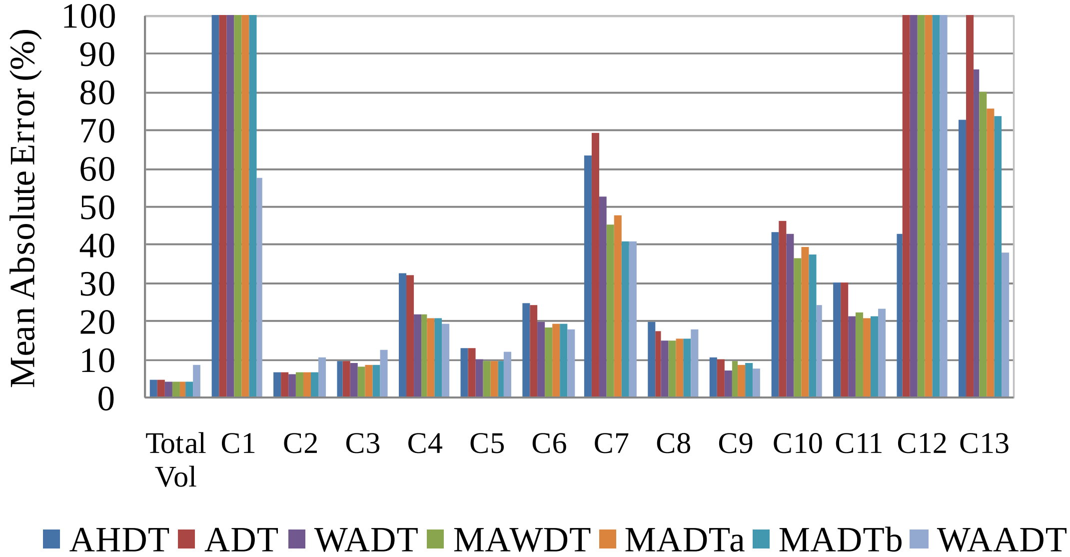


Figure D.4. ATRs Aggregate Classes - Functional Class 2.

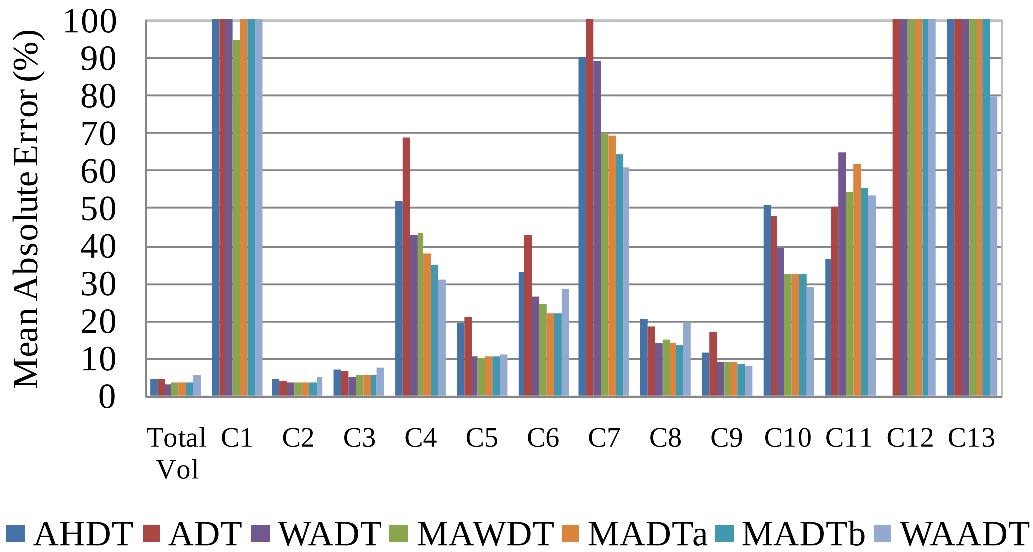


Figure D.5. ATRs Functional Class 7.

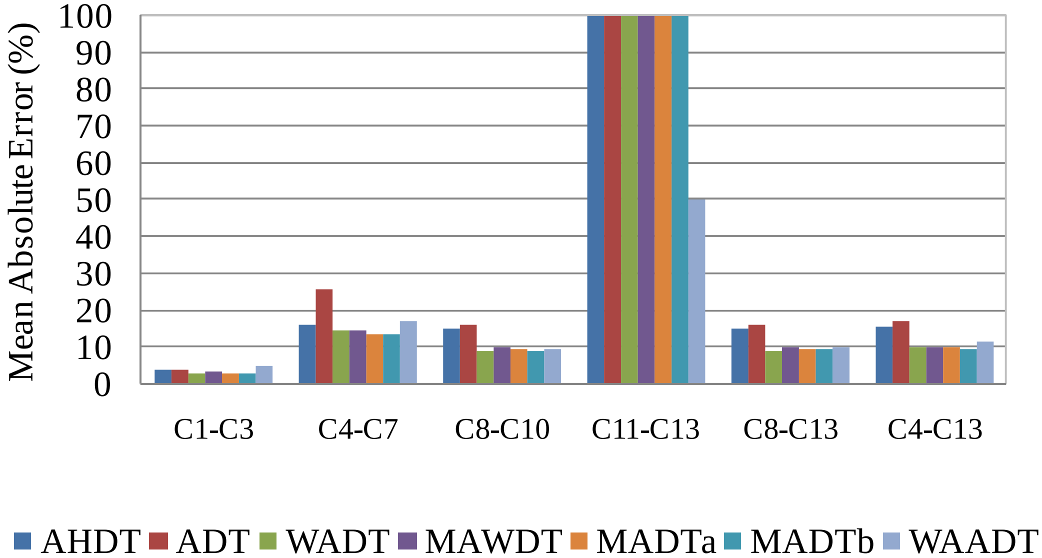


Figure D.6. ATRs Aggregate Classes - Functional Class 7.

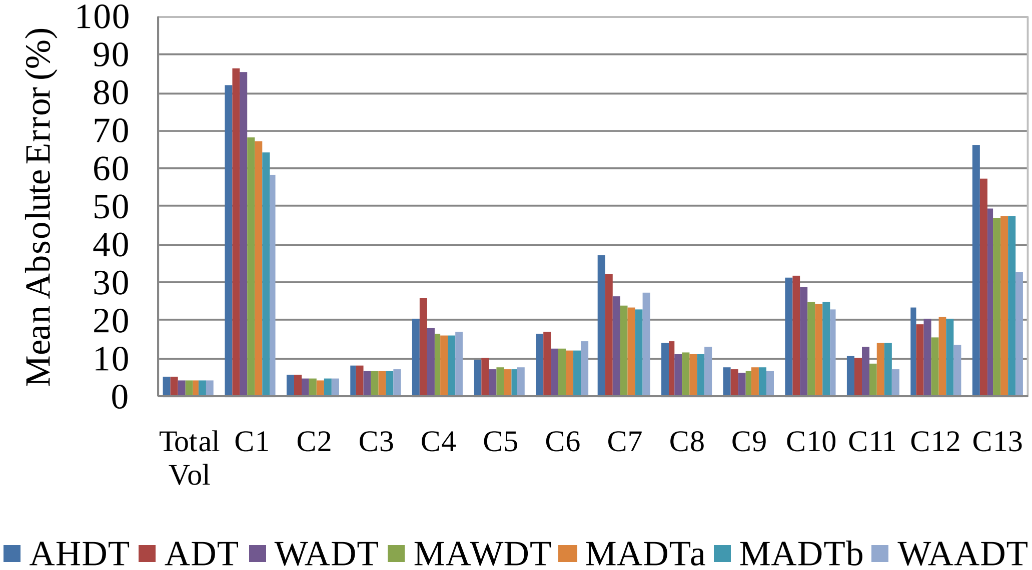


Figure D.7. ATRs Functional Class 11.

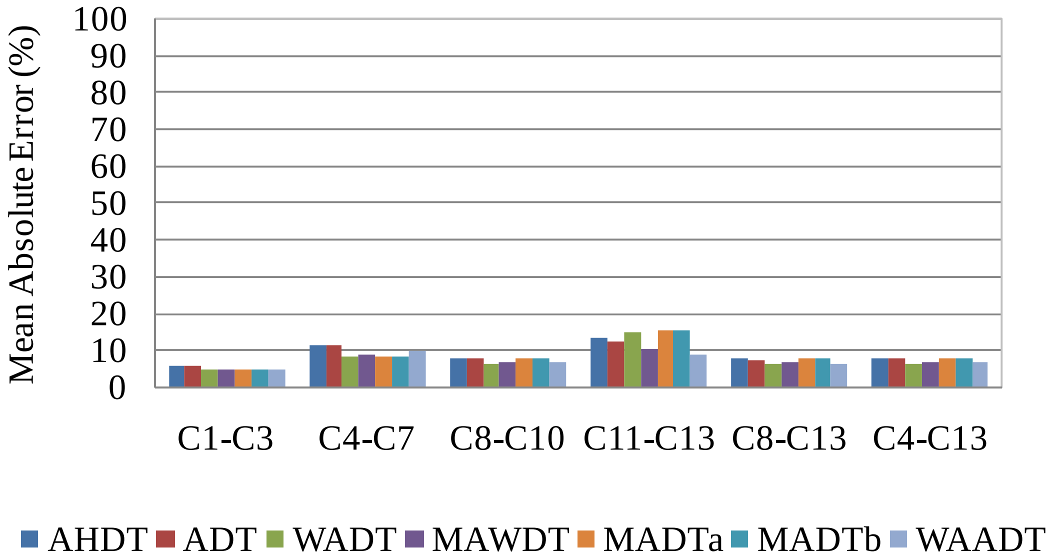


Figure D.8. ATRs Aggregate Classes - Functional Class 11.

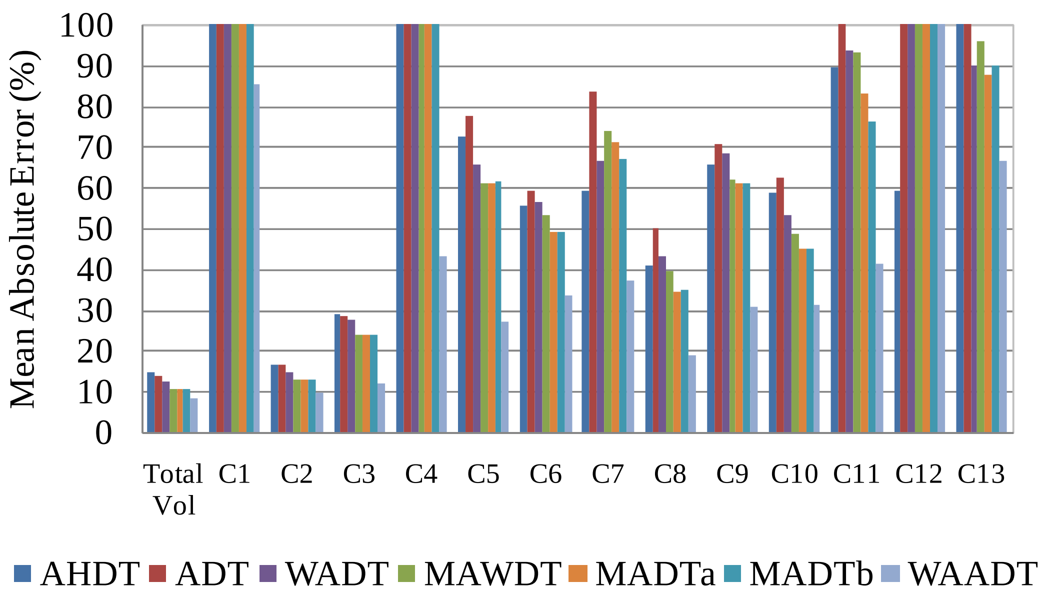


Figure D.9. ATRs Functional Class 12.

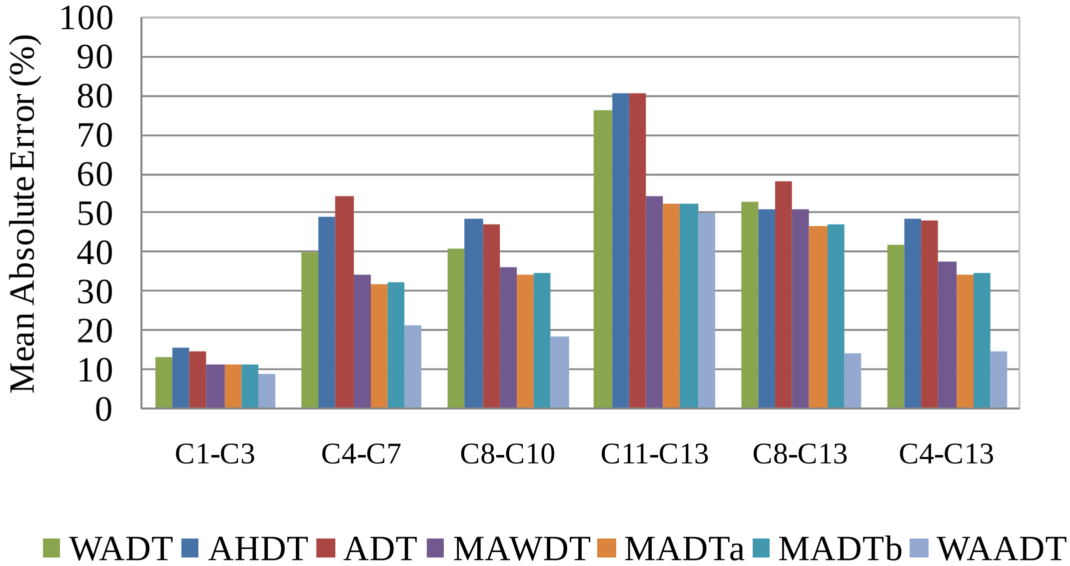


Figure D.10. ATRs Aggregate Classes - Functional Class 12.

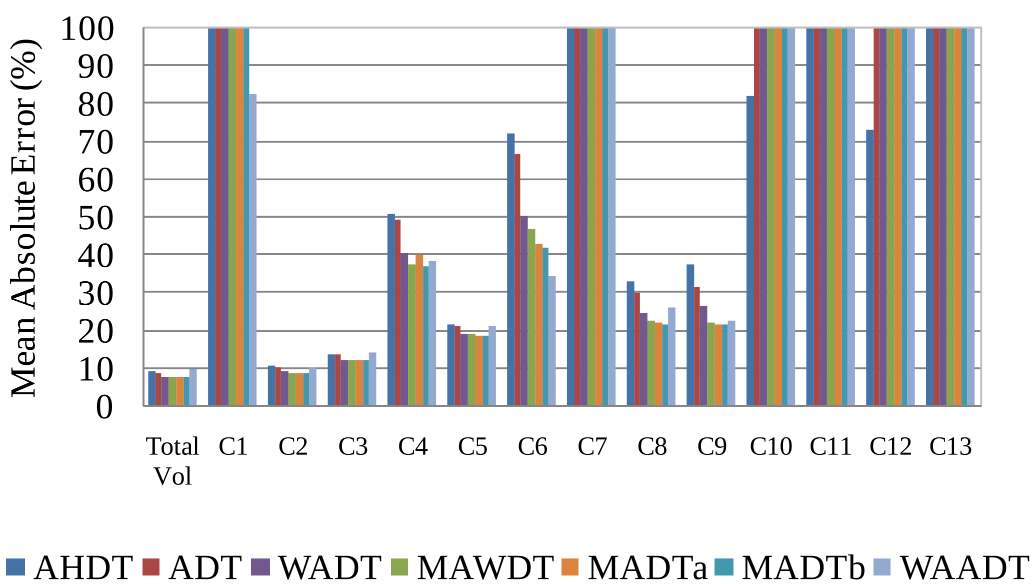


Figure D.11. ATRs Functional Class 14.

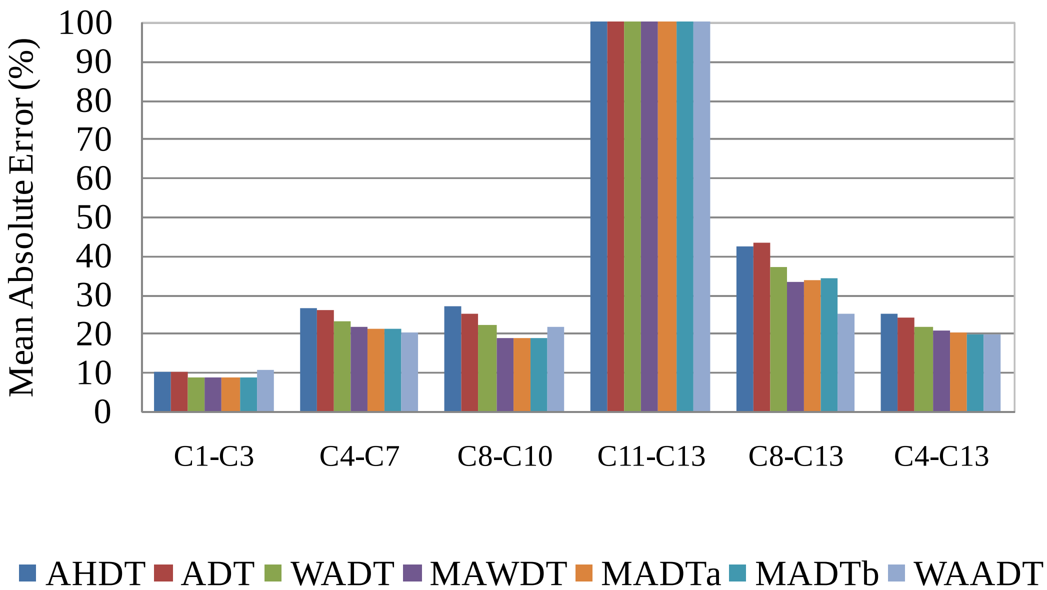


Figure D.12. ATRs Aggregate Classes - Functional Class 14.

WIMs

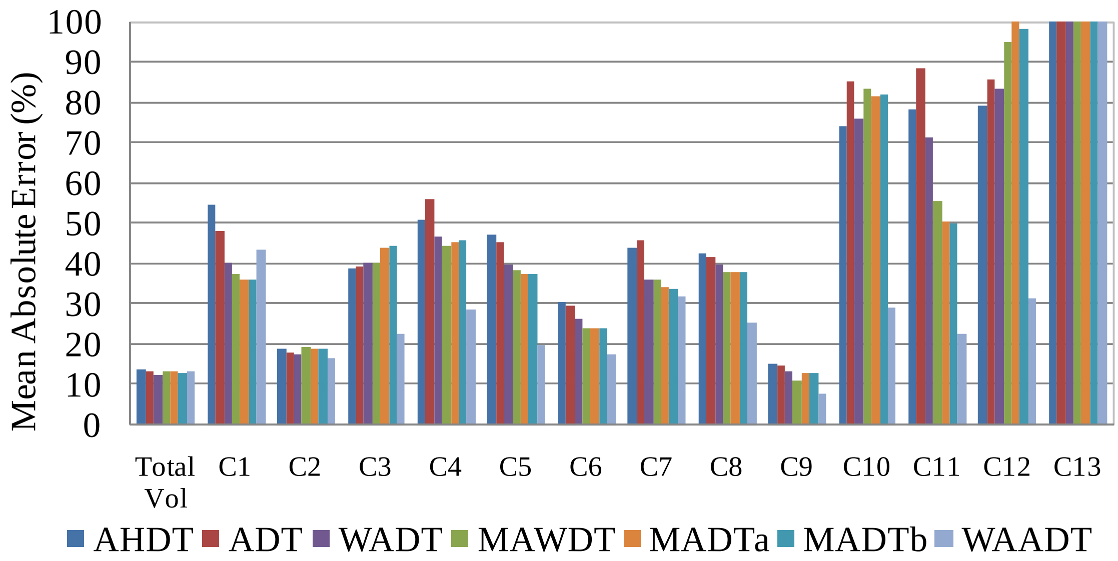


Figure D.13. WIMs Functional Class 1.

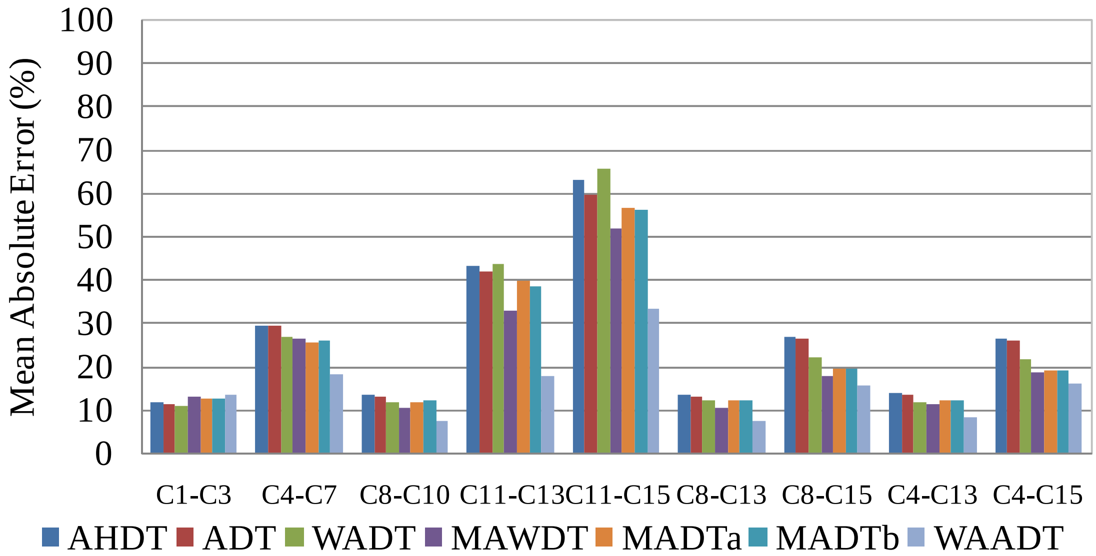


Figure D.14. WIMs Aggregate Classes - Functional Class 1.

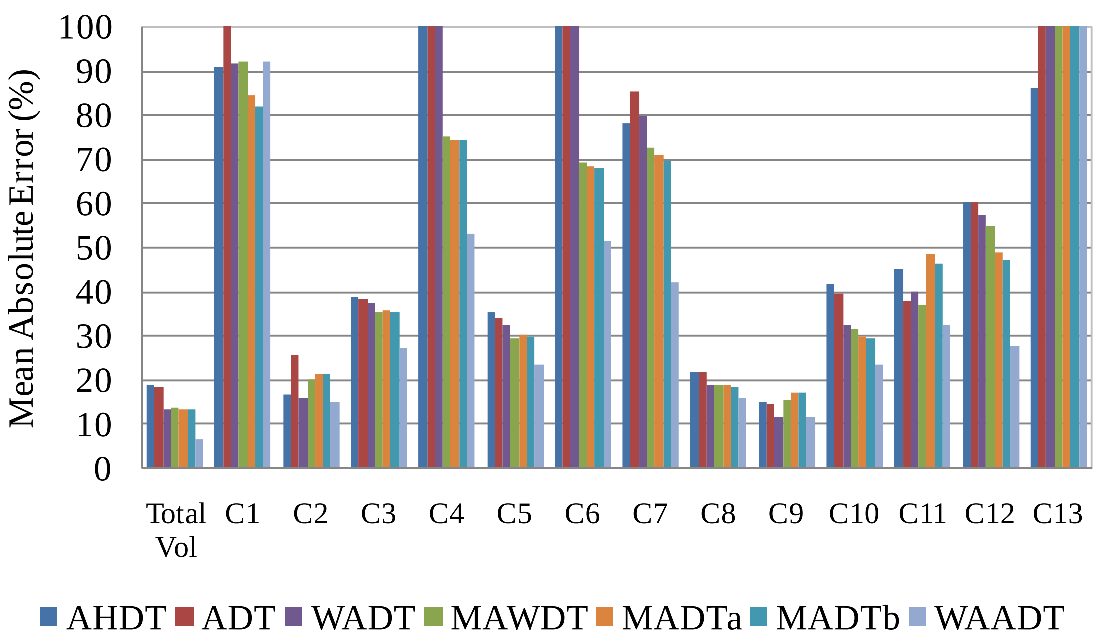


Figure D.15. WIMs Functional Class 2.

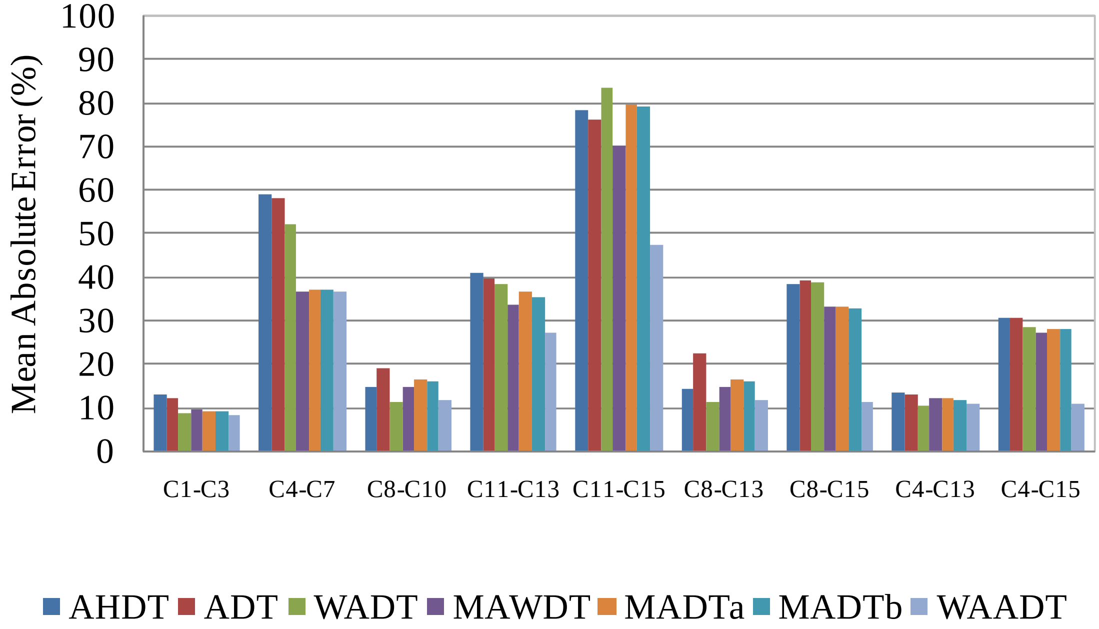


Figure D.16. WIMs Aggregate Classes - Functional Class 2.

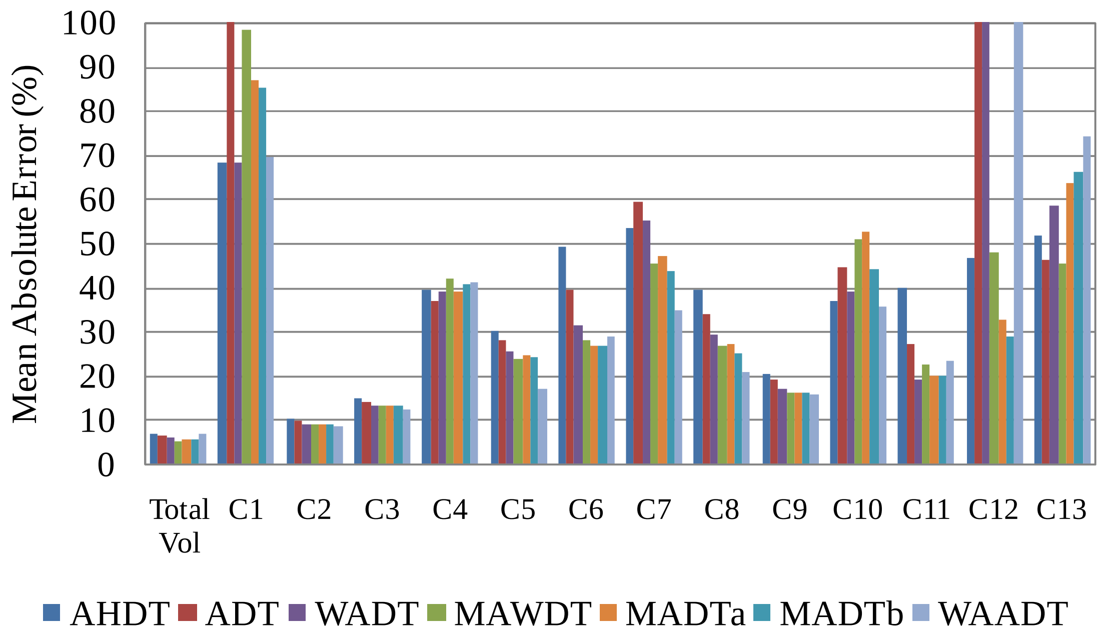


Figure D.17. WIMs Functional Class 6.

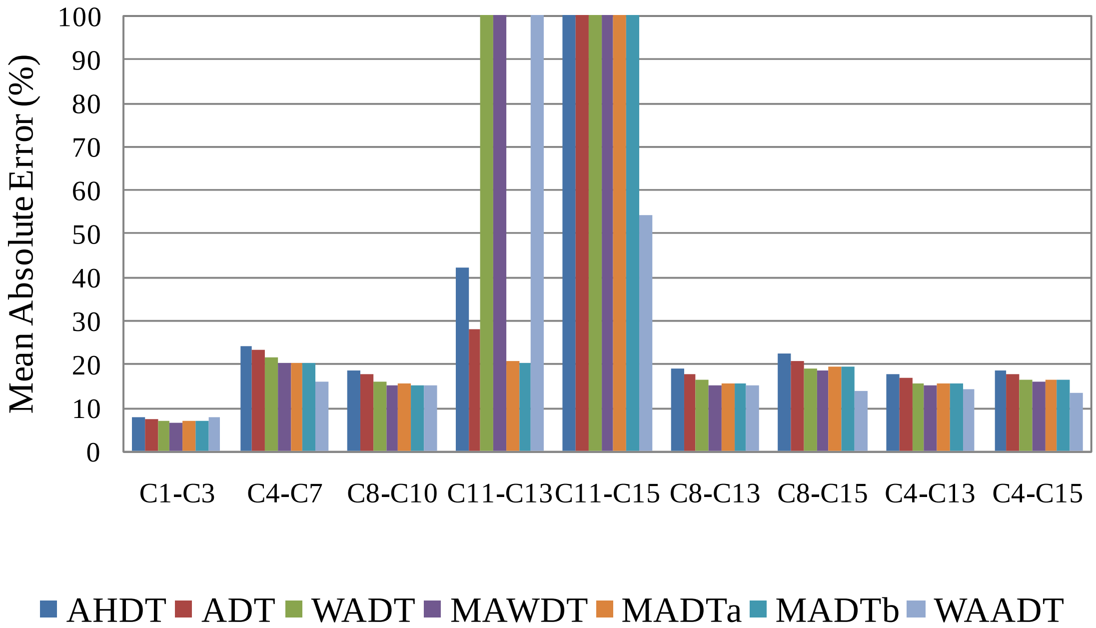


Figure D.18. WIMs Aggregate Classes - Functional Class 6.

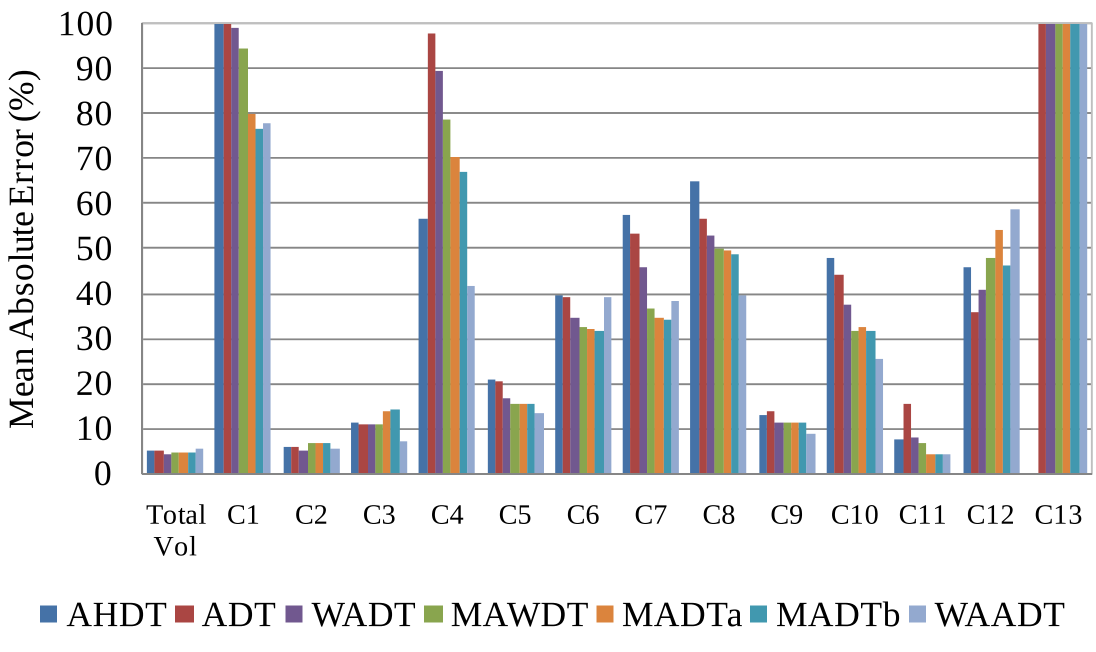


Figure D.19. WIMs Functional Class 7.

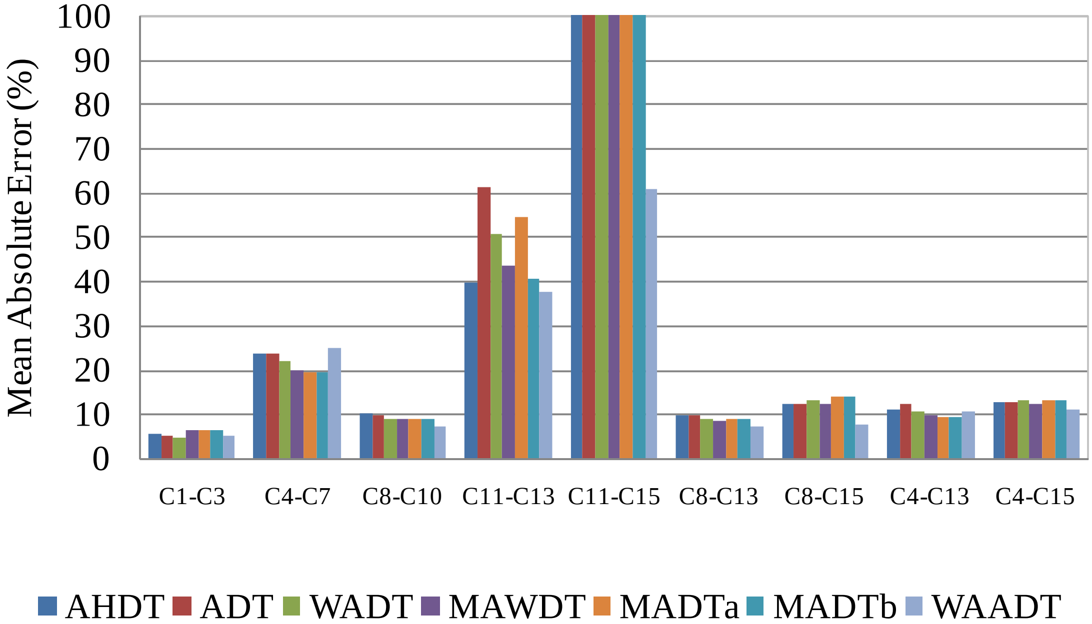


Figure D.20. WIMs Aggregate Classes - Functional Class 7.

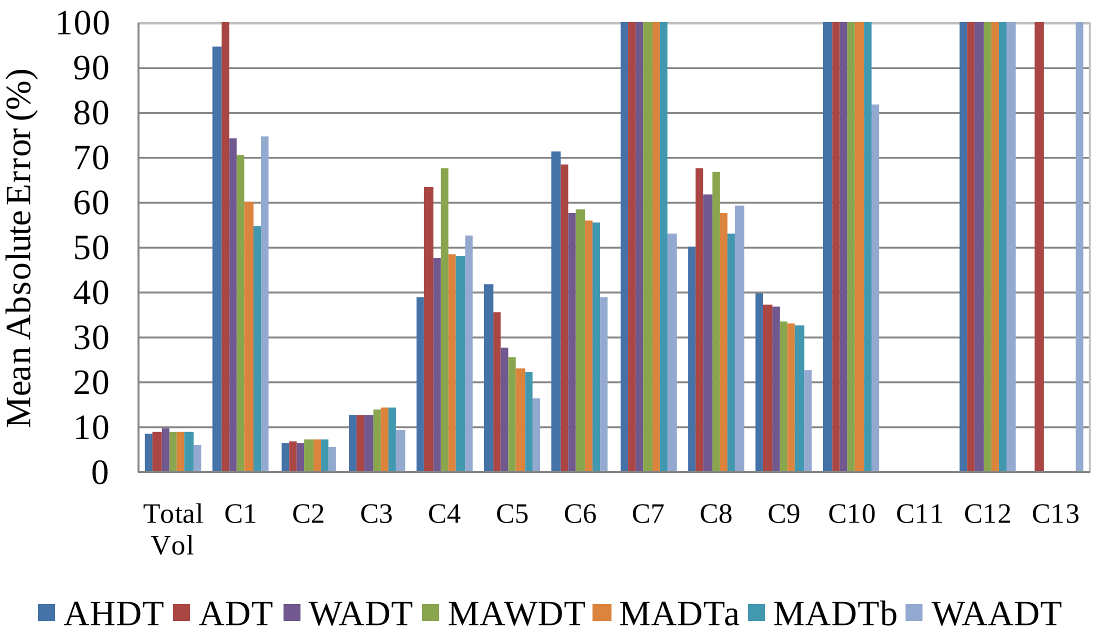


Figure D.21. WIMs Functional Class 8.

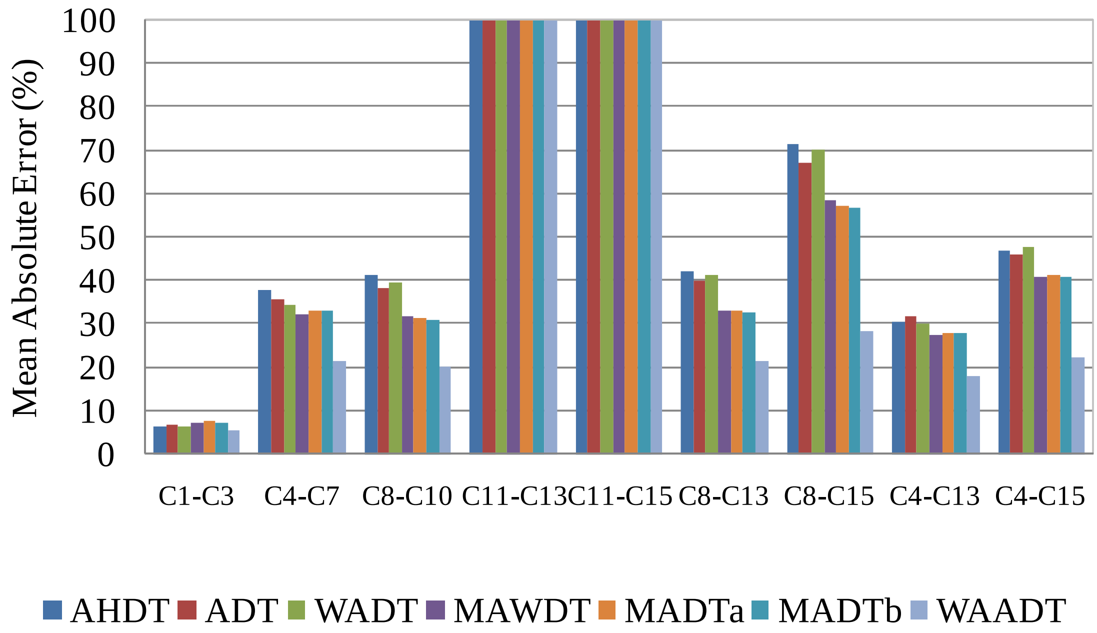


Figure D.22. WIMs Aggregate Classes - Functional Class 8.

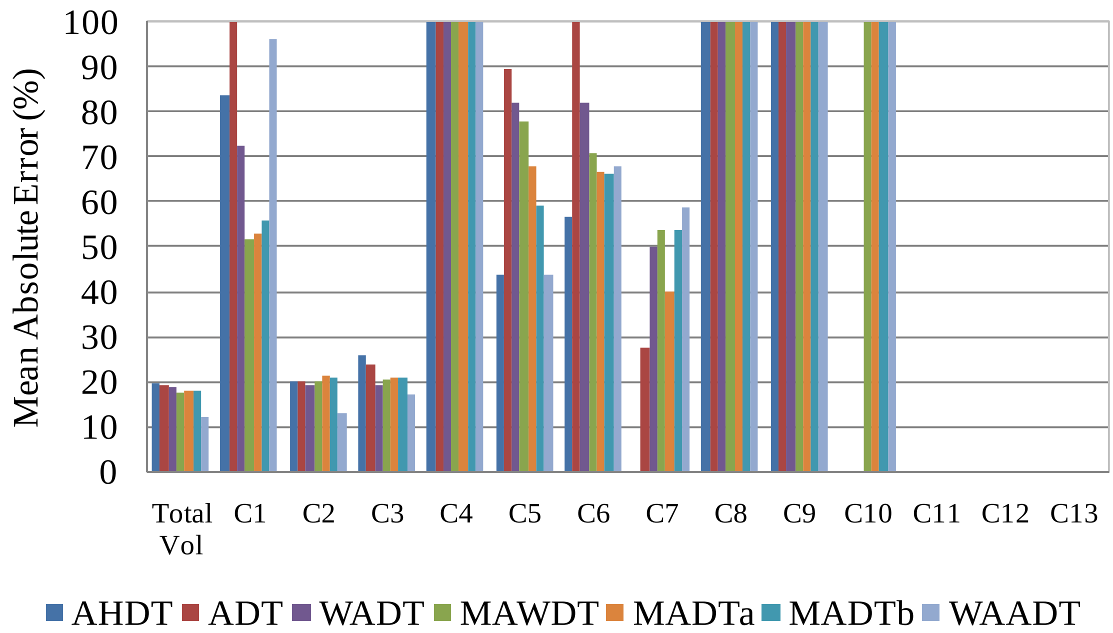


Figure D.23. WIMs Functional Class 9.

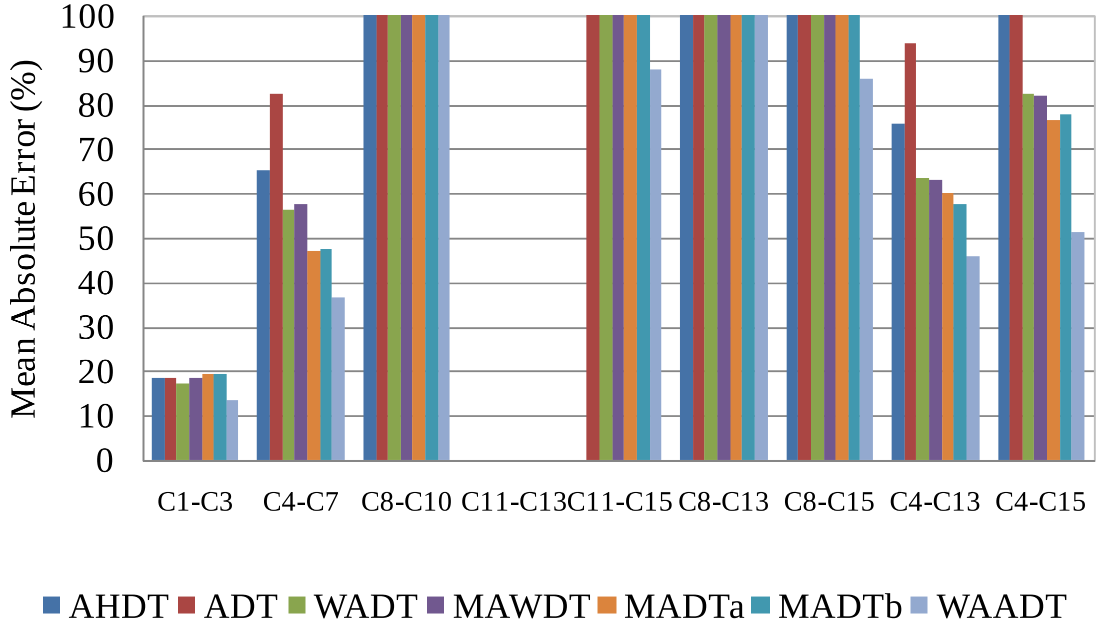


Figure D.24. WIMs Aggregate Classes - Functional Class 9.

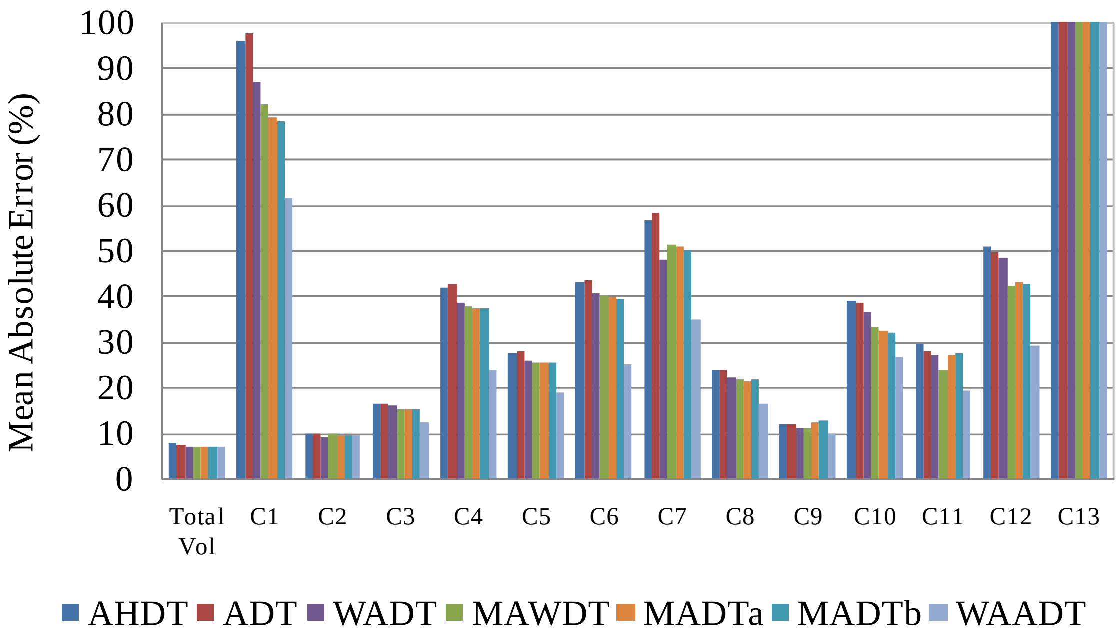


Figure D.25. WIMs Functional Class 11.

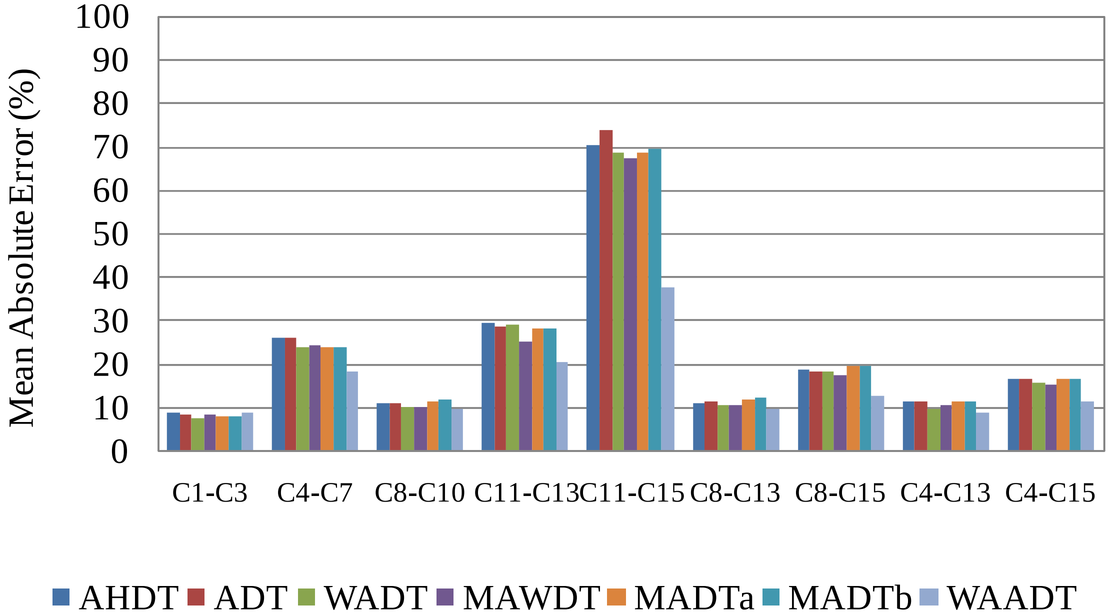


Figure D.26. WIMs Aggregate Classes - Functional Class 11.

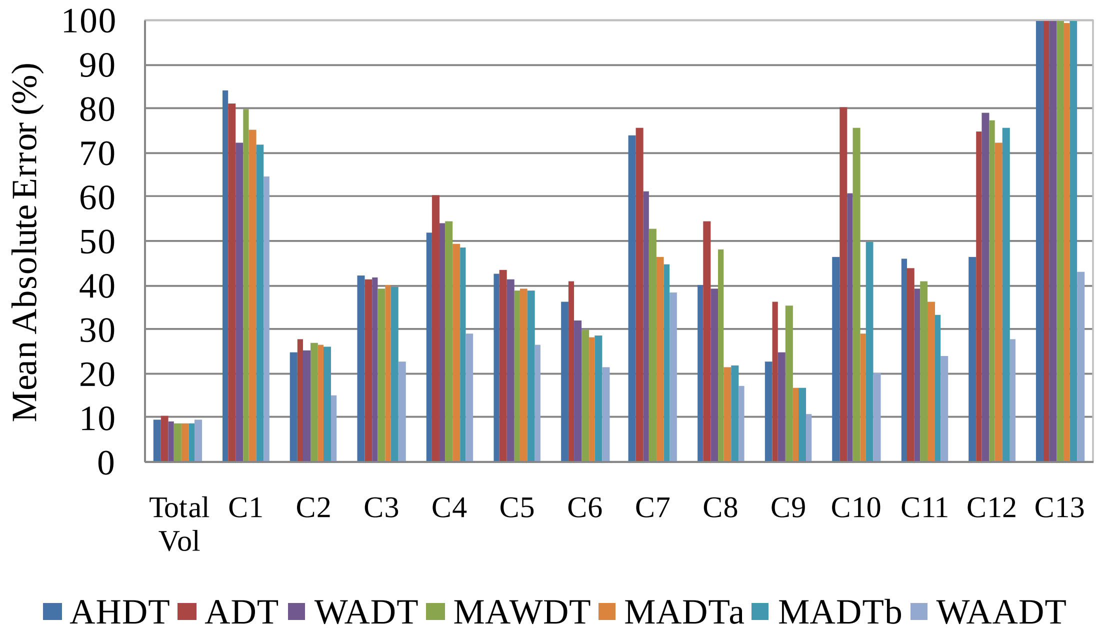


Figure D.27. WIMs Functional Class 12.

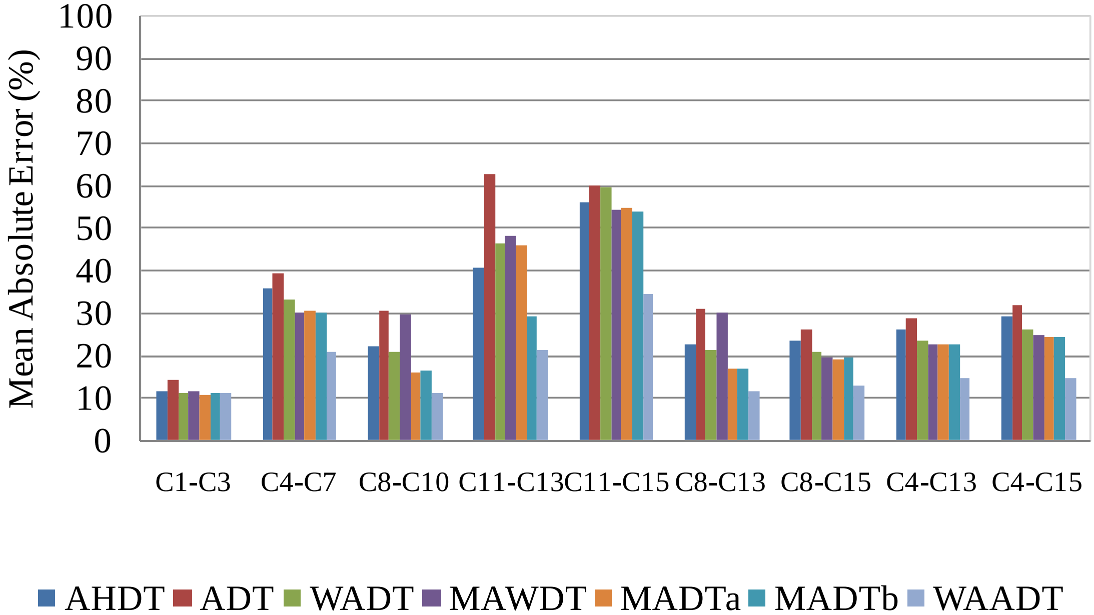


Figure D.28. WIMs Aggregate Classes - Functional Class 12.

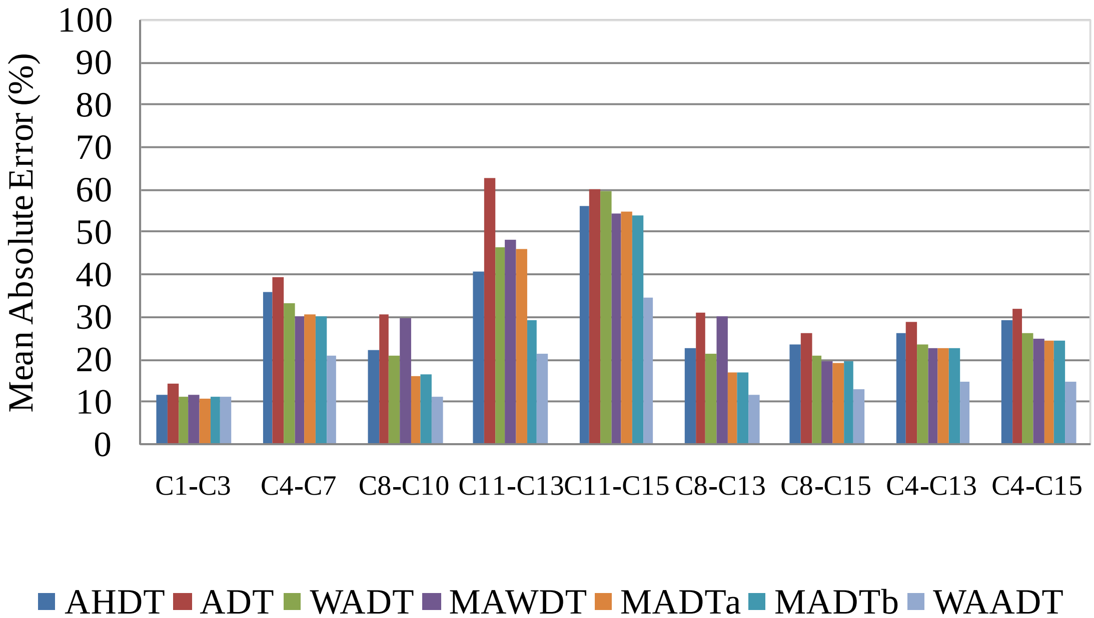


Figure D.29. WIMs Functional Class 14.

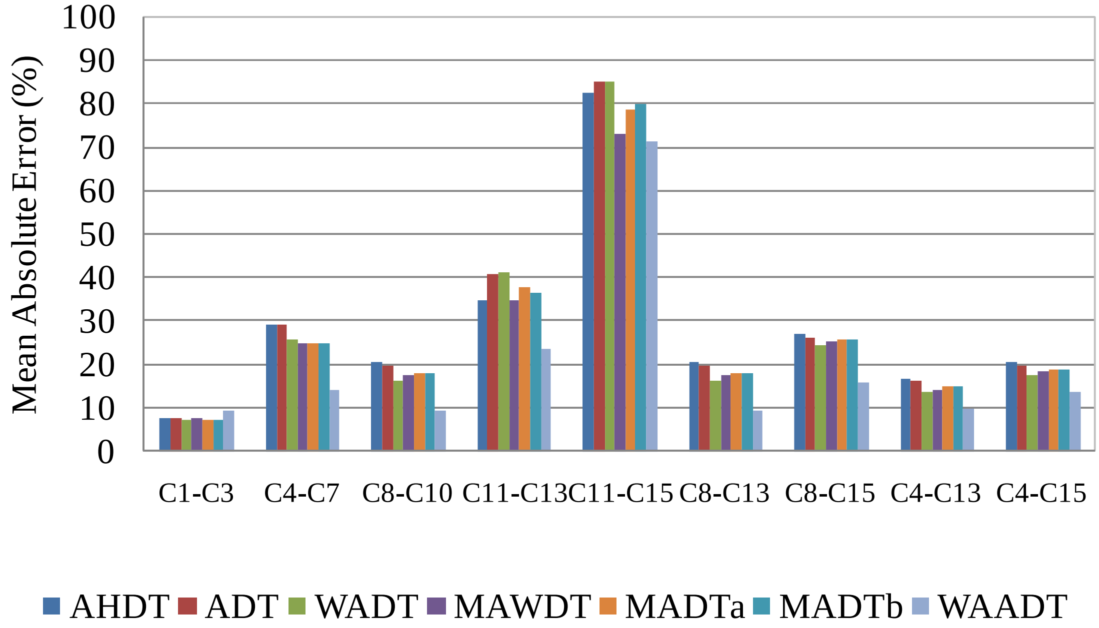


Figure D.30. WIMs Aggregate Classes - Functional Class 14.

APPENDIX E

SAF PER MONTH AND FUNCTIONAL CLASS

ATRs

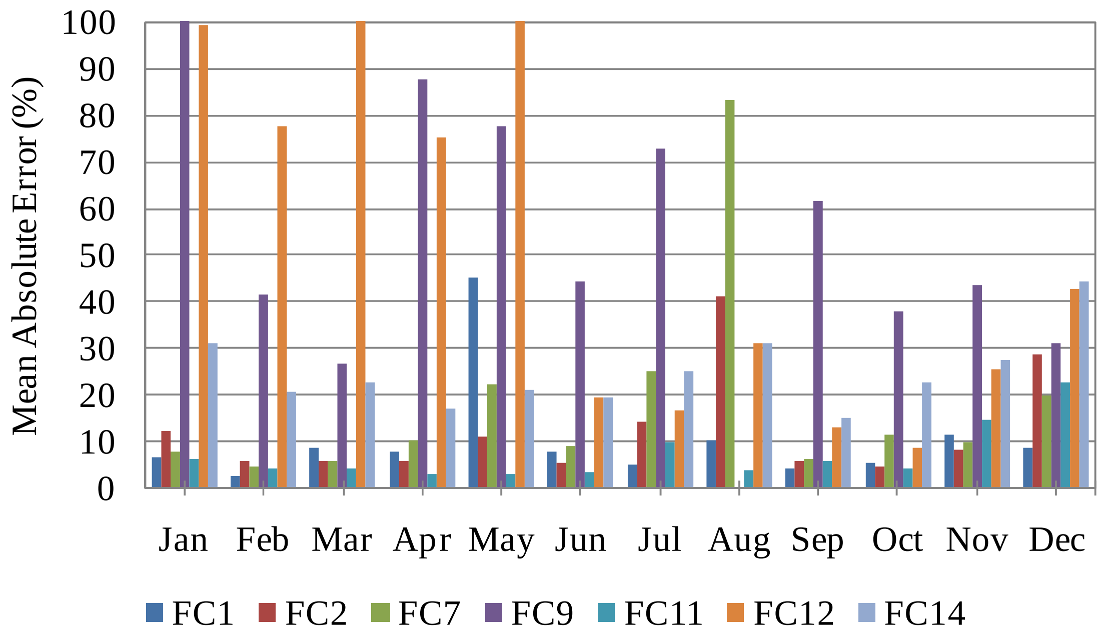


Figure E.1. Average MAE of ATRs based on WADT AHDT.

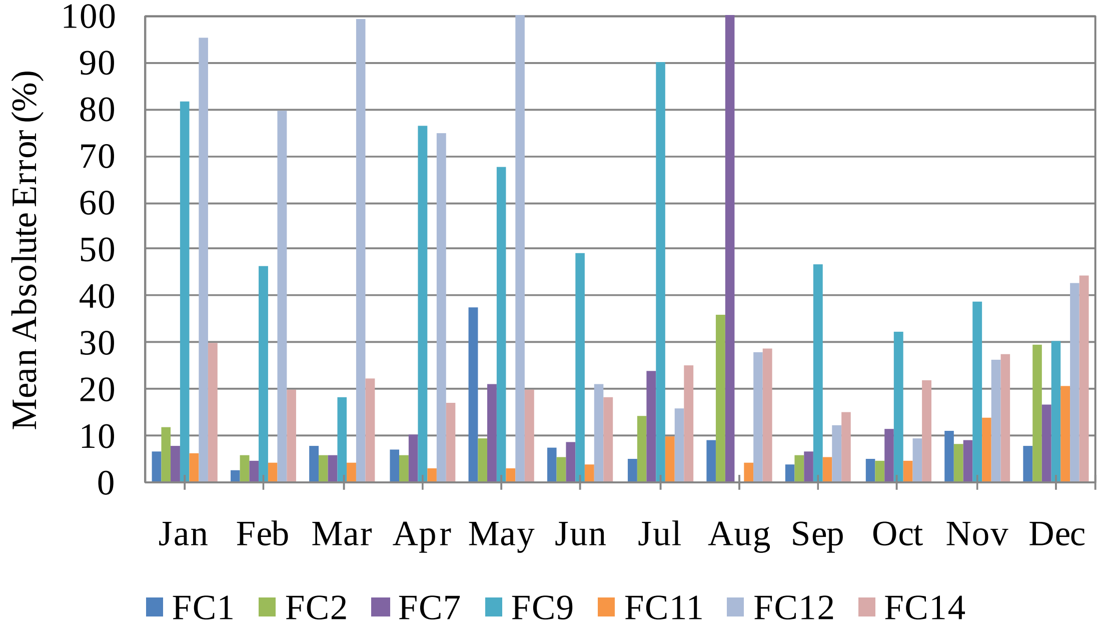


Figure E.2. Average MAE of ATRs based on WADT ADT.

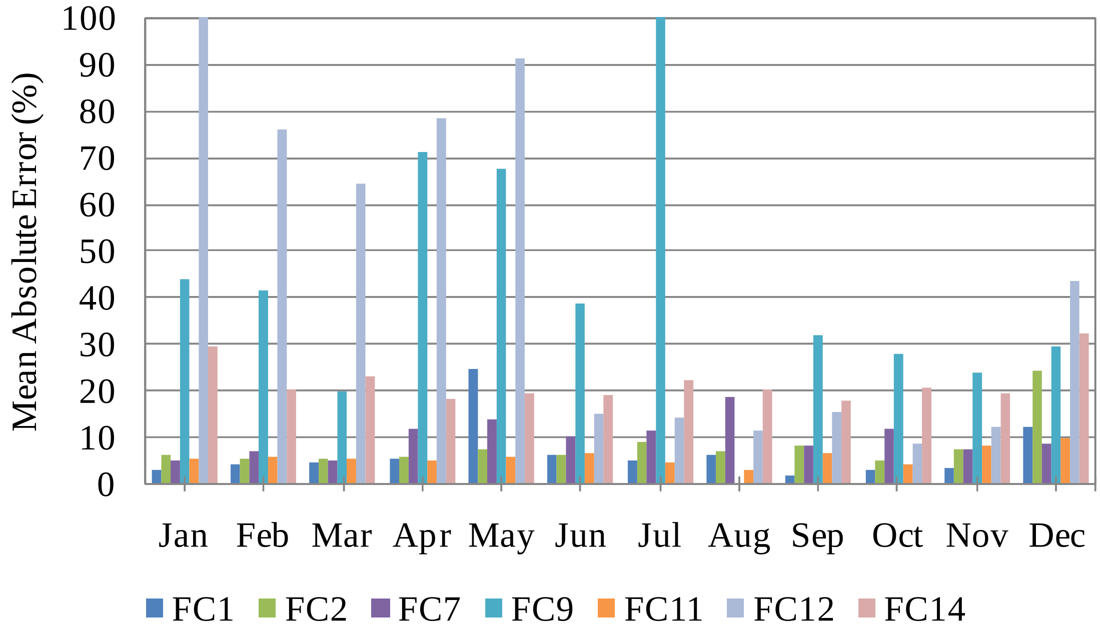


Figure E.3. Average MAE of ATRs based on WADT.

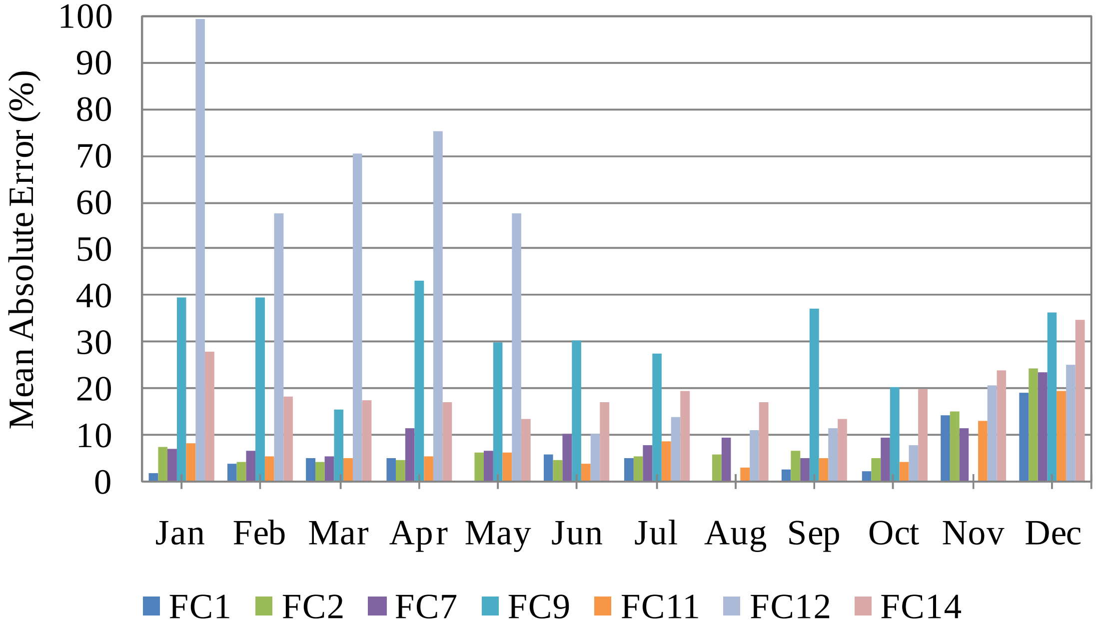


Figure E.4. Average MAE of ATRs based on MAWDT.

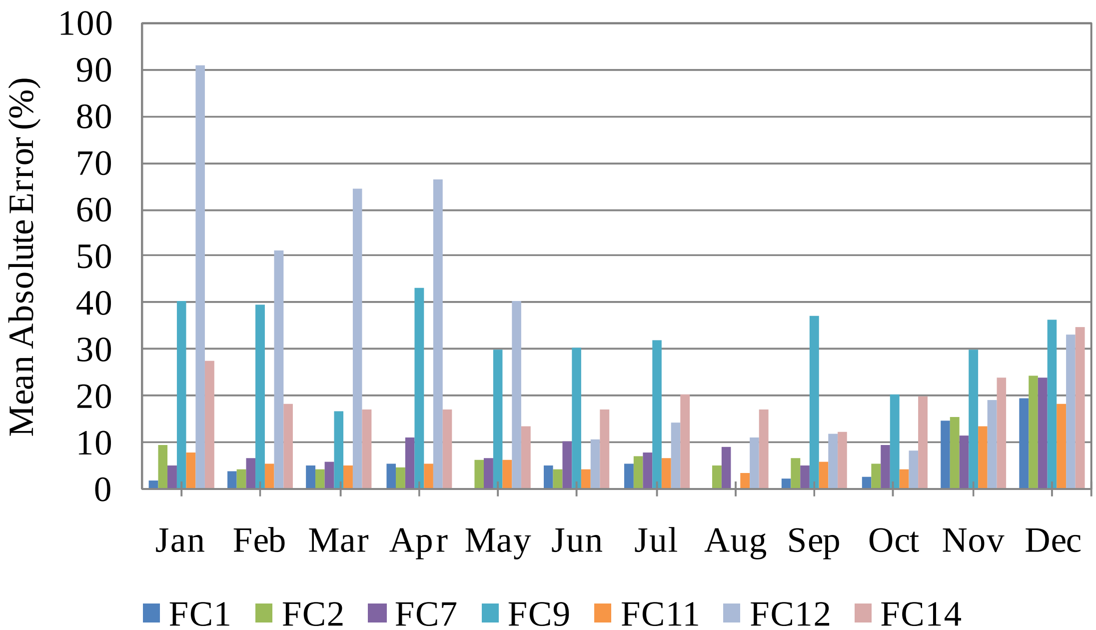


Figure E.5. Average MAE of ATRs based on MADT.

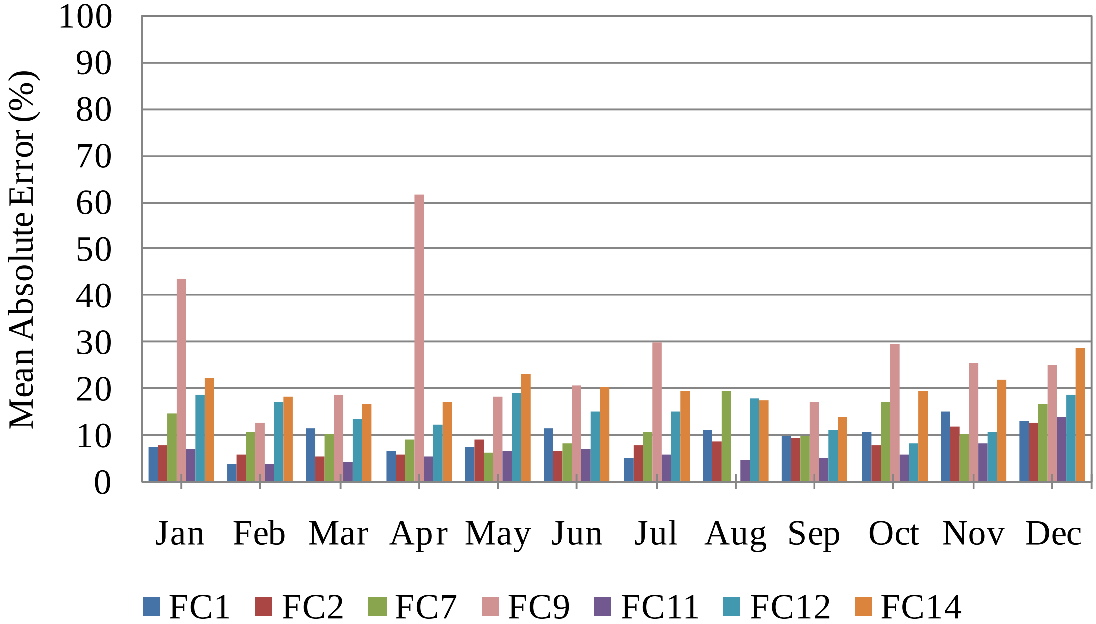


Figure E.6. Average MAE of ATRs based on WAADT.

WIMs

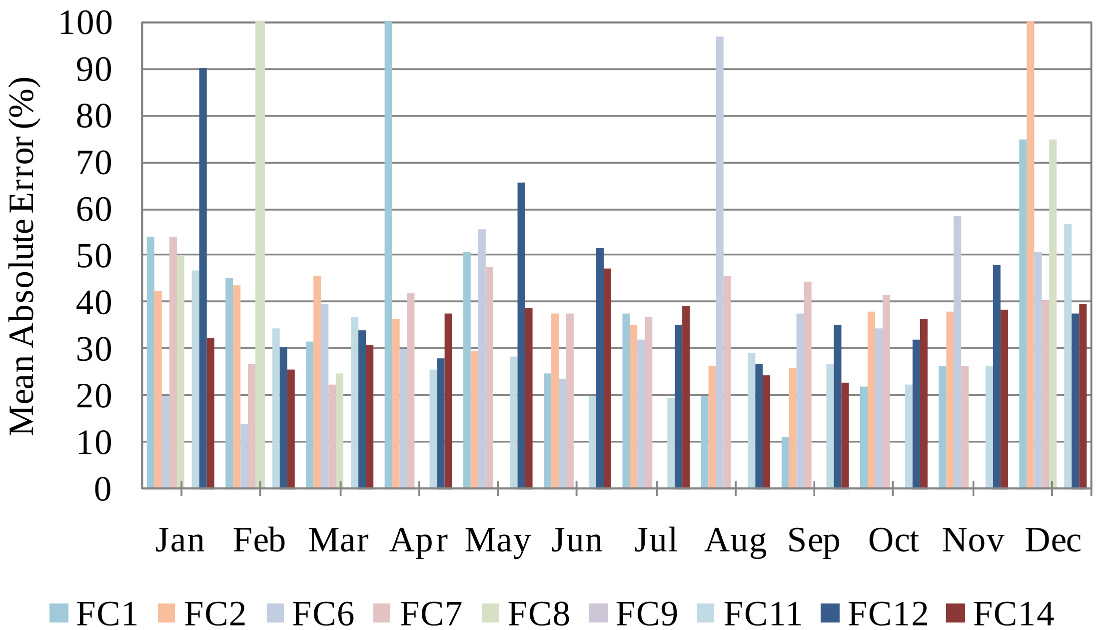


Figure E.7. Average MAE of WIMs based on AHDT.

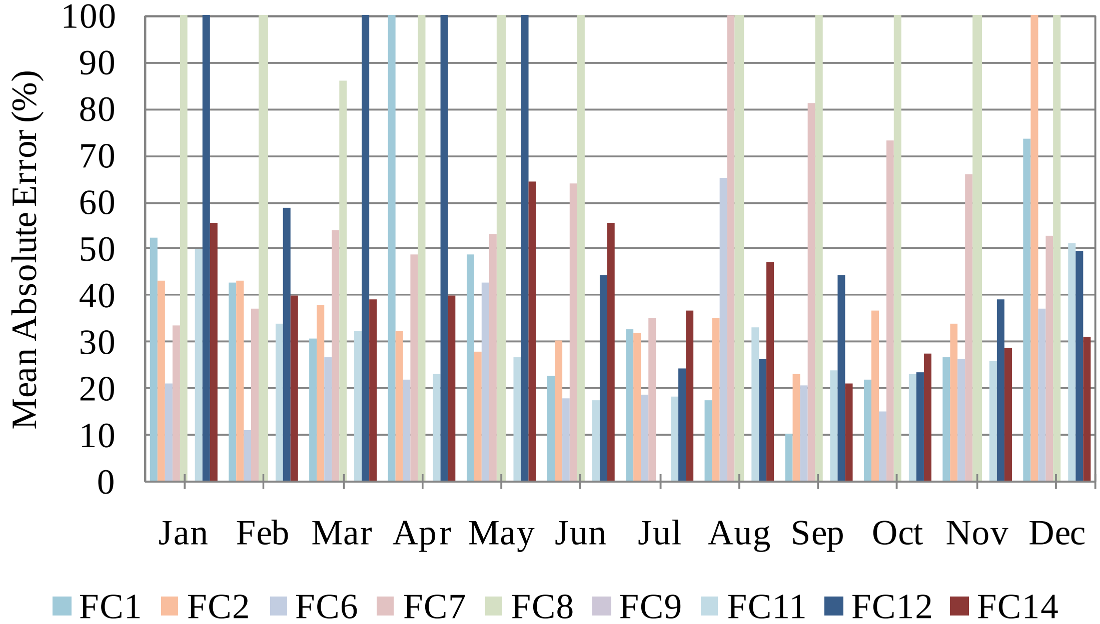


Figure E.8. Average MAE of WIMs based on ADT.

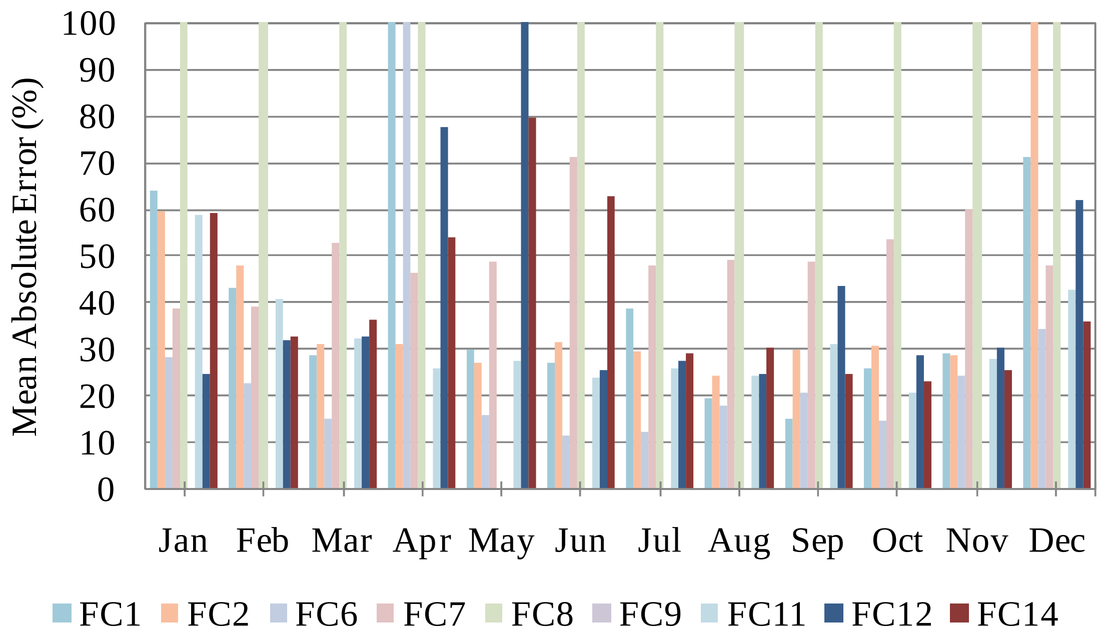


Figure E.9. Average MAE of WIMs based on WADT.

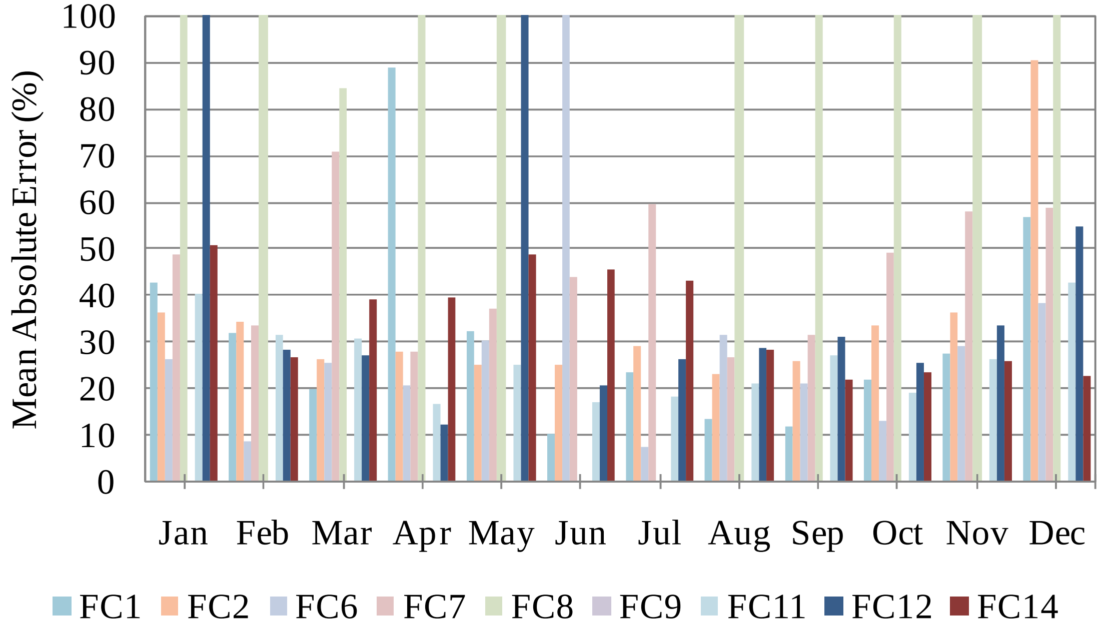


Figure E.10. Average MAE of WIMs based on MAWDT.

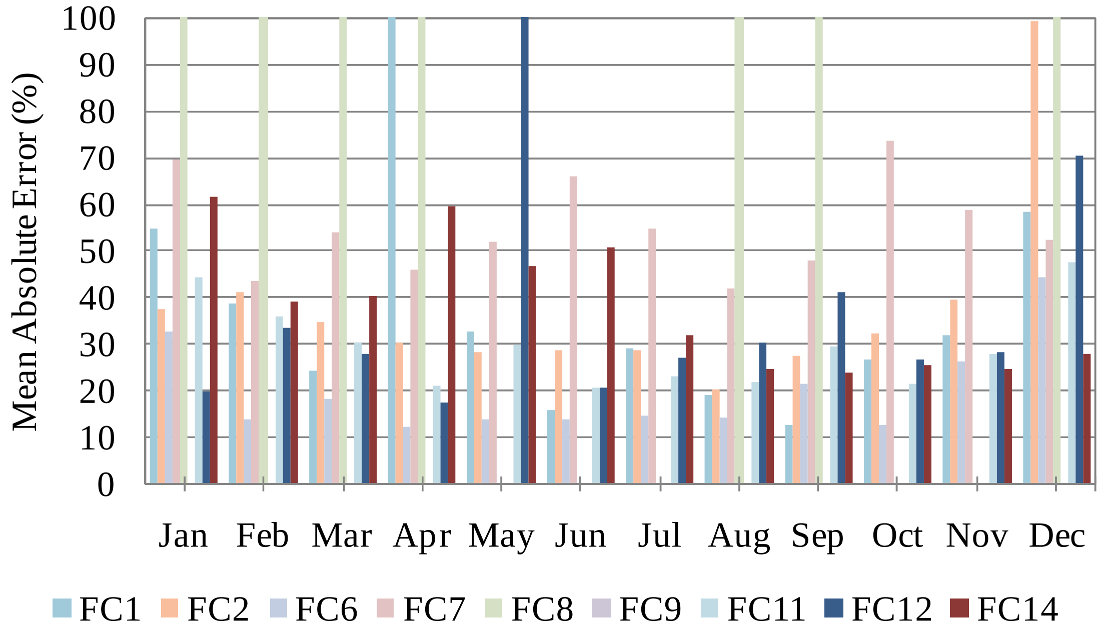


Figure E.11. Average MAE of WIMs based on MADT.

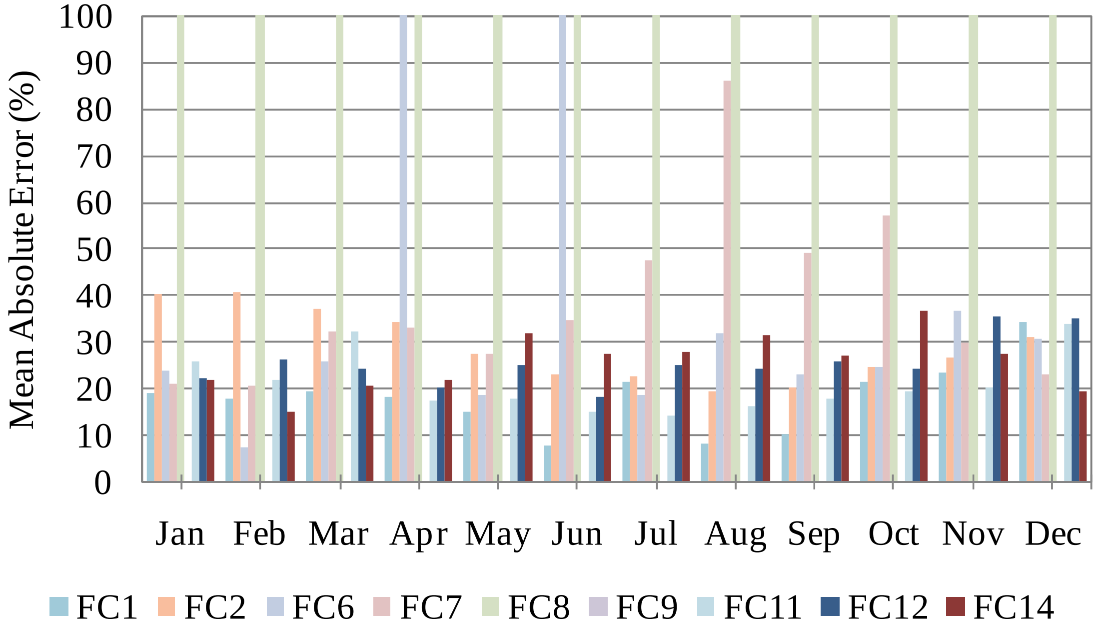


Figure E.12. Average MAE of WIMs based on WAADT.

APPENDIX F

RESULTS PER GROUPING METHOD

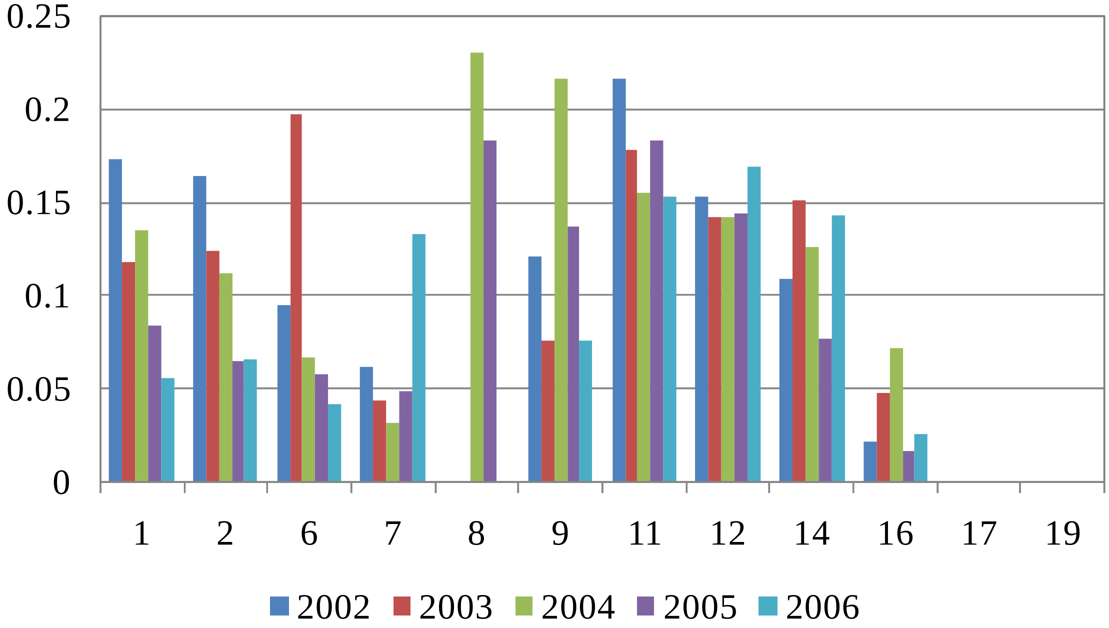


Figure F.1. Method One standard deviation for 3-Card Total volume.

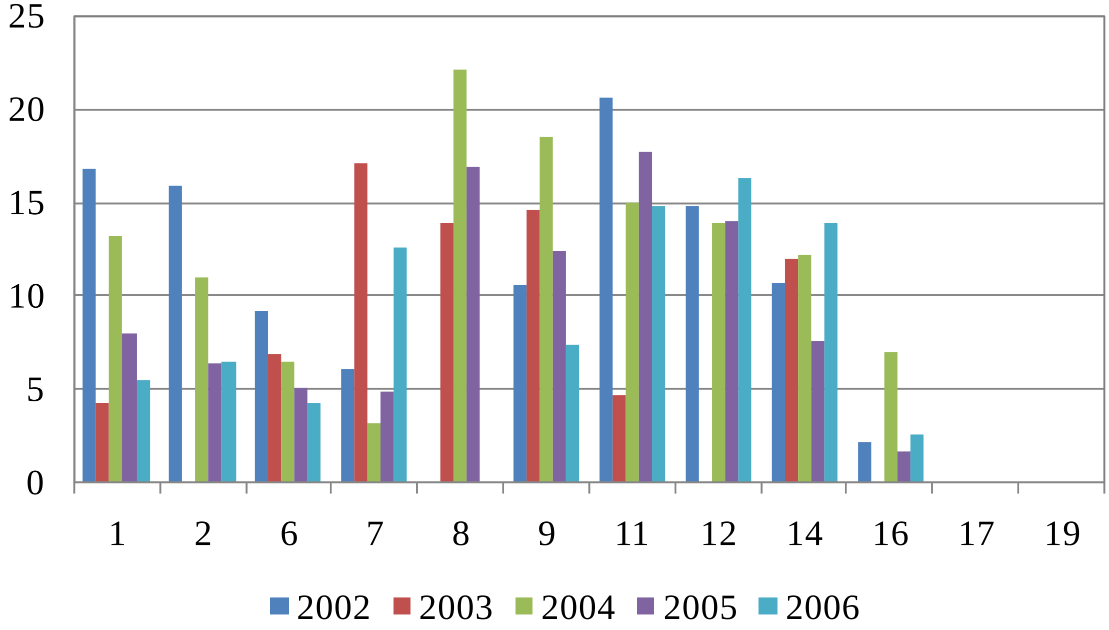


Figure F.2. Method One coefficient of variation for 3-Card total volume.

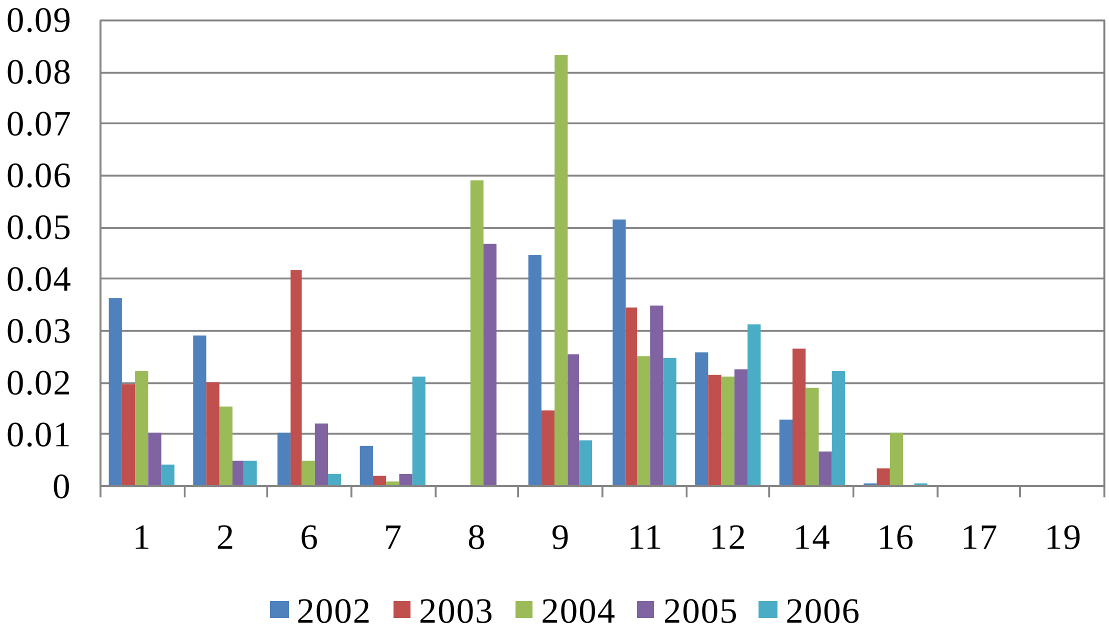


Figure F.3. Method One variance for 3-Card total volume.

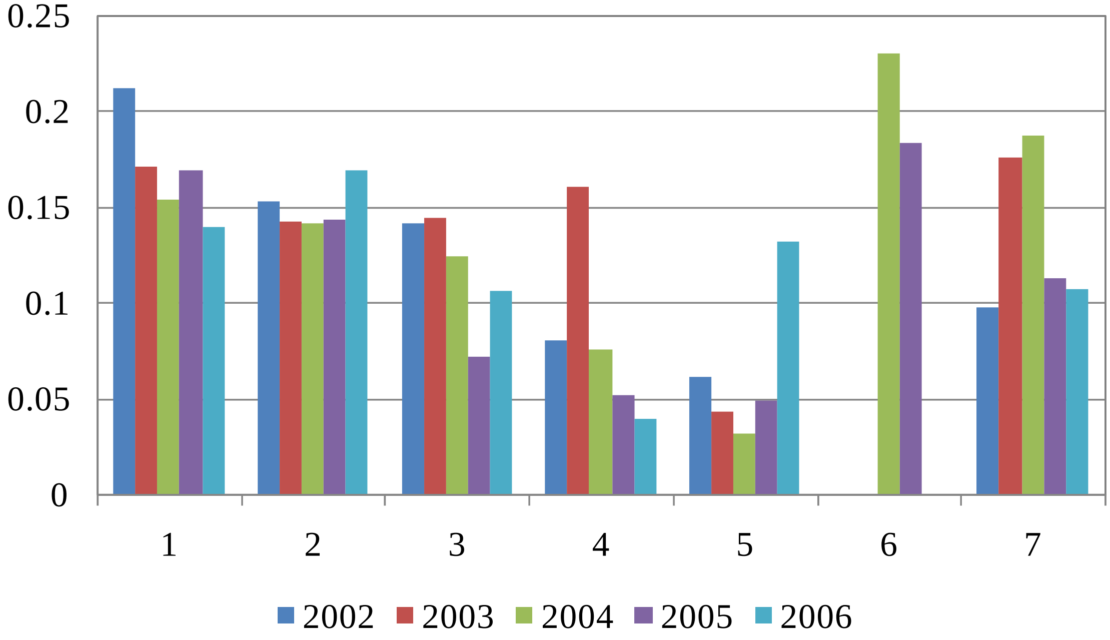


Figure F.4. Method Two standard deviation for 3-Card total volume.

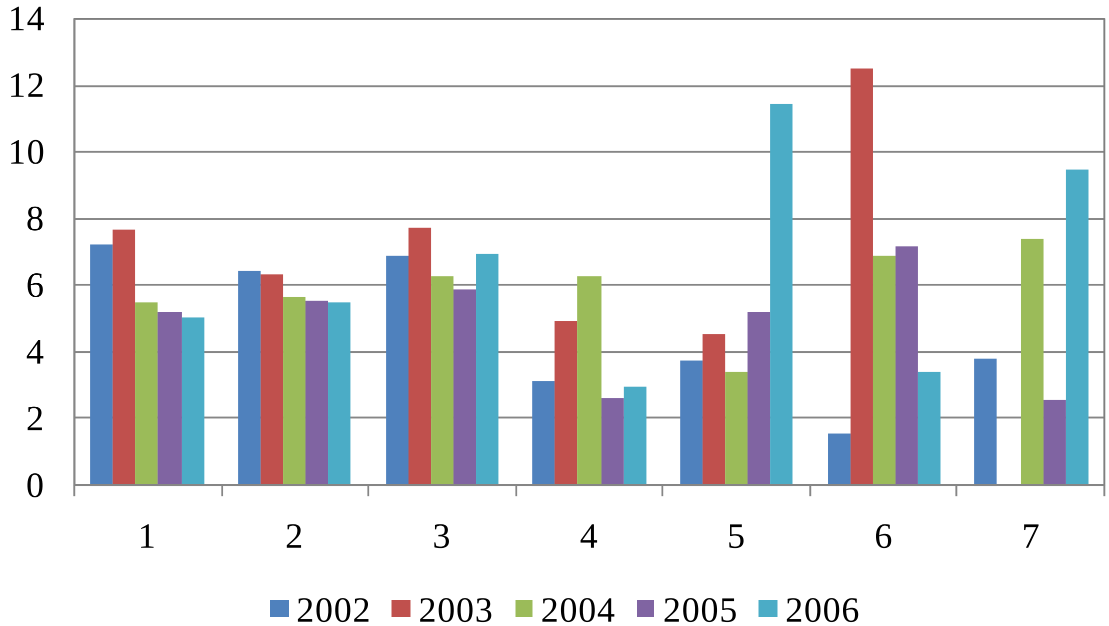


Figure F.5. Method Two coefficient of variation for 3-Card total volume.

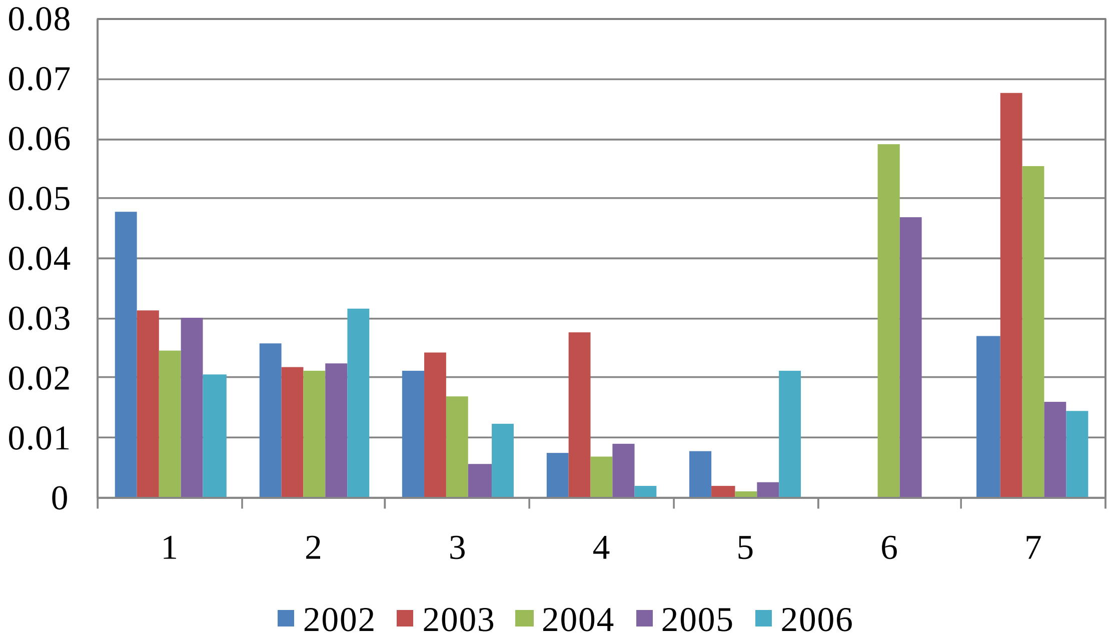


Figure F.6. Method Two variance for 3-Card total volume.

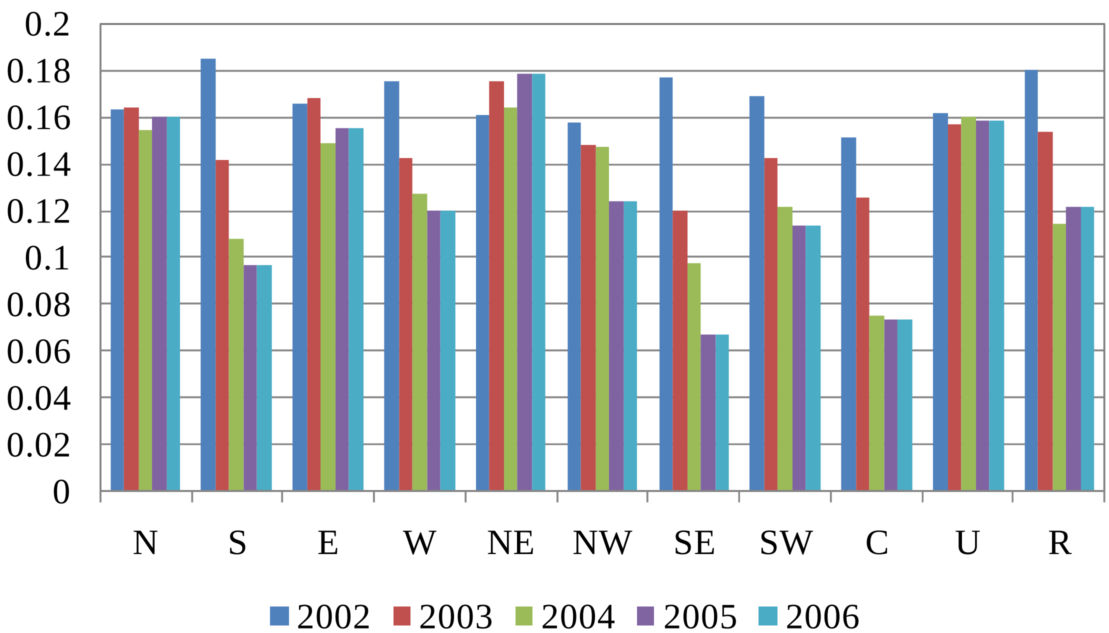


Figure F.7. Method Three standard deviation for 3-Card total volume.

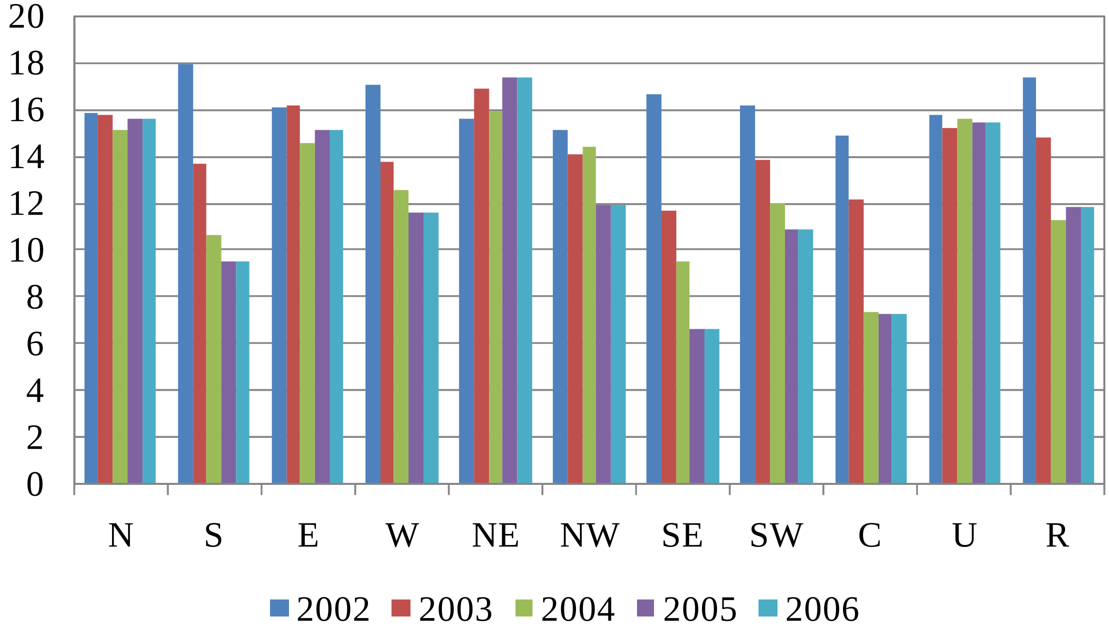


Figure F.8. Method Three coefficient of variation for 3-Card total volume.

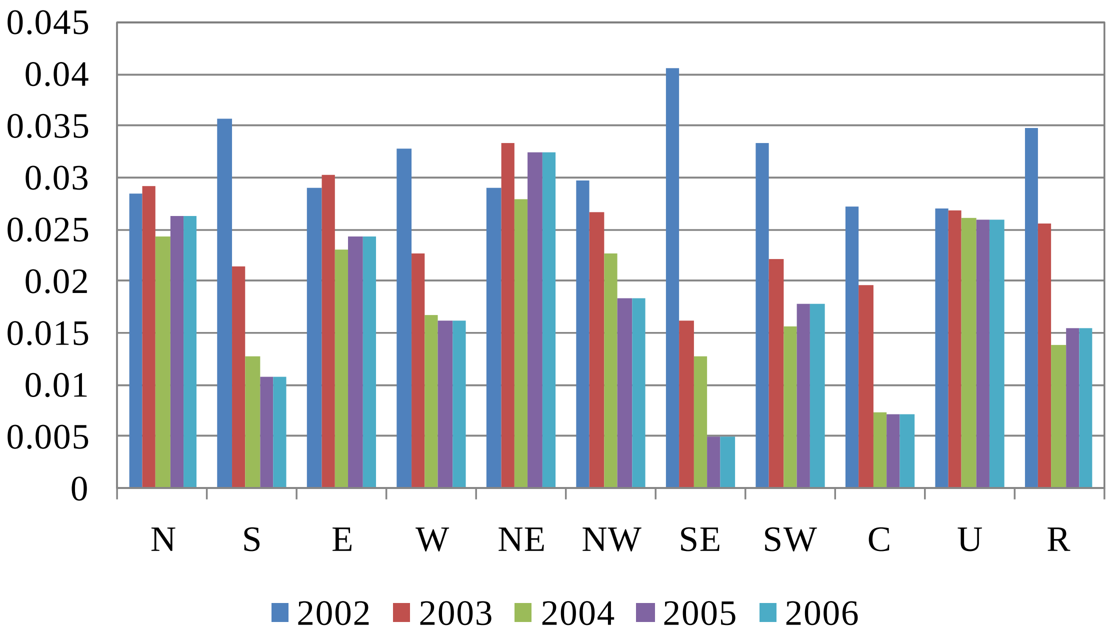


Figure F.9. Method Three variance for 3-Card total volume.

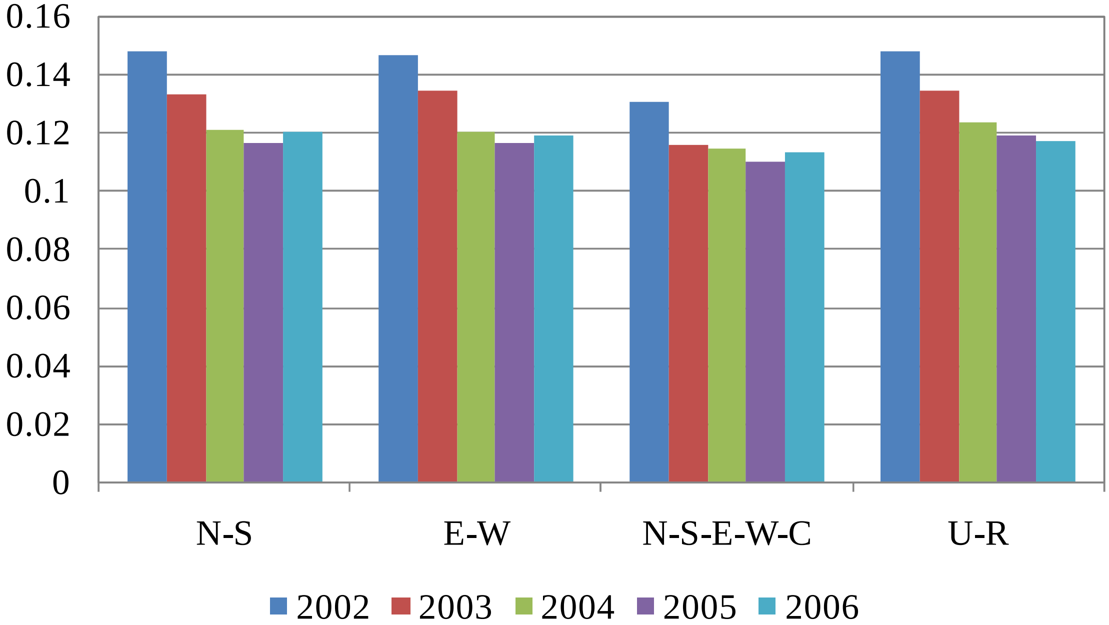


Figure F.10. Method Four standard deviation for 3-Card total volume.

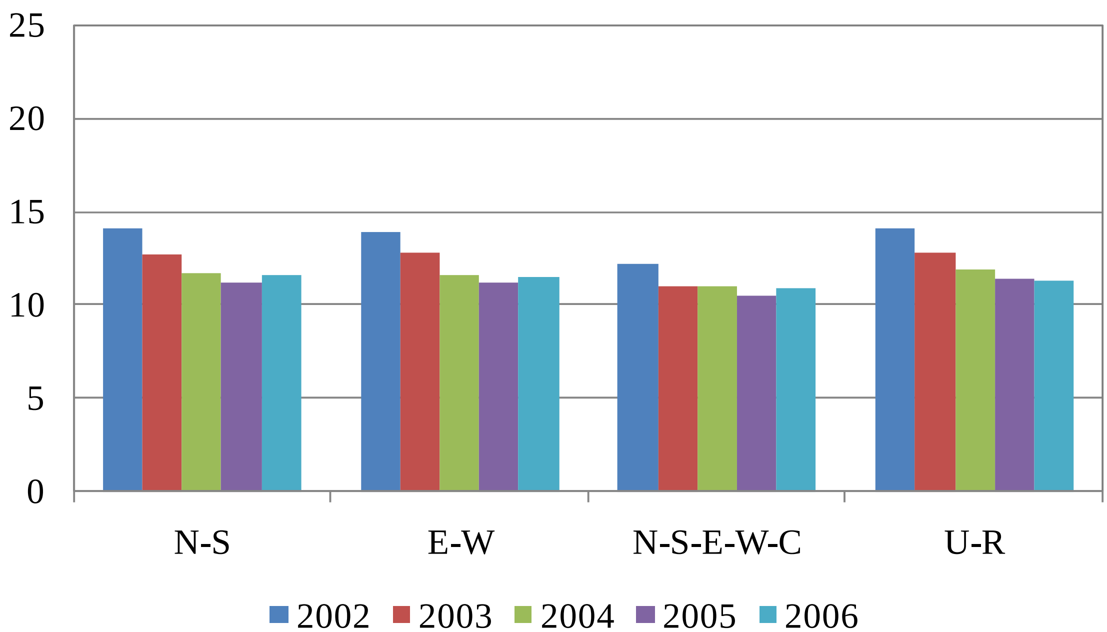


Figure F.11. Method Four coefficient of variation for 3-Card total volume.

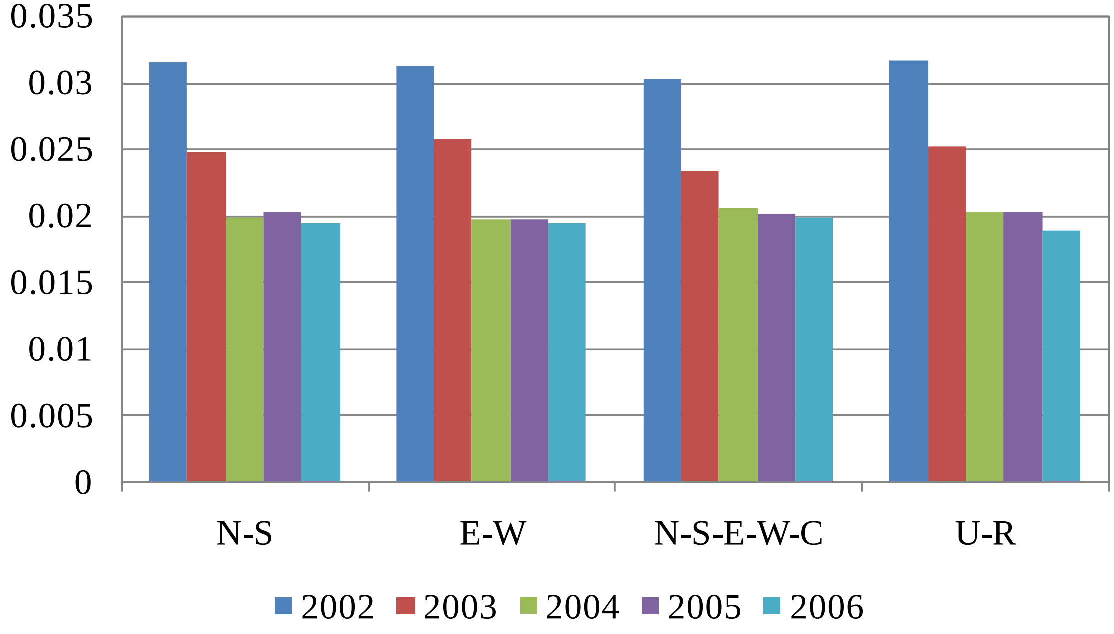


Figure F.12. Method Four variance for 3-Card total volume.

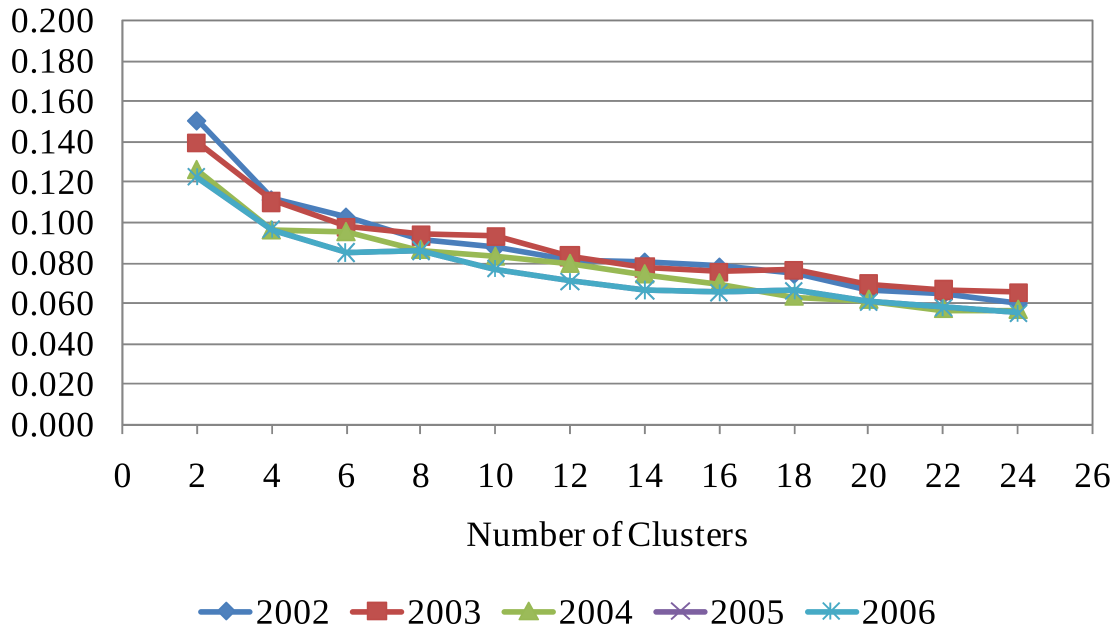


Figure F.13. Method Five standard deviation 3-Card total volume.

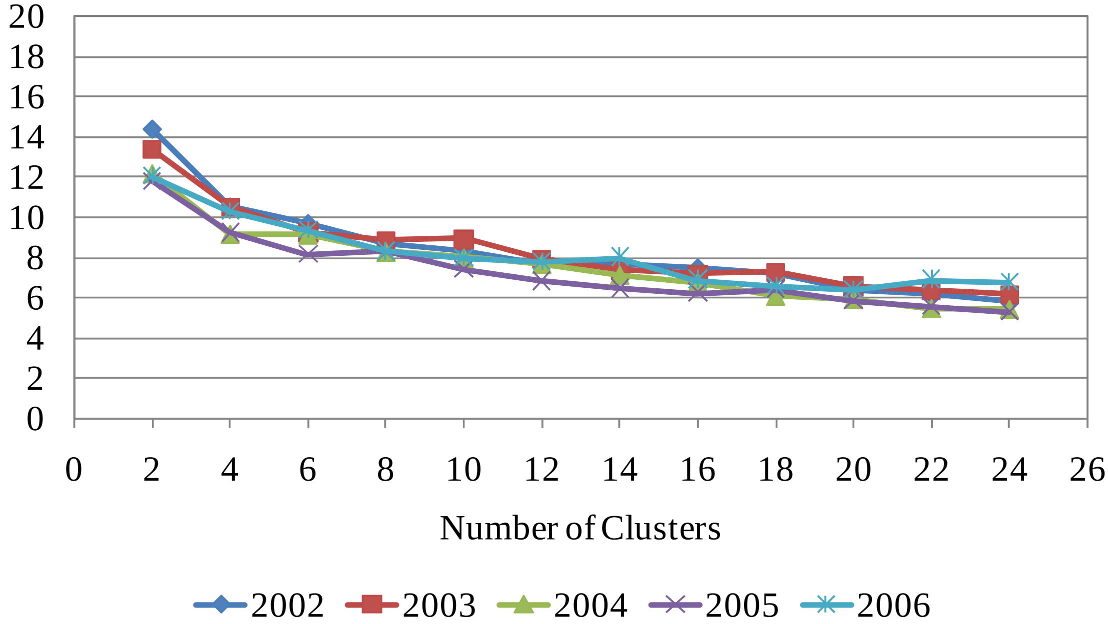


Figure F.14. Method Five coefficient of variation 3-Card total volume.

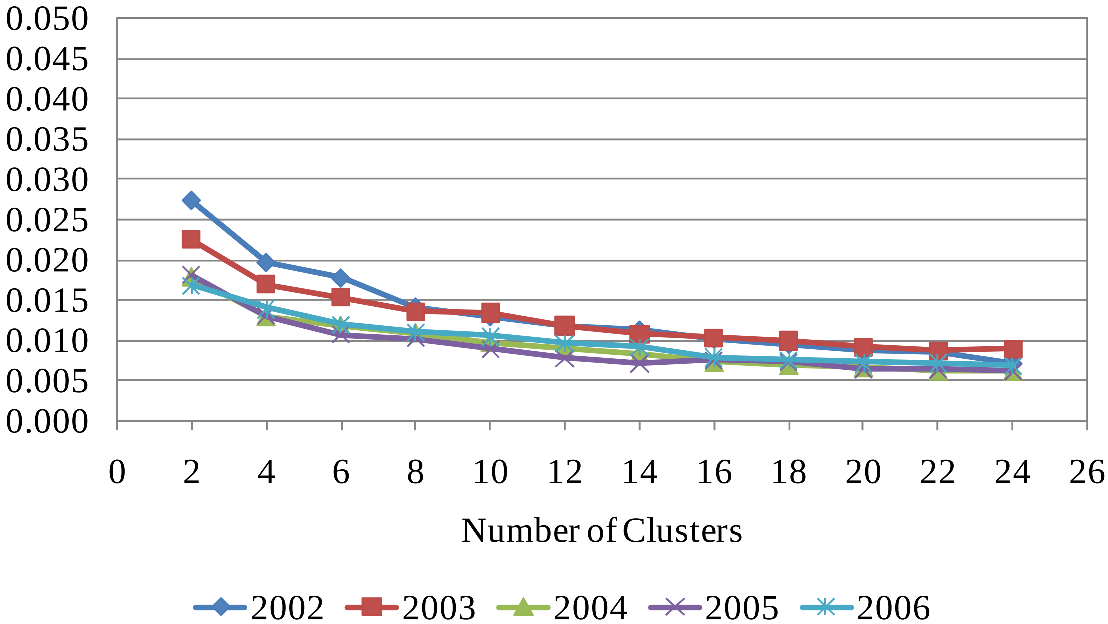


Figure F.15. Method Five variance 3-Card total volume.

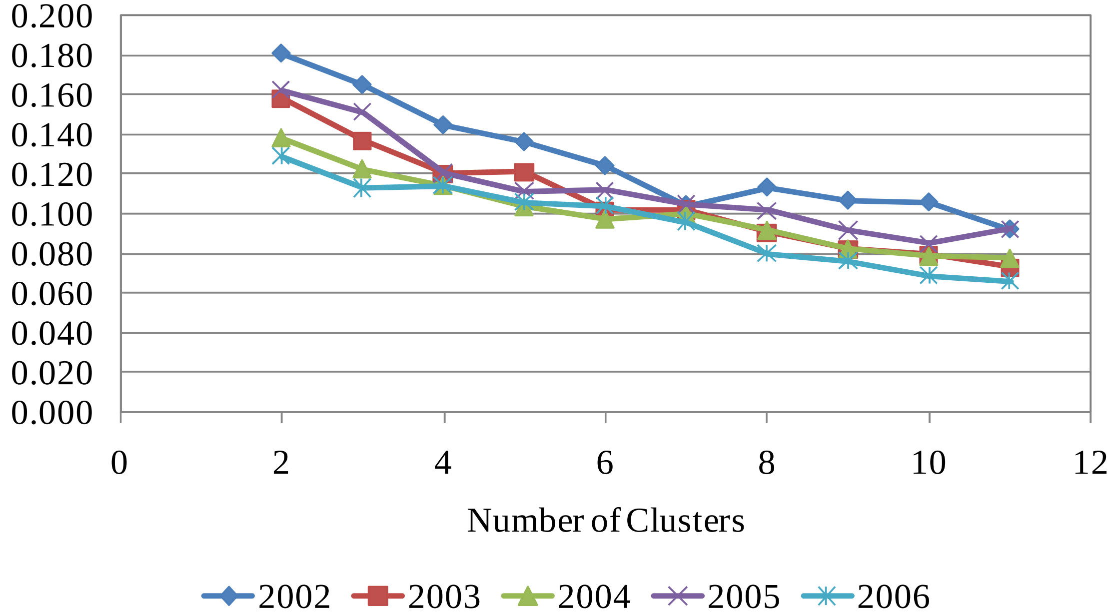


Figure F.16. Method Six standard deviation 3-Card total volume for roadway functional class 11.

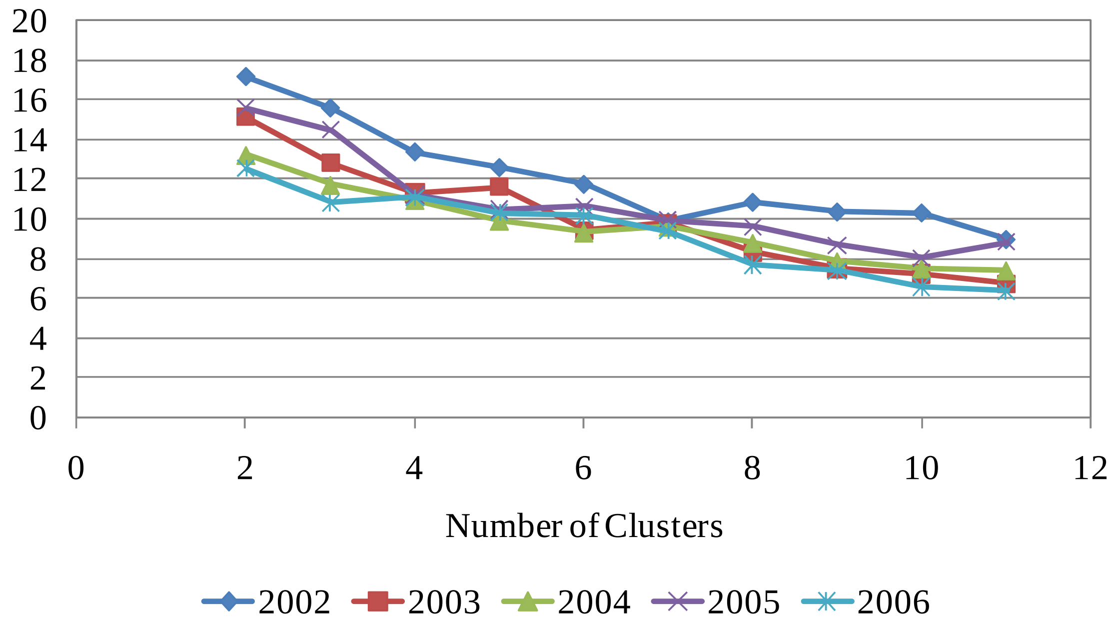


Figure F.17. Method Six coefficient of variation 3-Card total volume for roadway functional class 11.

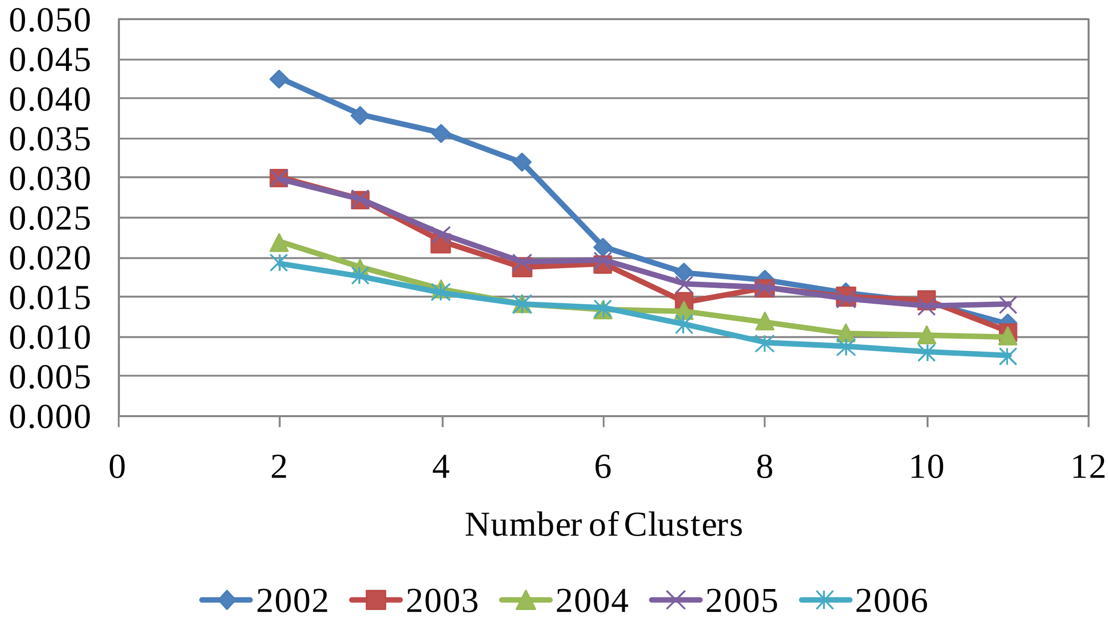


Figure F.18. Method Six variance 3-Card total volume for roadway functional class 11.

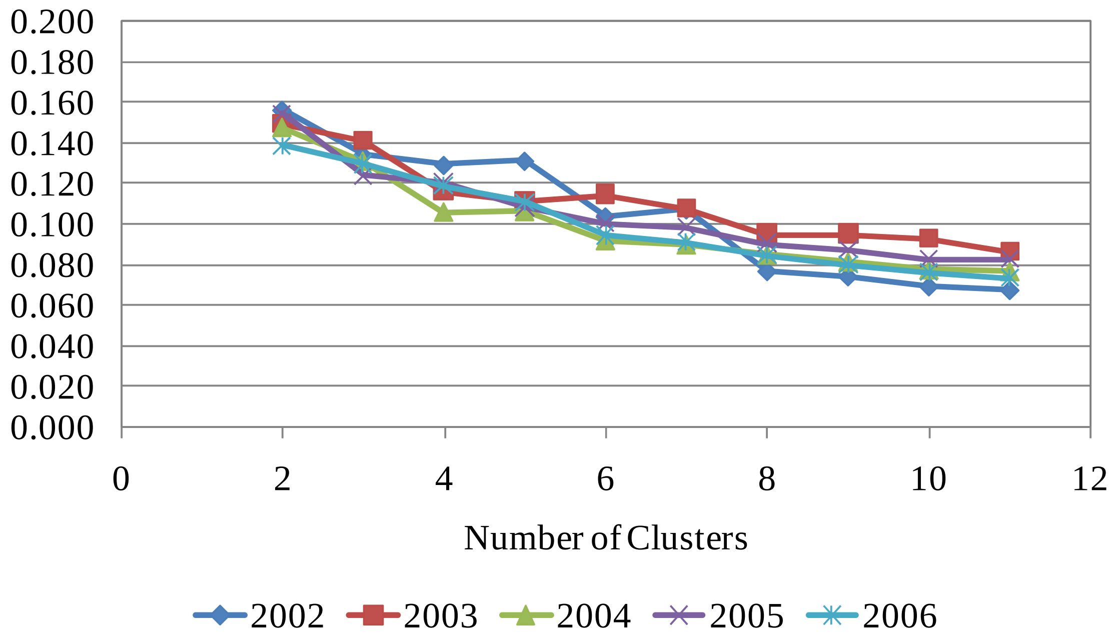


Figure F.19. Method Seven standard deviation 3-Card total volume for northeast Ohio.

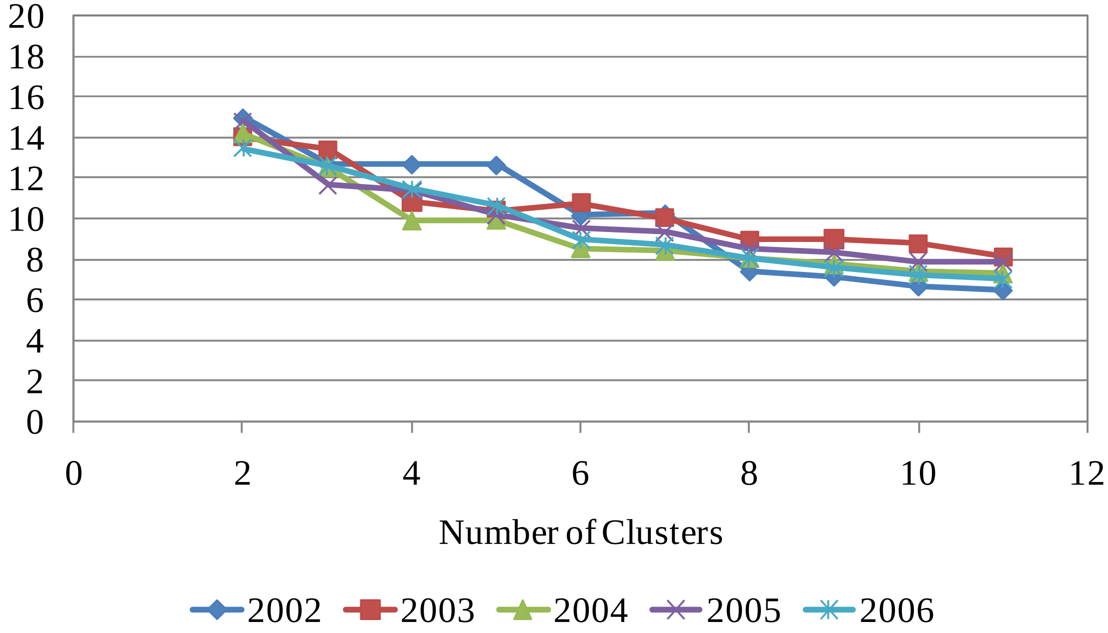


Figure F.20. Method Seven coefficient of variation 3-Card total volume for northeast Ohio.

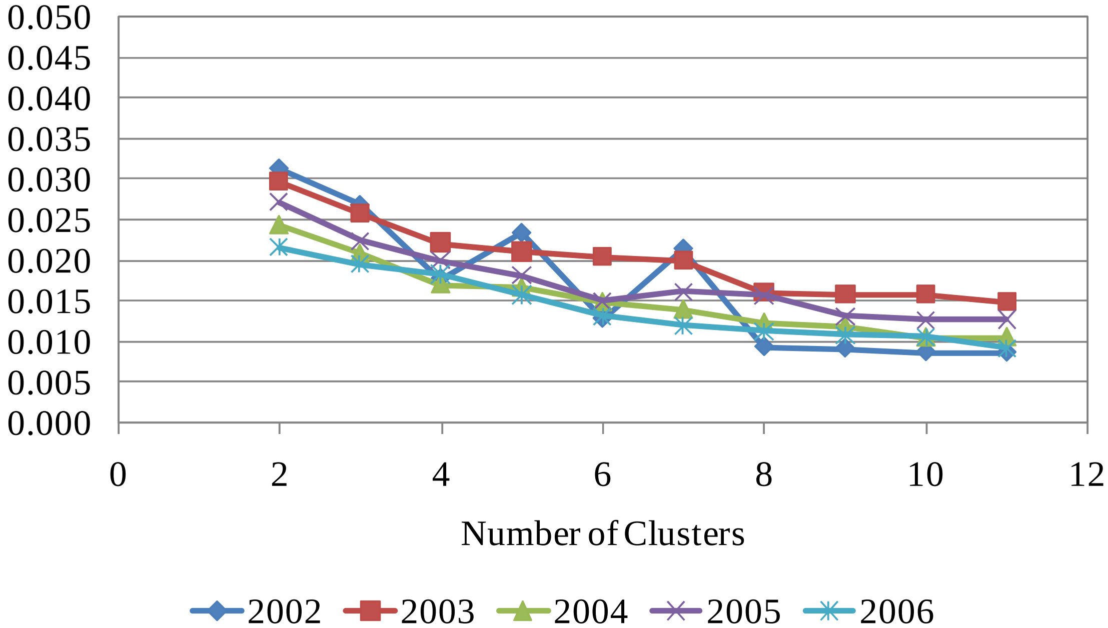


Figure F.21. Method Seven variance 3-Card total volume for northeast Ohio.

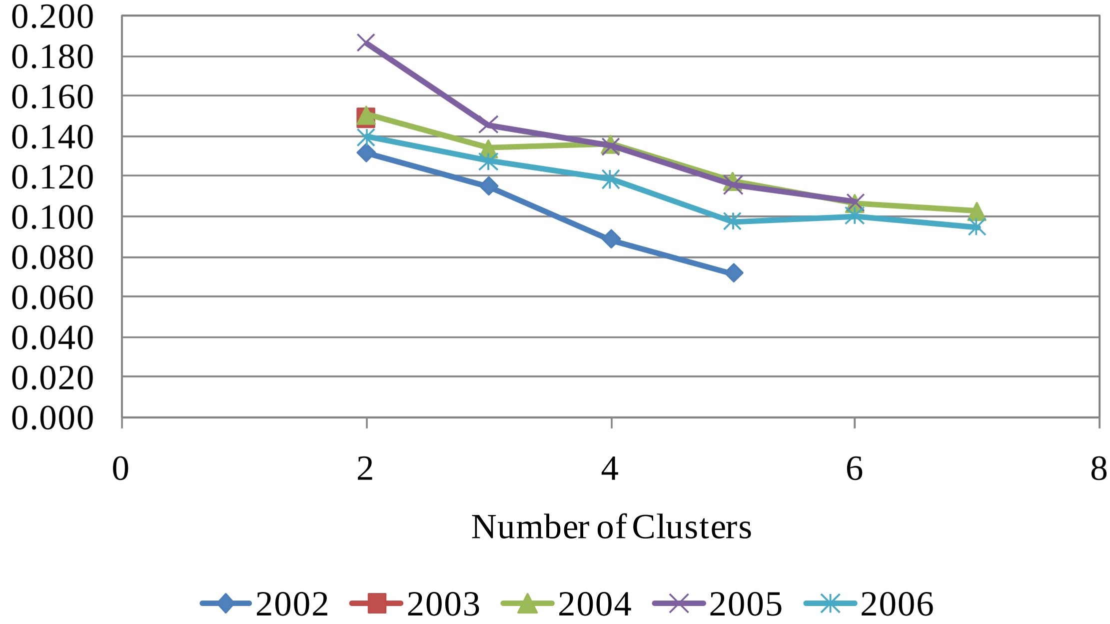


Figure F.22. Method Eight standard deviation 3-Card total volume for northeast Ohio functional class 11.

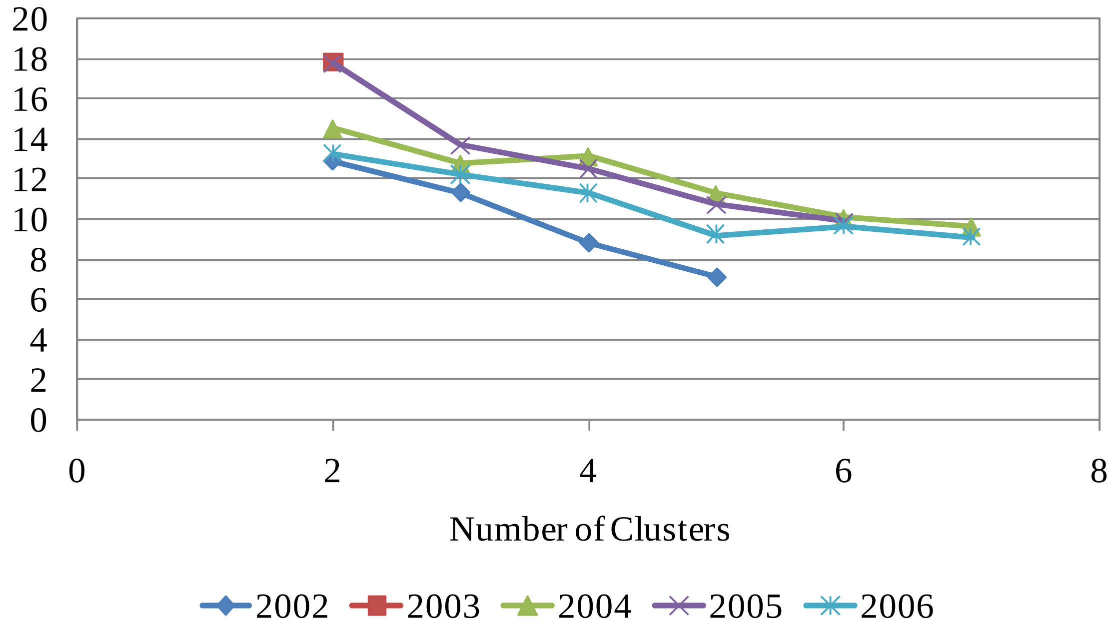


Figure F.23. Method Eight coefficient of variation 3-Card total volume for northeast Ohio functional class 11.

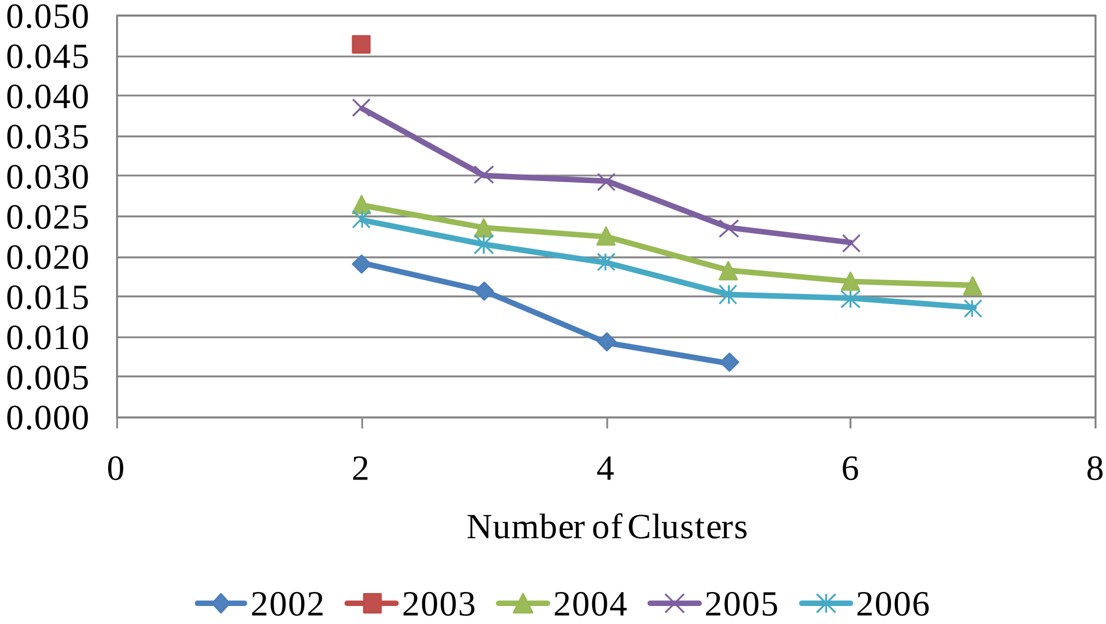


Figure F.24. Method Eight variance 3-Card total volume for northeast Ohio functional class 11.

APPENDIX G

COMPARISON OF GROUPING METHODS

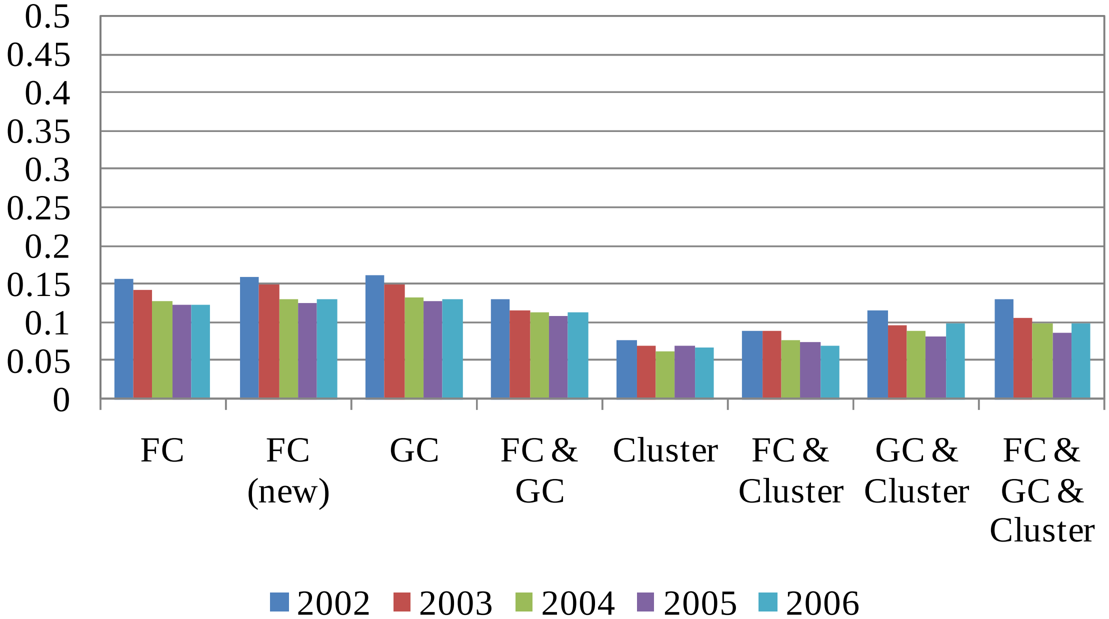


Figure G.1. Standard deviation summary results for 3-Card total volume.

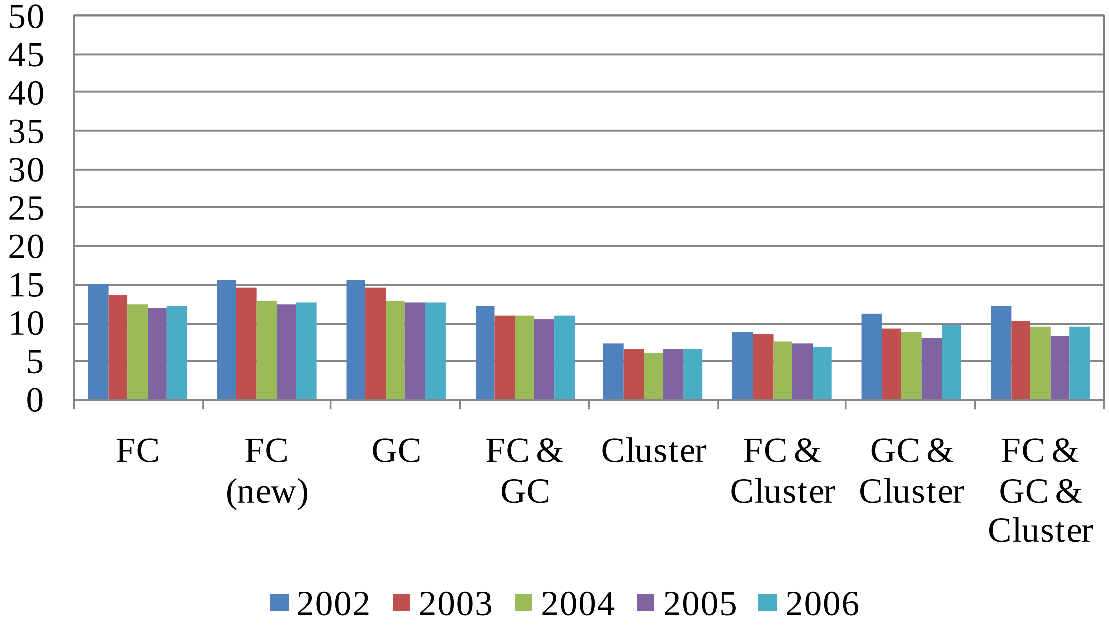


Figure G.2. Coefficient of variation summary results for 3-Card total volume.

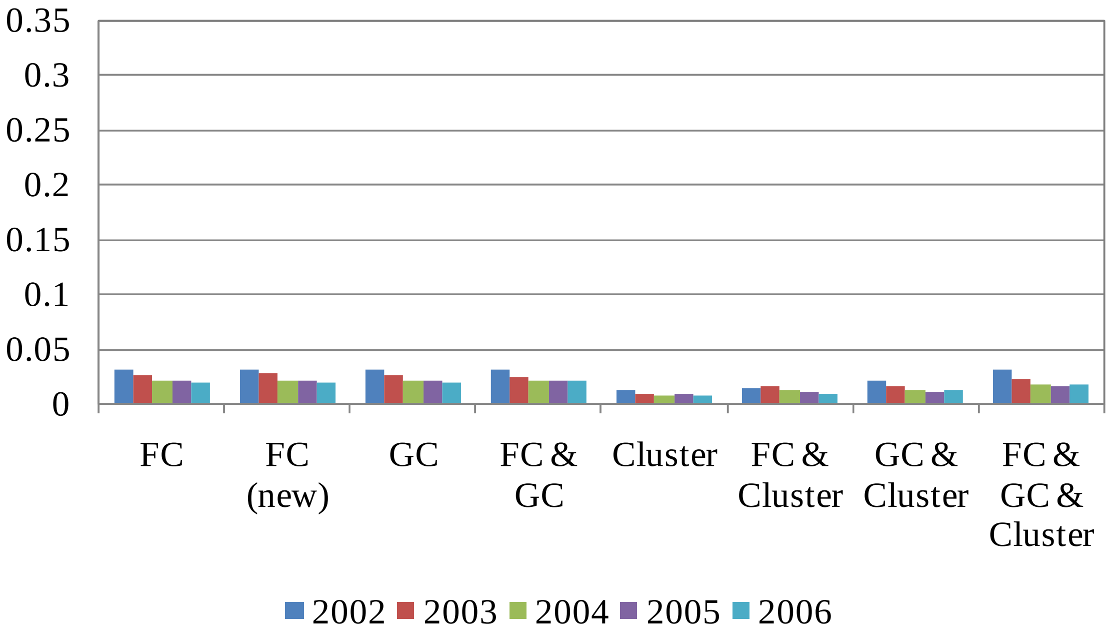


Figure G.3. Variance summary results for 3-Card total volume.

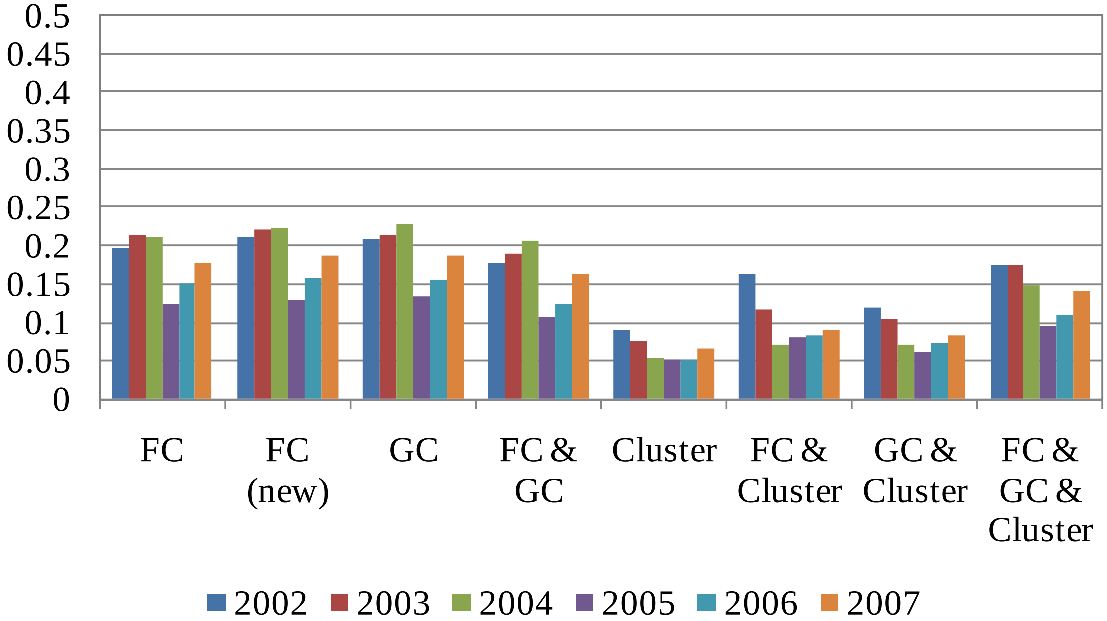


Figure G.4. Standard deviation summary results for C-Card total volume.

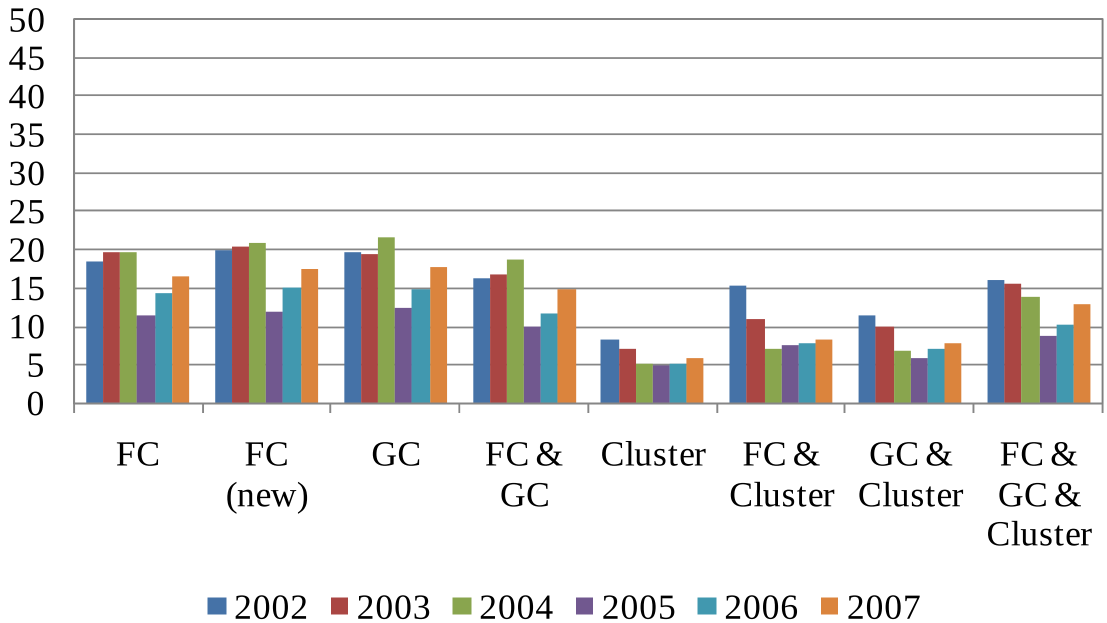


Figure G.5. Coefficient of variation summary results for C-Card total volume.

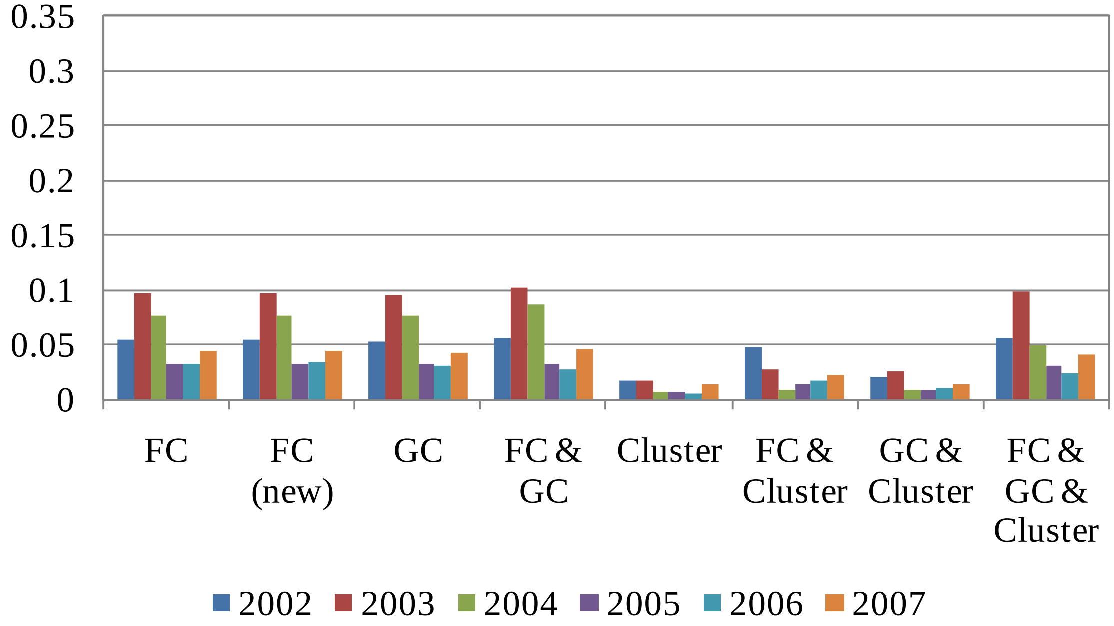


Figure G.6. Variance summary results for C-Card total volume.

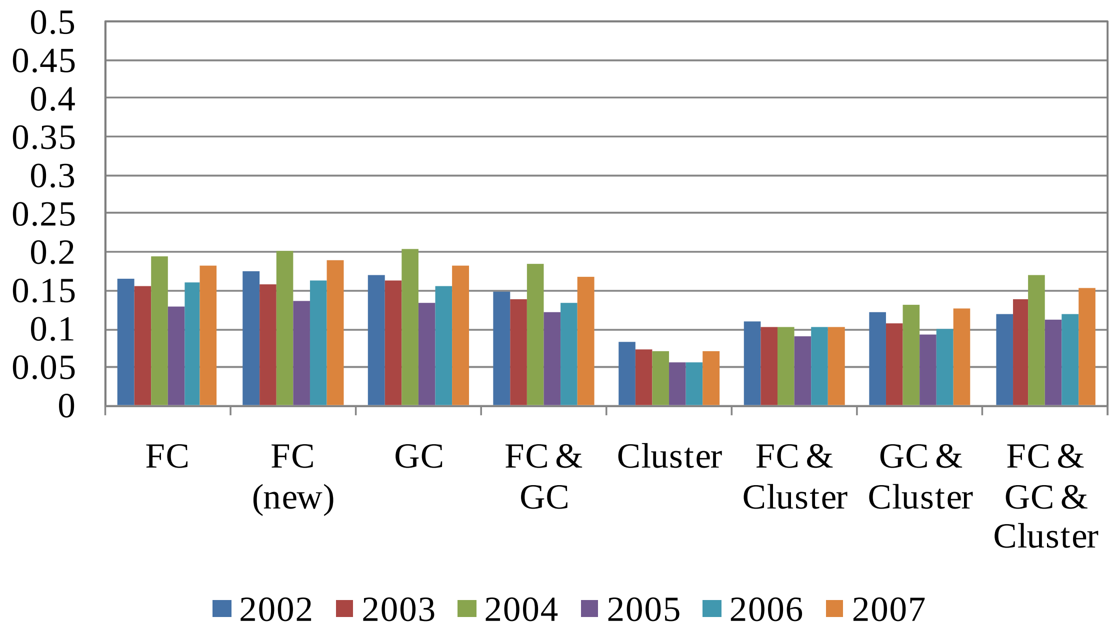


Figure G.7: Standard deviation summary results for C-Card vehicle classes 1 through 3 both directions.

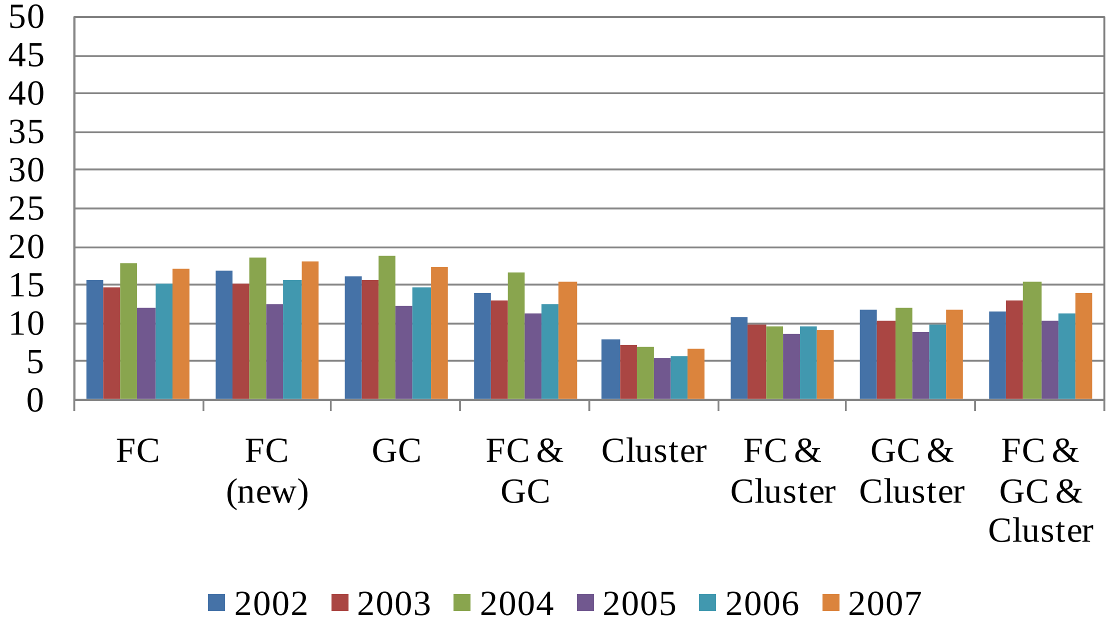


Figure G.8. Coefficient of variation summary results for C-Card vehicle classes 1 through 3 both directions.

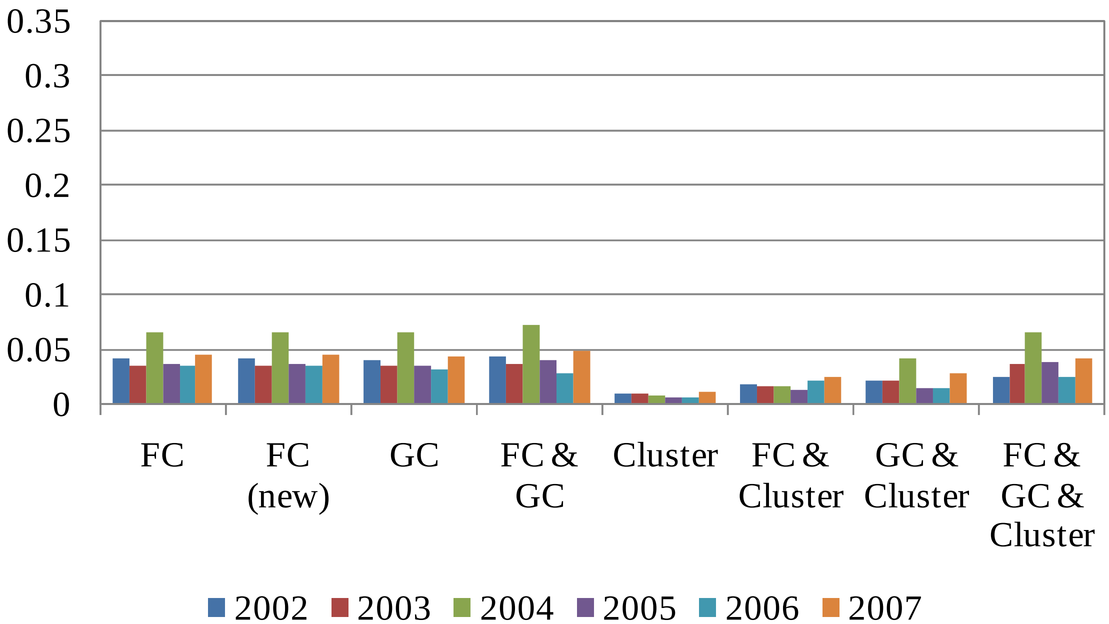


Figure G.9. Variance summary results for C-Card vehicle classes 1 through 3 both directions.

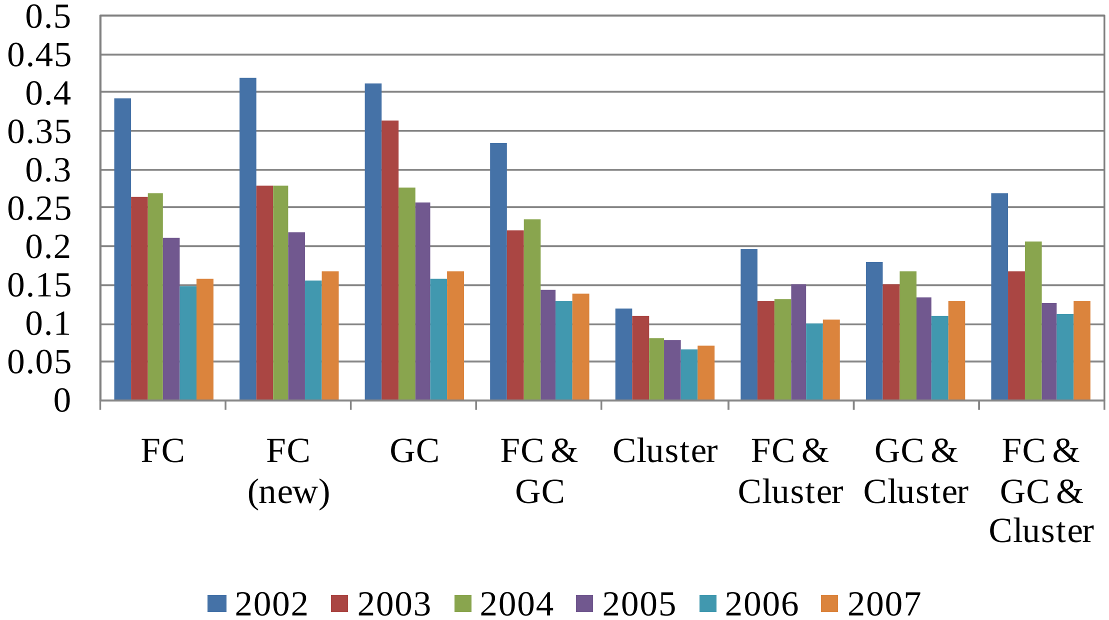


Figure G.10. Standard deviation summary results for C-Card vehicle classes 4 through 13 both directions.

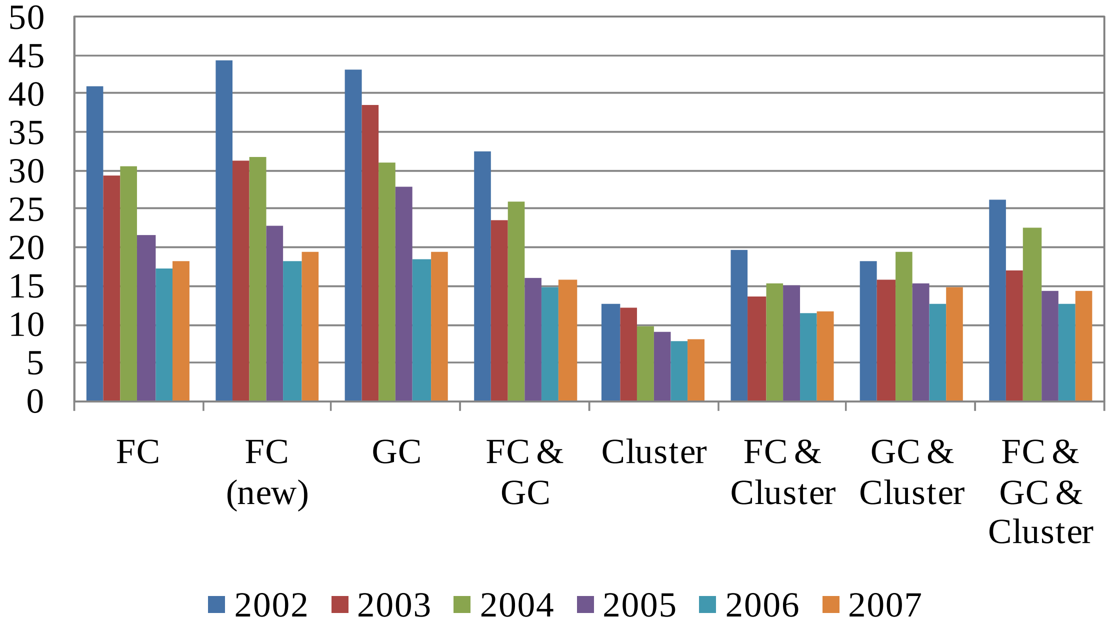


Figure G.11. Coefficient of variation summary results for C-Card vehicle classes 4 through 13 both directions.

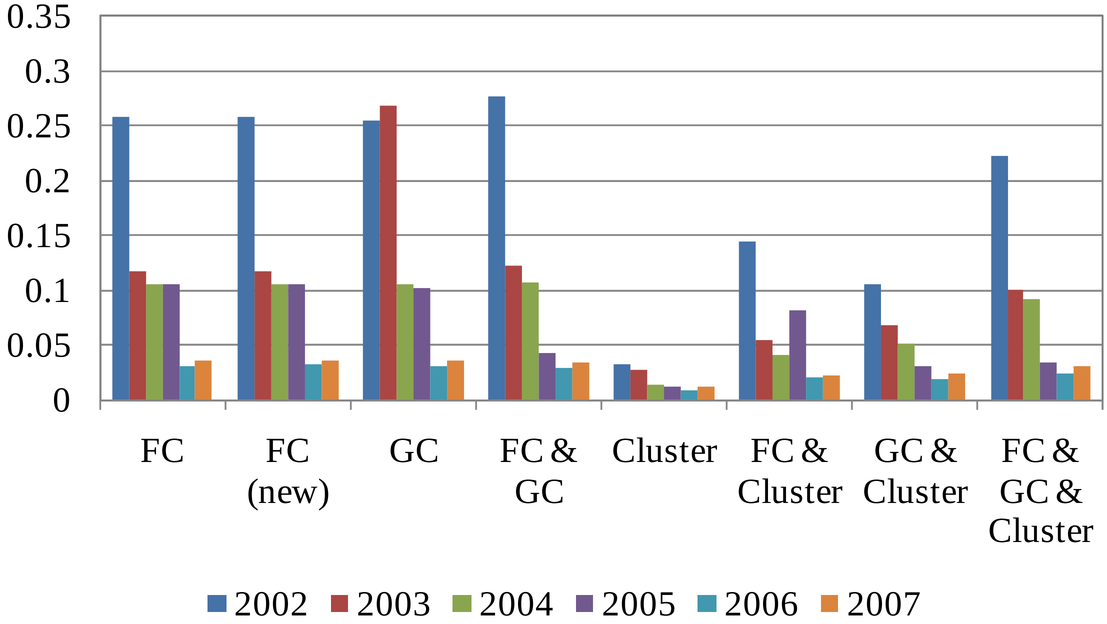


Figure G.12.Variance summary results for C-Card vehicle classes 4 through 13 both directions.

APPENDIX H

DIFFERENCE BETWEEN AADT ESTIMATES

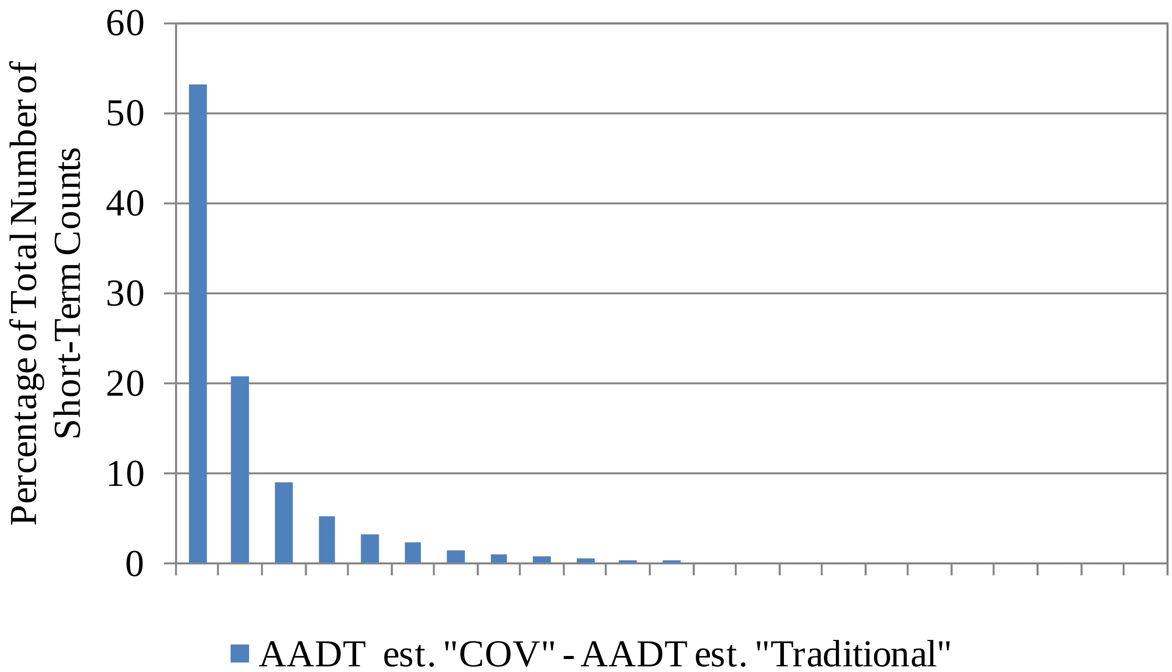


Figure H.1. Range and percentage of the absolute AADT difference between the COV approach and the traditional method for light-duty vehicles using directional factors.

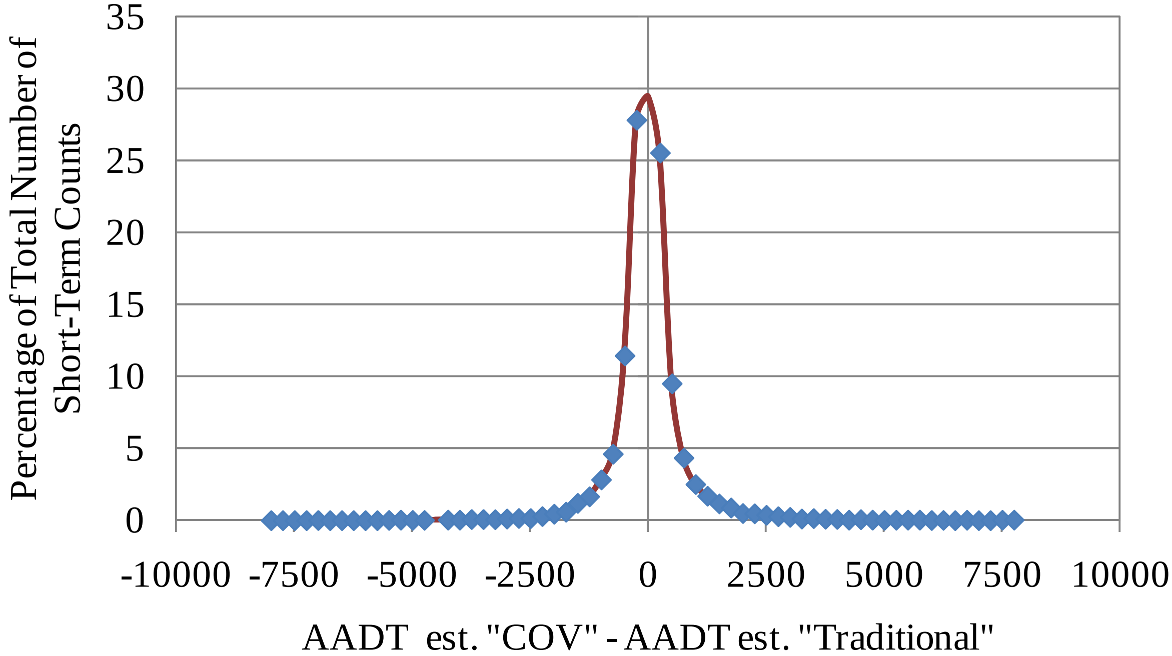


Figure H.2. Percentage of the AADT difference between the COV approach and the traditional method for light-duty vehicles using directional factors.

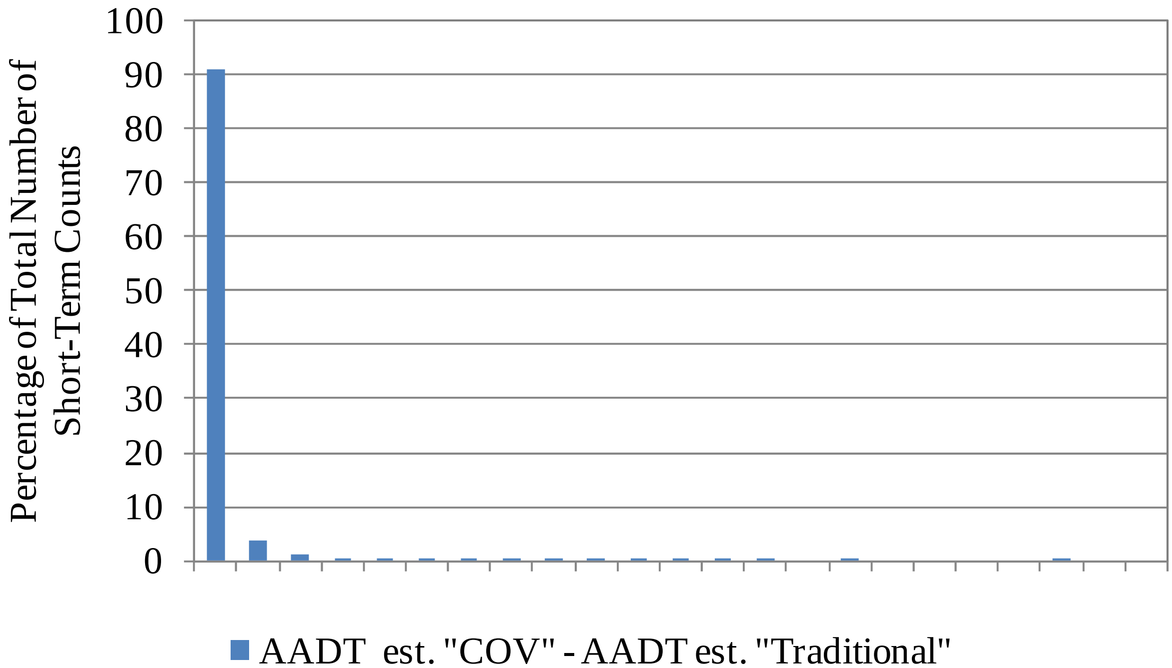


Figure H.3. Range and percentage of the absolute AADT difference between the COV approach and the traditional method for heavy-duty vehicles using directional factors.

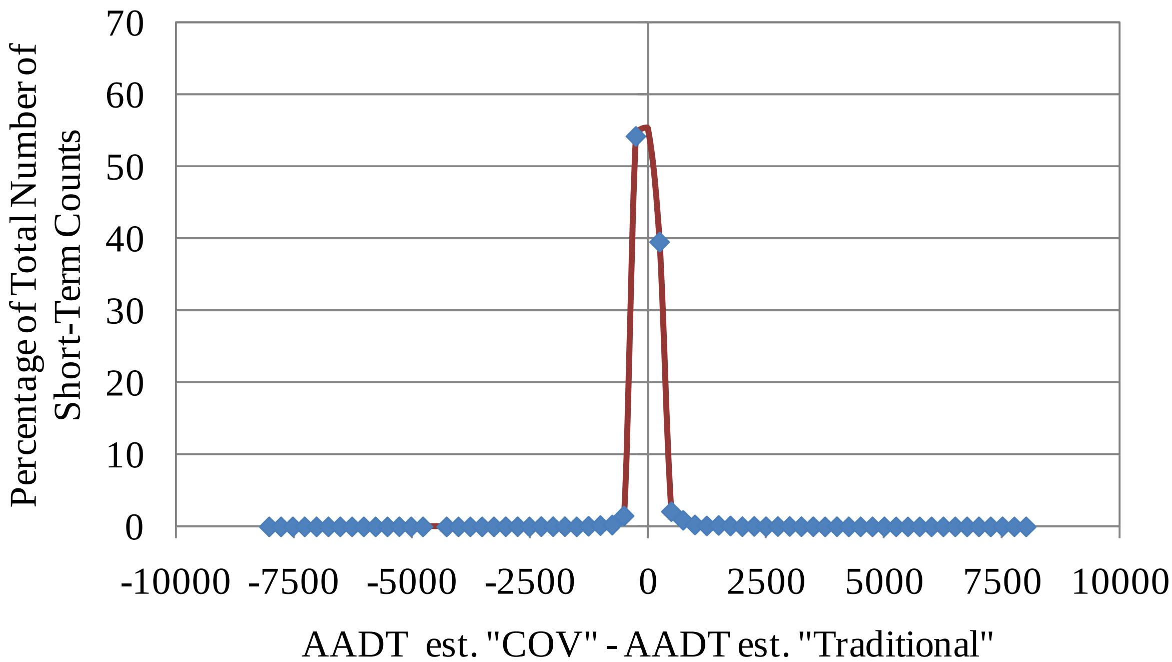


Figure H.4. Percentage of the AADT difference between the COV approach and the traditional method for heavy-duty vehicles using directional factors.

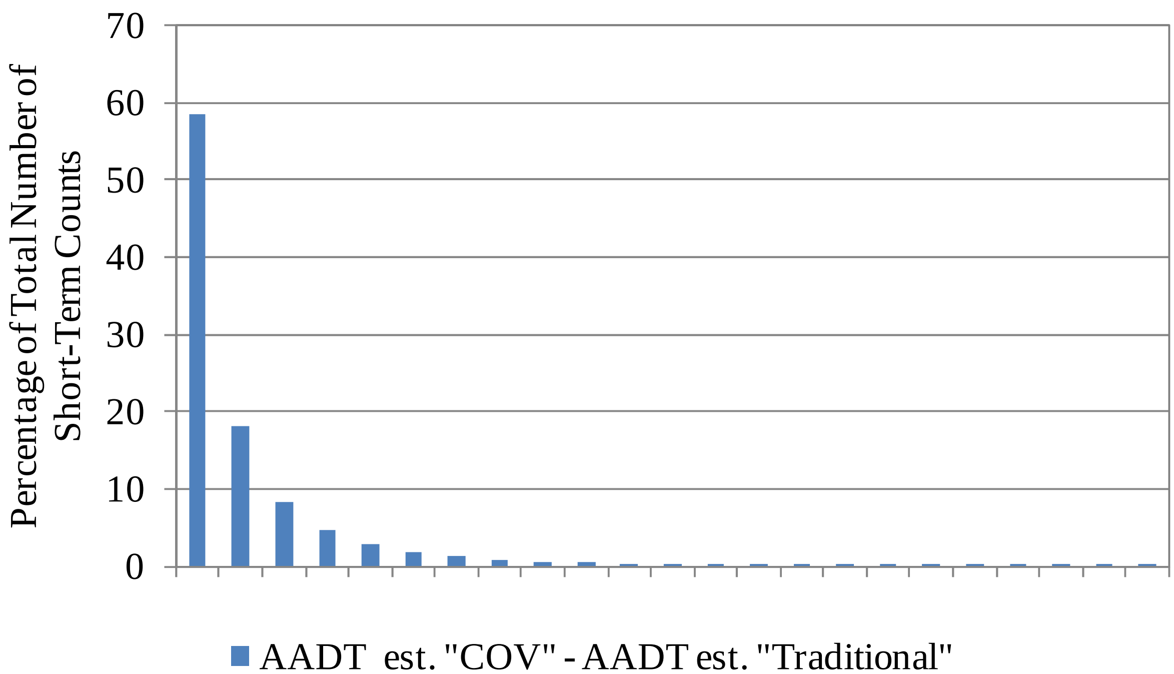


Figure H.5. Range and percentage of the absolute AADT difference between the COV approach and the traditional method for total volume using two-way volume factors.

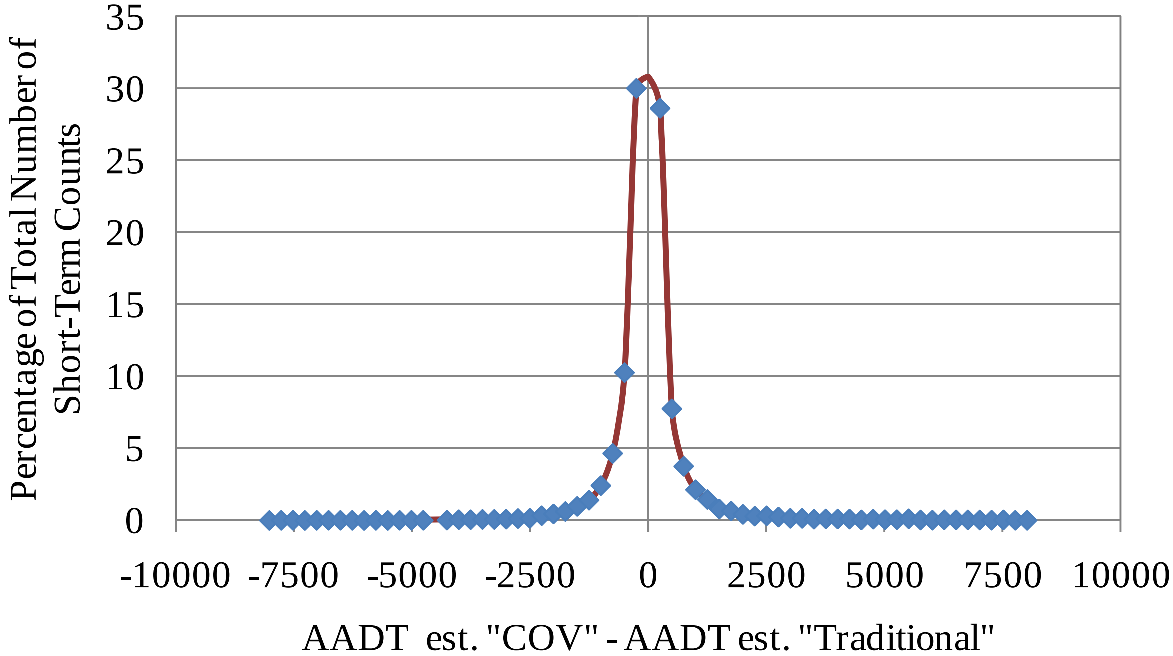


Figure H.6. Percentage of the AADT difference between the COV approach and the traditional method for total volume using two-way volume factors.

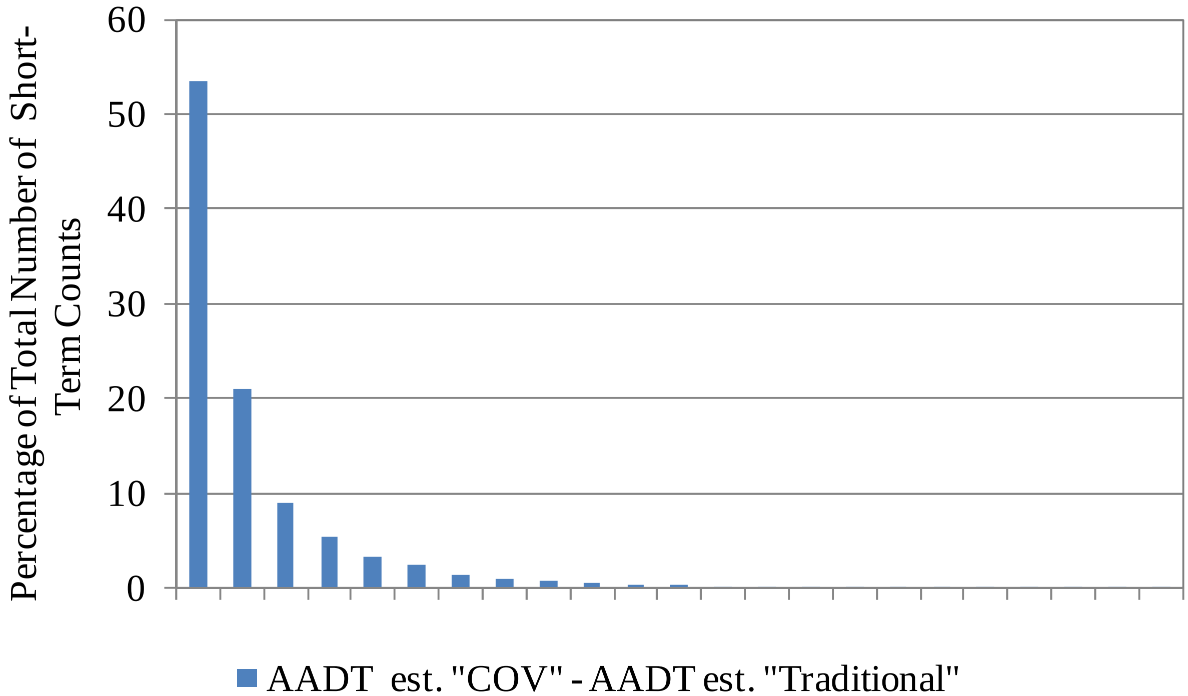


Figure H.7. Range and percentage of the absolute AADT difference between the COV approach and the traditional method for light-duty vehicles using two-way volume factors.

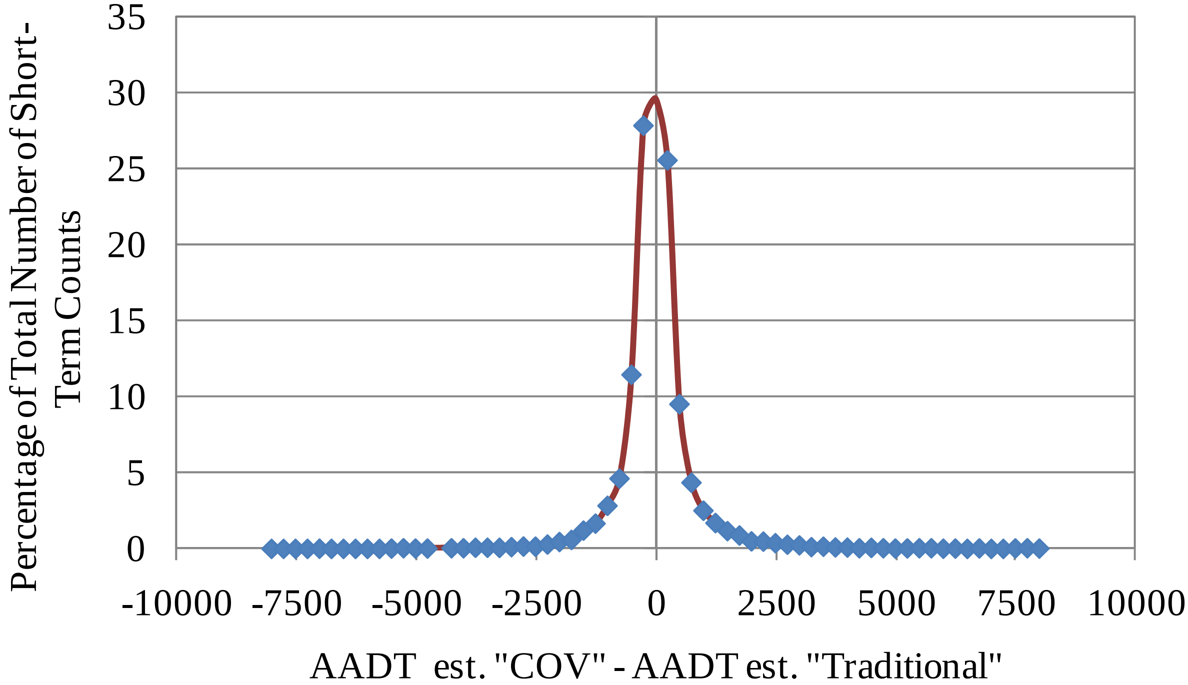


Figure H.8. Percentage of the AADT difference between the COV approach and the traditional method for light-duty using two-way volume factors.

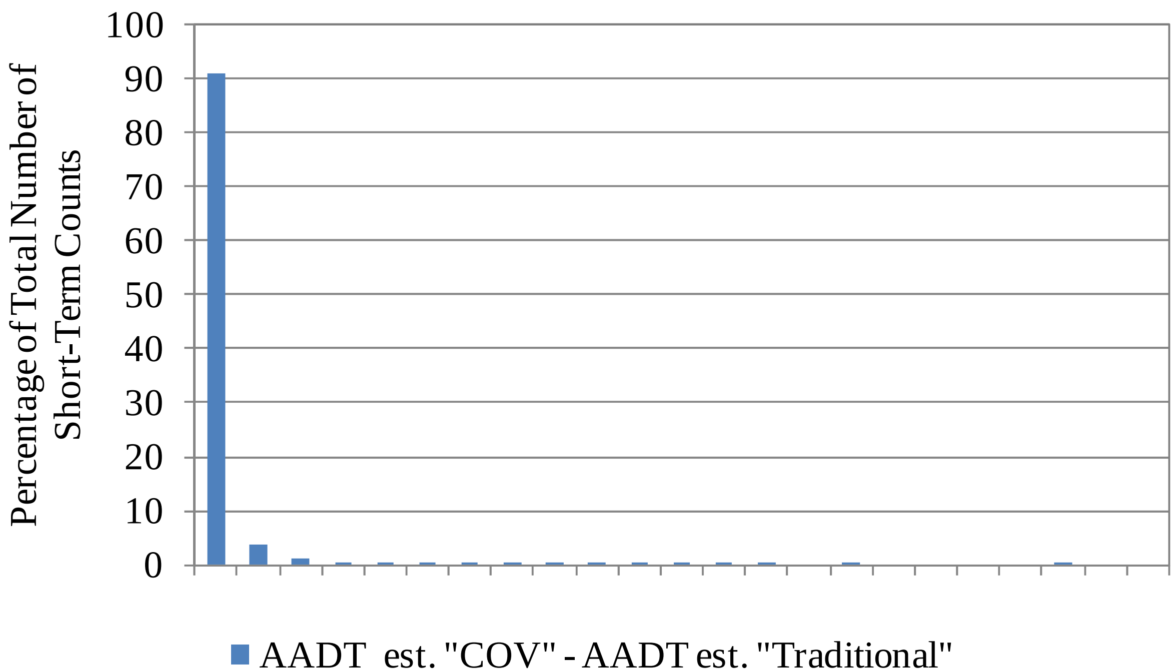


Figure H.9. Range and percentage of the absolute AADT difference between the COV approach and the traditional method for heavy-duty vehicles using two-way volume factors.

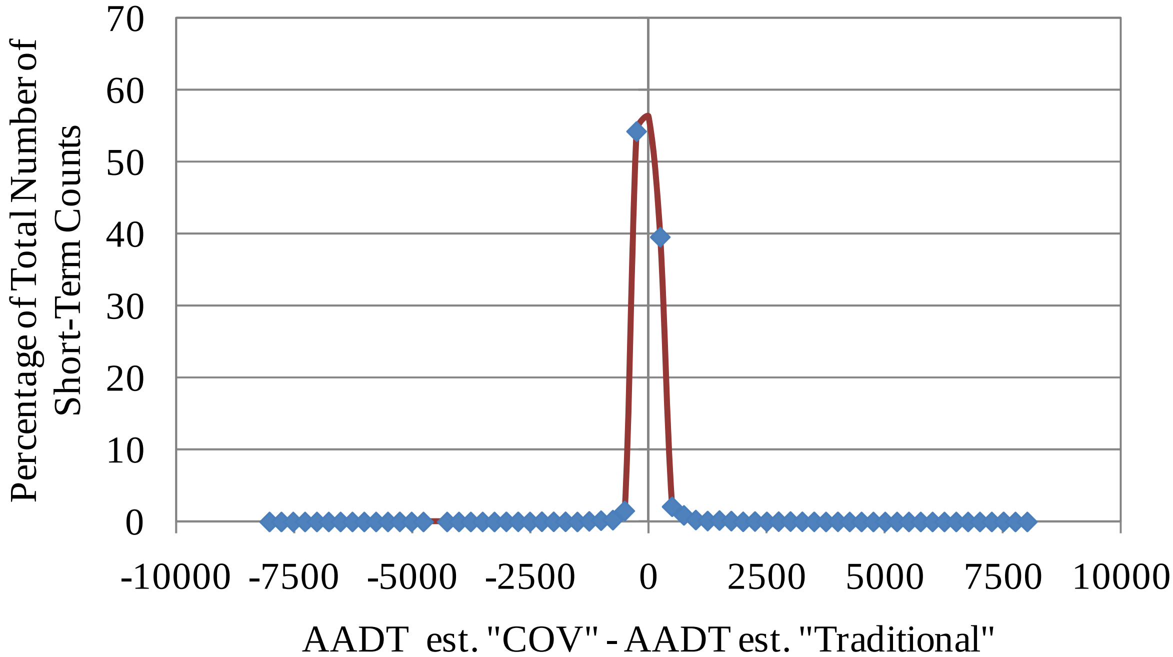


Figure H.10. Percentage of the AADT difference between the COV approach and the traditional method for heavy-duty using two-way volume factors.

APPENDIX I

LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
AAHDT	Average Annual Average Half Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ADT	Average Daily Traffic
AF	Adjustment Factor
AHDT	Average Half Daily Traffic
ART	Adaptive Resonance Theory
ATR	Automatic Traffic Recorder
ATRG	Automatic Traffic Recorder Group
CNT	Coordinated Network Test
COV	Coefficient of Variation
DA	Discriminant Analysis
DOT	Department of Transportation
FHWA	Federal Highway Administration
FC	Functional Class
GIS	Geographic Information Systems

HPMS	Highway Performance Monitoring System
IAE	Index of Effectiveness
MAE	Mean Absolute Error
MAWDT	Monthly Average Weekday Daily Traffic
MDT	Mean Daily Traffic
MPO	Metropolitan Planning Organization
MSE	Mean Squared Error
NLFID	Network Linear Feature Identification
NN	Neural Network
QA/QC	Quality Assurance Quality Control
ODOT	Ohio Department of Transportation
PTC	Permanent Traffic Counters
RAF	Reciprocal of the Adjustment Factors
RAMP	Responsible Alcohol Management Program
RI	Roadway Inventory
SAF	Seasonal Adjustment Factor
SD	Standard Deviation
SQL	Structured Query Language
TKO	Traffic Keeper of Ohio
TMG	Traffic Monitoring Guide
TTMS	Telemetry Traffic Monitoring Site

VOL	Volume
WAADT	Weekly Average Annual Daily Traffic
WADT	Weekly Average Daily Traffic
WCOV	Weighted Coefficient of Variation
WIM	Weigh in Motion